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Activities speak louder than words

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CHAPTER 2

Big (data) insights into what employees do

A comparison between task inventory and text mining job analysis methods

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Abstract

Although work has changed over the past decades, detailed studies on what it is that employees do in these changing jobs are lagging behind. Researchers and practitioners alike miss information about how work could best be organized to facilitate employee well-being. The development of methods such as text mining could provide a viable means of addressing the issues current job analysis methods have with uncovering what employees do in the broader context of the changing nature of work. Our findings show that it is possible to automatically extract and analyze tasks from online vacancies, which have relatively high correspondence with tasks collected using a task inventory. The text mining method generally performed better on average importance and inclusion ratings due to the lower level of detail of the automatically extracted tasks. In addition, the text mining method provided a wider variety of contextualized tasks drawn from a larger sample of jobs, whereas the task inventory yielded more detailed and more mundane tasks. Text mining thus complements rather than substitutes current job analysis methods. In addition, we showed that not all tasks were equally related to employees' job satisfaction, work overload, and emotional exhaustion, making it worthwhile to include more task data in studies on employee well-being.

There is a need for more and better insight into what employees do in their contemporary jobs. Work has changed immensely over the past decades due to fast technological changes and globalization (Grant & Parker, 2009; Parker, 2014). A lot of work has become more complex, knowledge-based, and demanding in terms of requiring teamwork and flexibility (Ashford, George, & Blatt, 2007). Furthermore, work has changed due to downsizing and restructuring efforts aimed at decreasing costs while increasing efficiency, which has resulted in increased job insecurity, flexible contracts, work hours, and (experienced) workload (Sparks et al., 2001; Spreitzer et al., 2017). These trends, often collectively referred to as 'the changing nature of work', have inspired research on topics including boundaryless careers (Arthur & Rousseau, 2001), the gig-economy and alternative work arrangements (Spreitzer et al., 2017), the de-jobbing of organizations (Singh, 2008), online (team)work or teleworking (Lautsch & Kossek, 2011), and the computerization of jobs (Frey & Osborne, 2013).

Lagging behind are detailed studies on what employees actually do in these changing jobs, which means researchers and practitioners alike miss information about how work could be designed, structured, and organized (Barley & Kunda, 2001), so as to optimize employee well-being and contribution to the goals of the organization. Due to the changing nature of work, employees are increasingly exposed to stress associated with doing more and more difficult work in less time (Page & Vella-Brodrick, 2009; Sparks et al., 2001; Spreitzer et al., 2017), which in the end compromises organizational performance (Taris & Schreurs, 2009). The extent to which employees derive happiness from engaging in particular tasks, as evidenced in their job satisfaction, instead of stressed and not able to execute all their tasks considering their time, abilities, and resources (i.e., work overload) (Rizzo, House, & Lirtzman, 1970), is therefore important to organizations that strive to deploy facilitative interventions (Page & Vella-Brodrick, 2009). Few studies, however assess employee well-being at the level of tasks (cf. Taber & Alliger, 1995), even though not all work activities are equally enjoyable, important, burdensome, or meaningful. The exploration and understanding of which tasks enhance and which tasks undermine employee well-being may be pertinent to the generation of targeted interventions aimed at improving employee well-being so as to ensure that work is sustainably meaningful for employees (Michaelson, Pratt, Grant, & Dunn, 2014).

Job analysis focuses on understanding what employees do, and can be defined as the "process through which one gains an understanding of the

activities, goals, and requirements demanded by a work assignment" (Sanchez & Levine, 2012, p. 398). Job analysis is critical to HRM, since it seeks to provide accurate information about what employees do (and employee requirements or characteristics needed for job performance), and forms the basis of strategic HR practices, such as selection, compensation, job design, and training (Sanchez & Levine, 2012; Schneider & Konz, 1989; Voskuijl, 2005). The changing nature of work has challenged this strategic role of job analysis and the assumptions on which it is based are increasingly being called into question. Due to the changing environment and the (pro)active role job incumbents have in tailoring their job to their needs and desires (Wrzesniewski & Dutton, 2001), we no longer think of jobs as stable (Cronshaw, 1998) or fully amenable to standardization (Sanchez & Levine, 2012). Based likely in part on a lack of appropriate methodologies to address these challenges and therewith the dynamic nature of jobs, interest in job analysis has been steadily dropping since 1990 (Morgeson & Dierdorff, 2011; Sanchez & Levine, 2012).

The evolution of the data driven society may help address at least some of these challenges in job analysis by tackling the issue of nonstandard and dynamic jobs, as 'big data' may provide pioneering and powerful means of understanding what employees in different jobs currently do. Indeed, a big data based approach to job analysis could complement traditional methods, while addressing some of its limitations (Fine, Harvey, & Cronshaw, 2004; Sanchez & Levine, 2001, 2012). Despite technological advances in the collection, storage, and maintenance of large amounts of job data (McEntire et al., 2006), job analytical methods so far have remained virtually untouched by modern technology. Data-gathering procedures in job analysis still often rely on time consuming face-to-face interviews, (un)structured observation, and paper-and-pencil surveys. This is noteworthy in light of the vast amount of mostly untapped and potentially rich sources of job information contained in 'big' data, including for instance electronic records of performance monitoring (Sanchez & Levine, 2001). By building and demonstrating text mining algorithms that are able to automatically categorize job information from online vacancies, we aim to explore whether such big data sources can indeed offer valuable insights about what employees do and whether text mining can form a potentially new and useful tool in job analysis.

The purpose of this study is to examine whether text mining of vacancies can inform researchers and practitioners about what employees do in a way

comparable in thoroughness and/or complementary to current job analysis methods. In a survey study among German nurses we compare and contrast two lists of tasks, one collected by means of a task inventory and the other by means of text mining job vacancies, especially in terms of the quality of output. In addition, we aim to use explorative task level analyses to show that it is indeed worthwhile to know what employees do, by demonstrating that individual tasks can explain variance in employee well-being. The contribution of this study is threefold. First, we add to the job analysis literature by introducing a new method that could potentially help solve some of the problems the field has faced in the past decades. As such we set out to exploit the recognized potential of alternative (big) data sources (McEntire et al., 2006; Sanchez, 2000). Second, our text mining algorithm builds on the job analysis literature and its definitions of job information and we show how big data and conventional job analysis derived knowledge about what employees do can complement one another. Third, we illustrate why it is important to gain an understanding what it is that employees do, because not all tasks are equal as some tasks are related to job satisfaction and other tasks to work overload or emotional exhaustion. As argued by Barley and Kunda (2001), detailed studies on work are key in building and evaluating the fit of organizational theories to 21st century work.

THE NEED TO UNDERSTAND WHAT EMPLOYEES DO

To reinvigorate studies about what employees do, there is a need for detailed job information which encompasses all work-related information and data (Morgeson & Dierdorff, 2011). Especially work-oriented job information is needed, referring to the objective (employee independent) aspects of jobs and the nature of the work itself (e.g., tasks, general work activities, or responsibilities) (Brannick, Levine, & Morgeson, 2007; Harvey, 1991; Sackett & Laczo, 2003; Voskuijl, 2005). Moreover, tasks, defined as specific work activities (Morgeson & Dierdorff, 2011), best represent what employees do based on a negotiation between employee and employer and the initiative of the employee (Wrzesniewski & Dutton, 2001).

What employees do and how work is structured in terms of tasks are inextricably linked, as work is altered when new structures are imposed by managers, and vice versa structures must be adapted when work changes. Organizational theory must at the very least be implicitly linked to what employees do at work, as it is aimed at describing and explaining those activities. The current

changes in the nature of work thus create a need for organizational theorists and researchers alike to rethink theoretical foundations and assumptions. Studies of what employees actually do can thus inform such theory development. However, detailed studies about work have mostly become a thing of the past due to a focus on generalizability, the dominance of quantitative research, and the diffusion of theories about the nature of work across a variety of disciplines (Barley & Kunda, 2001).

Without studies on what employees do researchers miss out on valuable information about how work is performed and experienced, and how it could best be organized (Barley, 1996). The concept of emotional labor, for example, might not have been discovered without the seminal study on exactly what airline flight attendants do (Hochschild, 1983). Ethnographies among technicians helped challenge ideas about hierarchy and vertical careers in organizational theory (Barley, 1996; Zabusky & Barley, 1996), because it turned out that technicians were generally most satisfied and productive working in a horizontal structure that focused on their individual expertise. A study on what security screeners do, showed that female security screeners spend more time on emotionally and physically straining pat-downs compared to their male counterparts, which explained their higher experienced work intensity and emotional exhaustion (Chan & Anteby, 2016).

Not only researchers and their theories seem to need high quality information about what employees do, practitioners as well increasingly understand the value of ensuring that organizational decisions and practices match the reality of employees' work. For example, putting flexible work arrangements in place for employees without the knowledge that face-to-face meetings still take place every day restricts employees to actually work from home. The growing popularity of evidence-based management, defined as the translation of principles based on evidence into practice (Rynes, Giluk, & Brown, 2007), shows that practitioners aim to base their practices on what employees actually do. Despite this, organizational decisions are often based on rather loose inferences and hunches (Chermack, 2003; McEntire et al., 2006). Studying what employees do could thus help base organizational decisions on evidence related to what employees actually do in their jobs.

Specifically, a focus on what employees do may facilitate a more detailed, and nuanced understanding of employee well-being. Researchers have rarely employed a task-level perspective on work in efforts aimed at understanding

the stress and satisfaction that employees experience at work (Taber & Alliger, 1995). An exception is the work on illegitimate tasks, that shows that tasks characterized as unnecessary and unreasonable are a specific source of stress that hinder performance (Semmer et al., 2007, 2015; Semmer, Tschan, Meier, Facchin, & Jacobshagen, 2010). That taking a task-perspective is the exception rather than the rule is surprising when one considers that employees experience tasks that are incongruent with (professional) identity (Aiken et al., 2001; Kira & Balkin, 2014; Pratt et al., 2006; Semmer et al., 2007) and tasks that require the display of emotions as stressful (Steinberg & Figart, 1999); tasks that are congruent with (professional) identity as motivational (Shamir, 1991); and tasks that show employees how they make a significant contribution in the lives of others as meaningful (Grant, 2007, 2008a, 2008c). Interventions aimed at improving employee well-being may thus need to differentiate between tasks to identify tasks that are stressors, as is done in the literature on illegitimate tasks (Semmer et al., 2007, 2010, 2015) or by Chan and Anteby (2016) in their study among security screeners. In sum, it is relevant to look at employee well-being at the level of specific tasks, because carrying out certain discrete tasks may enhance employee well-being while others may diminish it.

Taking a task focus

Taking a task-perspective in studies about what employees do is further supported by the usefulness of tasks. There are fundamental differences between the expression of a job in terms of objective and verifiable work behavior or hypothetical psychological traits (Harvey & Wilson, 2000). This means that based on favorable differences in observability and proneness to bias, tasks can be seen as more informative than other forms of job information (Cucina, Martin, Vasilopoulos, & Thibodeuax, 2012; Dierdorff & Morgeson, 2009; Morgeson & Campion, 1997, 2000). Below we elaborate on the usefulness of taking a task focus by focusing on the high degree of contextualization, specificity, and understandability of tasks.

The contextualization of tasks

First, tasks are a useful because of their high degree of contextualization. The contextualization of job information ranges from the very general to the very context-specific and determines whether the information is generalizable across virtually all jobs, such as teamwork skills or conscientiousness

(i.e., low contextualization), or applies only to a select number of jobs, such as experience with structural equation modelling in Mplus (i.e., high contextualization) (Dierdorff & Morgeson, 2009; Harvey, 1991). Contextualization is comparable to the distinction between an idiographic and nomothetic approach to human behavior, by either focusing on its unique characteristics or on the common dimensions (Cunnigham, 1996). The appropriate level of contextualization depends on the purpose for which the information is to be used (Voskuijl, 2005). Job analysis as a field has moved towards more general worker-oriented forms of job information, such as skills, to facilitate cross-job comparisons and classification. This is evidenced, for example, in the development of O*Net (Peterson et al., 2001), in which generic information types such as Generalized Work Activities (GWAs; Jeanneret & Strong, 2003) have replaced tasks as the main building block of work in job analysis (Cunnigham, 1996; Fine et al., 2004).

Highly contextualized forms of job information, however, capture the dynamic and complex nature of work better than general job information. In the contemporary workplace, what employees do is susceptible to change and differences between employees in execution of tasks or performance are present even within the same job (Sanchez, 1994; Singh, 2008). The idiosyncratic ways in which work is performed therefore harbors relevant and meaningful insights, that are simply not observable when one focusses on general job information because general job information tends to be stable over time (Harvey, 1991). Indeed, simple models usually cannot accurately capture unstable phenomena (Marion & Uhl-Bien, 2002; Regine & Lewin, 2000). Reducing complexity in work by focusing on the general aspects of jobs could facilitate understanding between jobs (e.g., comparing skills of I/O psychologists with those of truck drivers) in a more cost-efficient way, but it comes at a high price because of the loss of information (Barley & Kunda, 2001). In using GWAs to assess what teachers do, for example, one could wrongly conclude that there have been but a few changes over the past decades as teachers continue to 'teach others' and 'perform administrative duties'. A focus on tasks, however, could reveal that technology has drastically affected both the way in which teachers teach (e.g., using online testing, using educational software) and how they go about their administrative work (e.g., using student tracking systems and learning analytics).

The specificity of tasks

Second, tasks are useful because of their high degree of observability.

The observability of job information ranges from the easily observable to the not-easily observable depending on the level of abstraction (Harvey & Wilson, 2000), varying from the very broad and abstract to the very narrow and detailed (Brannick et al., 2007). This distinction is also referred to as molar versus molecular, with molar referring to broad interpretations based on similarity and molecular referring to behaviorally specific reports about the job (Cunnigham, 1996). For example, general duties and responsibilities are abstract and thus not easy to observe (e.g., managing a team), whereas detailed tasks or even elemental motions (e.g., placing dishes on a tray and carrying the tray) are narrow and observable. Again, the appropriate level of abstraction depends on the purpose for which the information is used (Clifford, 1994). However, similar to the level of contextualization a trend may be discerned towards the use of more abstract and thus less observable forms of job information in job analysis over the last two decades (Dierdorff & Morgeson, 2009; Lievens, Sanchez, & De Corte, 2004; Sanchez & Levine, 2001).

Highly observable and detailed forms of job information, however, are more discernable and therefore likely to result in more accurate inferences as to the nature of work compared to non-observable and abstract job information. For instance, determining whether a task is part of a job is likely to be more clear-cut than determining whether openness to experience is required. Furthermore, differences between employees assessing general job information types do not necessarily reflect inaccuracy, but may potentially reflect systematic (social and or cognitive) sources of variance (Morgeson & Campion, 1997) or systematic differences between jobs (Campion, Morgeson, & Mayfield, 1999; Sanchez & Levine, 2000, 2009). Ability statements, for example, are more likely to be subject to inflation due to self-presentation bias compared to task statements (Morgeson et al., 2004). As a result, one could erroneously conclude that a job requires a wider range of abilities than is actually the case, which may subsequently imply the derivation of selection cutoff scores that are too strict, or overspending on training. The rating of less observable job information thus requires a bigger inferential leap than the rating of visible work components (i.e., what skills are needed for leadership responsibilities compared to assessing and recording a patient's blood pressure) due to lacking tangibility of the former and the concomitant reliance on subjective judgment (Harvey, 2009; Morgeson & Campion, 1997, 2000). The information overload and recall problems associated with this subjective judgment are likely to result in greater inaccuracy of abstract

job information (Butler & Harvey, 1988; Gibson, Harvey, & Harris, 2007; Harvey & Wilson, 2010).

The understandability of tasks

Third, tasks are a highly understandable form of job information. The understandability of job information ranges from easily understandable to very difficult to grasp and indicates the ease of comprehension and communication, and the lack of ambiguity (Bowen & Ostroff, 2004; Sanchez & Levine, 2009). Job information is understandable when it is short and clearly worded. Understandability is similar to face validity, which pertains to the evaluation on the part of key stakeholders, that a specific operationalization is a credible representation of some pertinent hypothetical construct (Anastasi, 1968). Job incumbents can usually easily describe their jobs in terms of tasks, whereas it is rather uncommon, for example, to find employees who are naturally inclined to describe their jobs in terms of abilities, competencies, or traits (Dierdorff & Morgeson, 2009). The expression of job information in such job-analytic terms requires familiarity with the terminology before it can be understood and/or accepted (Clifford, 1994). Without sufficient comprehensibility to the end users (the main informants or job incumbents), it is therefore unlikely that such job information will become the language of choice for understanding work (Sanchez & Levine, 2009). Providing information about tasks, however, is likely much easier for employees, since tasks represent what they do in their jobs on a daily basis. Tasks therefore have a great potential for both research on job analysis and employee well-being, and practical applications such as work (re)design interventions.

The role of job analysis

Job analysis, then, is a technique for collecting and analyzing job information, including tasks (Sanchez & Levine, 2012), with the aim to create valuable insights for employees, organizations, policy makers, and researchers alike into what it is that employees (ought to) do. There are many possibilities when it comes to collecting job information as there is a wide variety of job data and associated methods to collect and analyze them (Prien et al., 2004). Depending on the desired job information, job analysis methods include task inventories, time-and-motion studies, the critical incident technique (Brannick et al., 2007), functional job analysis (Fine, 1955; Fine & Cronshaw, 2009), competency modelling (Shippmann et al., 2000), cognitive task analysis

(Militello & Hutton, 1998), and the position analysis questionnaire (McCormick, Jeanneret, & Mecham, 1972). However, the available job analysis methods have struggled with the aforementioned challenges inherent in changing nature of work, (Sanchez & Levine, 2012), as these methods insufficiently take into account the fact even within the same occupation many jobs are no longer stable entities that consist of standardized tasks (Fine, 1996).

The analysis of big data, in particular the application of text mining, could form a valuable addition to the job analysis methods available to date. Text mining is the automatic extraction of information from text (Kao & Poteet, 2007). Text mining goes beyond the mere counting of word frequencies and patterns as is done in computer-aided text analysis (CATA), in that it draws on techniques from natural language processing, machine learning, and statistics (Kobayashi et al., 2017b). Considering the fact that many employees nowadays perform their jobs by generating textual information, together with the amount of untapped and potentially rich textual job information, including but certainly not limited to online vacancies, e-mails, meeting minutes, training manuals, and electronic records of performance monitoring (Sanchez & Levine, 2001), text mining may be appropriate for the analysis of 21st century jobs. Studies in the field of information technology show that it is possible to extract job information, such as skills, from online vacancies using a preselected set of keywords (Smith & Ali, 2014; Sodhi & Son, 2010). However, the emphasis in these early studies has been on technological innovation as opposed to specifically addressing the potential for job analysis through the generation of insight about what it is that employees do.

Moreover, the use of text mining to collect and analyze tasks addresses three limitations of existing job analytical methods. First, text mining, makes it possible to analyze vast amounts of job information in a cost-effective way, since the traditionally used interviews and observations are expensive in terms of invested time and effort (McEntire et al., 2006; Sanchez, 2000). Second, with the help of text mining it is possible to not only obtain easily updatable information but also information pertaining to temporal dynamism in jobs (Sanchez & Levine, 2012). Third, text mining methods could be used to reduce the bias inherent in existing job analysis methods (Morgeson & Campion, 1997; Sanchez & Levine, 2000). Inaccuracy in current job analysi ratings can reflect idiosyncrasies in performance as opposed to measurement error (Sanchez & Levine, 2012), thus challenging the assumption that jobs are standardized. With the help of text

mining, larger volumes of job information would make it possible to distinguish between what is not part of all or most jobs and what is just part of some jobs. Moreover, text mining can facilitate the analysis of contextualized tasks from a wide variety of sources and may hence offer a means to address as opposed to eschew complexity in jobs.

METHOD

Context

One particular profession that has been under pressure due to an increasing emphasis on efficiency and regulation (cf. Oldham & Hackman, 2010; Parker, 2014) is nursing. Nurses, together with teachers, are known to be relatively likely to suffer from stress and burn-out compared to other professionals (Hakanen, Bakker, & Schaufeli, 2006; Hartnett & Kline, 2005; Le Blanc, Bakker, Peeters, van Heesch, & Schaufeli, 2001; Martin, Bender, & Fore, 2002; Sherman, 2004; Vigoda-Gadot, 2007). For nurses, the push for emphasis on efficiency and control implies an increasing amount of administrative work that comes at the cost of doing the job they professionally identify with, namely taking care of patients. Nurses in the Netherlands, for example, complained that they spend 25-40% of their time on administrative tasks instead of caring for their patients (Heijne, 2015b). The same is true in Germany, where 61% of the health care organizations reported issues with filling up nursing related vacancies (Schlegel, 2015). It is therefore worthwhile to take a closer look at what tasks nurses in Germany fulfill in an effort to relate these to work overload, emotional exhaustion, and job satisfaction so as to understand what specific tasks are burdensome and could potentially be changed, outsourced, or even robotized and vice versa what specific tasks are enjoyable and need to be kept intact.

Method for comparing two job analysis techniques

We conducted two job analyses of nursing work to compare a text mining alternative to a current job analysis method, namely a task inventory. Each method resulted in a list of tasks that nurses (are expected to) perform that were individually validated by a Subject Matter Expert (SME). After this, both task lists were presented to job incumbents in an online questionnaire to rate these tasks on representativeness for the nursing job, frequency, and importance. Both methods are explained below, followed by an explanation of the questionnaire.

Task inventory method

The task inventory method compiles job information from interviews with, and observations of SME's (Brannick et al., 2007). In our case, these SME's were three nurses and one head nurse working in a German hospital, who were each interviewed for one and a half hours[1]. The coded interview transcripts resulted in a preliminary list of 99 tasks, which were defined in terms of an action verb, the object of the action, the source of information or instruction, and the results of that action as is advocated in the job analysis literature (Morgeson & Dierdorff, 2011). The preliminary task list formed the basis for the observations of two different shifts (i.e., morning and afternoon) by one researcher who listed any additional tasks not identified through the interviews[2]. This resulted in 22 new tasks including detailed descriptions and an extension of the descriptions of the 99 tasks.

The 121 tasks (e.g., assisting patients with eating, distributing medication, checking the temperature of patients) were clustered into 23 task clusters (e.g., patient rounds, medication, information sharing) based on the content similarity between tasks and temporal proximity (i.e., executed around the same time during the course of a shift). Based on a validation by two researchers and another SME (i.e., nurse training expert) two doubles were merged (i.e., prepare next shift was merged with prepare documentation and technical requests was merged with other requests) and one task (i.e., change clothes) was deleted, resulting in a final set of 118 tasks divided into 22 clusters and five inductively derived meta-clusters (i.e., medical care, basic care, internal management, patient management, and teamwork). The task inventory consisted of tasks such as "check the temperature of the patient with a thermometer and document temperature" and "dispose of medical waste of the isolation patient, needles and medications in a safe manner" (see Appendix B).

Text mining method

The text mining based job analysis method involved the iterative development of an algorithm that automatically analyzed the texts in nursing vacancies. Vacancies are relatively easy and inexpensive to obtain online and can be analyzed quickly and efficiently in huge quantities using text mining techniques

[1] The interview protocol and examples of the transcripts and coding can be found in Appendix A.
[2] The observation protocol and examples of the observations can be found in Appendix A.

(Kobayashi et al., 2017b). Moreover, vacancies are likely to include task data, as it is important for employers to communicate what they expect from future employees. We performed web scraping and collected 14,712 German nursing vacancies posted in various online job boards. The raw vacancies contained elements not relevant for our purposes, hence we applied html parsing in order to get only the information relevant for job analysis. Information about the tasks is typically found within the job description therefore only the text data in the 'job description' part of the vacancy was used.

After parsing, only the relevant text elements remained and were subsequently transformed into structure suitable for the application of analytics (i.e., a document by term matrix in which the presence or absence of each term in the corpus was scored for each document). We used the sentence as the unit of analysis as sentences often contain a minimal 'information unit' about tasks as opposed to using just words or phrases and used the vector space model to represent each sentence. For an extensive elaboration on these steps see Kobayashi et al. (2017a; 2017b). A total of 50,666 sentences were obtained. After this, a training dataset was created through the manual labelling of 2,501 sentences into information pertaining to the work (i.e., tasks), information pertaining to the worker (i.e., worker attributes), or non-relevant sentences using a predetermined coding scheme based on the definitions of tasks and attributes from the job analysis literature (Sackett & Laczo, 2003). With the use of the training dataset, in which 651 sentences were labelled as tasks, various classifiers were built, namely, Naive Bayes (NB), Support Vector Machines (SVM), and Random Forest (RF) (Kobayashi et al., 2017b). We combined the predictions of the three classifiers into an ensemble approach to get a more reliable prediction and obtained an additional 528 tasks from the sentences not used in the training data set.

A total of 1,179 identified sentences containing tasks were validated by two researchers and one SME (i.e., nurse training expert), and the input was used to retrain the classifiers. The process of retraining and validation was repeated until a desired performance was reached, namely that 93.3% of the sentences automatically classified as containing task information actually contained it. These sentences were subsequently clustered to deal with duplication and similarity because some of the tasks were redundant and were mentioned in more than two vacancies. Hierarchical clustering based on Ward's method was used and the cosine distance to measure the distance between sentences (El-

Hamdouchi & Willett, 1989). The best cut dendrogram generated 71 clusters, thus representing 71 unique tasks that were further clustered into the same five meta-clusters (i.e., medical care, basic care, internal management, patient management, and teamwork) as input for further work. Examples of these tasks include "participating in resuscitations" and "caring for patients post OP (see Appendix C).

Participants and procedure

An online questionnaire was used to obtain data from nurses in Germany as part of the EU funded Pro-Nursing Project[3], which received approval from the ethical committee of the university. Respondents received an anonymous link to the questionnaire by email either through the Pro-Nursing network or through a Qualtrics panel comprised of nurses working in hospitals across Germany. The final sample for the questionnaire consisted of N = 65 nurses working in Germany. A majority of 81.3% of the nurses who participated self-identified as female and were between 20 and 62 years old (M_{age} = 37.52; SD = 12.45). Job tenure of the nurses ranged between one and 45 years and was 15.31 years on average (SD = 11.62). The nurses in the sample worked an average of 31.05 contractual hours per week (SD = 8.96).

Measures

Respondents each rated 68 tasks, which represented a third of the total 199 tasks randomly assigned from the task inventory (N = 118), text mining (N = 71), and bogus task list (N = 10) in order to reduce the cognitive load placed on each respondent and to increase validity (Morgeson & Campion, 1997). The 65 respondents were thus randomly divided over three subsamples (N1 = 14; N2 = 22; and N3 = 29). The bogus tasks (i.e., tasks from network administrators and network developers obtained from online vacancies) were included to check for discriminant validity and as an attention check (Morgeson et al., 2004). Three bogus tasks were more often rated by respondents as being part of the nursing job (e.g., "translate functional needs into practical, technical solutions as part of

[3] The ProNursing Erasmus Plus project used a job training approach in an effort to modernize the learning content and curricula of nurses in order to address the shortage of nurses in Germany. The project resulted in an online ontology based test platform that can help nurses to update their knowledge and skills (see http://www.pro-nursing.eu).

the development department"), and were therefore excluded from our analyses. Each of the 68 tasks in the three subsamples was rated on inclusion, frequency of execution, and importance. In addition, respondents completed measures of job satisfaction, work overload, emotional exhaustion, and demographics including age, gender, work hours, and job tenure. All response options unless indicated otherwise ranged from 1 = *totally disagree* to 5 = *totally agree*.

Task inclusion. Respondents were asked to rate if a task was part of their job to establish whether the tasks that were collected by means of both methods correctly represented nursing work (Brannick et al., 2007). It is possible that some tasks are not part of all nursing jobs (Fine, 1996; Wrzesniewski & Dutton, 2001), but also that some tasks were wrongfully included and not really representative of what nurses do. We created a binary variable indicating whether a task was either perceived to be part of the job (1) or not (0). The inclusion rating is thus indicative of whether our methods resulted in tasks that are irrelevant or context-specific (i.e., not part of all nursing jobs).

Task frequency. Respondents were asked how often they performed a task, if a task was part of their job (i.e., inclusion rating of "1"), to establish the extent to which tasks represent what nurses do (Brannick et al., 2007). In order to adequately represent what employees do, a job analysis method should especially collect tasks are part of the daily routine, compared to tasks that are rarely executed and thus less representative of nursing work. The frequency of each task, or 'how often do you execute this task?' was rated on a 5-point Likert scale ranging from 1 = *less than once a month* to 5= *more than once a day*. The frequency rating thus indicates how big a part of the job specific (included) tasks are.

Task importance. Respondents were also asked to rate the relative importance of each task for their job, since an adequate job analysis method should mainly collect tasks that are of relatively high importance and that thus capture the core or essence of what nurses do (Brannick et al., 2007). The importance of each task, or 'how important is this task?' was rated on a 5-point Likert scale ranging from 1 = *not at all important* to 5 = *extremely important*.

Job satisfaction. The extent to which employees are satisfied with their job is seen as the most common conceptualization of well-being (Blanchflower & Oswald, 1999). Since happy employees are found to be productive (Taris & Schreurs, 2009), we included job satisfaction as a positive indicator of nurses' well-being. We assessed job satisfaction using a three item measure (Tims,

Bakker, & Derks, 2013) including items such as "I am really satisfied with my job" (α = .74; in the three subsamples α ranged between .72 and .84).

Work Overload. Work overload captures the experience of employees that they have too many activities or responsibilities considering their available resources (Rizzo et al., 1970). When nurses are exposed to work overload for a longer amount of time, they may start to struggle to complete all their tasks and overload may ultimately culminate into a burnout (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). Work overload is therefore a relevant short-term indicator of stress and potentially burnout. We used the measure from Bolino and Turnley (2005), which included three items such as "it often seems like I have too much work for one person to do" (α = .84; in the three subsamples α ranged between .82 and .84).

Emotional Exhaustion. Emotional exhaustion is considered an important dimension of burnout of which nurses are at risk (cf. Sherman, 2004), and is defined as a chronic state of emotional and physical depletion (Maslach & Jackson, 1981). We used eight items from the Oldenburg Burnout Inventory (OLBI) (Demerouti, Bakker, Vardakou, & Kantas, 2003), an example item being "during my work, I often feel emotionally drained" (α = .79; in the three subsamples α ranged between .79 and .83).

Data analysis strategy

First, we rated tasks from both lists as synonyms (i.e., exactly the same), similar (i.e., different wording, same meaning), or dissimilar (i.e., different wording and meaning) based on the decision rules of Tett, Guterman, Bleier and Murphy (2000) to determine the percentages of overlapping and unique tasks. This comparison or data triangulation was validated by an SME to ensure its quality and no adjustments turned out to be necessary. The qualitative similarities and differences between the two methods were described based on this comparison (see below). Second, we used repeated-measures ANOVA in SPSS to compare the average inclusion, frequency, and importance ratings based on the within-participants variance, because it allowed us to account for the fact that respondents rated clusters for both task lists as well as bogus tasks. We used the Greenhouse-Geisser correction when Mauchly's test for Sphericity was violated and the Bonferroni method for post-hoc tests to contrast both methods with the bogus tasks due to said violation (Field, 2009). Third, we used correlation and regression analyses to explore the extent to which individual tasks were

related to employee well-being (i.e., work overload, emotional exhaustion, and job satisfaction). Regression analyses were performed in Mplus using structural equation modelling (SEM) to account for the interrelationships between the three dependent variables.

RESULTS

Comparison between the task inventory and text mining method

Our qualitative comparison (see Table 1) established that 64.6% of tasks (*N* = 189) from both lists overlapped, whereas 22.7% were unique to the task inventory and 12.7% were unique to the text mining method. Looking at only the task inventory tasks (*N* = 118), 63.6% of tasks were similar to the text mining tasks and 36.4% were unique, whereas looking only at the text mining tasks (*N* = 71), 66.2% were similar to the task inventory tasks and 33.8% were unique. The correspondence (≥ 63-66%) is much higher than the interrater reliability generally found for tasks (.29) and similar to the interrater reliability for behavior (.62) or job dimensions (.60) (Voskuijl & van Sliedregt, 2002). The relatively high correspondence between the text mining based task list and the task inventory based task list thus established preliminary convergent validity, but also showed that the two lists are not interchangeable.

There are some noticeable differences between our task inventory and text mining method. First, the task inventory resulted in a larger number of tasks (*N* = 118) compared to the text mining method (*N* = 71). The task inventory, for example, produced five tasks and extensive descriptions about medication (i.e., prepare medication, arrange medication new patients, check medication, and distribute medication), whereas the text mining counterpart is restricted to only 'administration of medication'. In other words, the level of detail of the task inventory tasks appears to be greater than that of the tasks derived through text mining[4].

Second, a closer look at the unique tasks of the text mining method showed more context-specific medical care tasks (e.g., caring for patients with spine surgery, caring for mentally ill patients, assisting in surgical interventions, conducting ECG). These tasks are likely not performed by all nurses but specific to particular contexts in which nurses might work and thus represented

[4] Extensive and detailed descriptions of the task inventory tasks can be found in Appendix B.

Table 1: Overlapping and Unique Tasks of the Task Inventory (see Appendix B) and Text Mining Task Lists (See Appendix C)

Overlapping Tasks		
Task Inventory Tasks	=	**Text Mining Tasks**
Prepare medication Arrange medication new patients Check medication Hand out medication		Administrating of medication
Injections		Preparing and administering of injections
Decide extra medication		Providing medication on demand
Blood test		Collecting blood
Document blood test Smears Urine test		Doing laboratory tests
IV/drips		Preparing and administering intravenous drugs
Oxygen		Operating the technical equipment
Gavage		Assisting at intake of food
Bandages		Realizing the wound management
0:00 balance		Operating the technical equipment
Monitor patients		Caring for critical care patients Checking vital signs
Prepare surgery		Preparing patients for surgery
Anesthesia medication		Assisting and monitoring anesthesia
Post-op care		Caring for patients post OP Caring for patients in the recovery room
Documentation surgergy & special care		Providing nursing documentation
Deal with emergencies		Identifying early emergency symptomes Participating in resuscitations
Documentation emergencies		Providing nursing documentation
Emergency case		Realizing interventions of quality assurance
Basic check		Assisting at diagnostical interventions Providing basic or general care Monitoring the patients' therapy Developing an individual care planning
Mobilisation		Supporting of rehabilitation
Personal attention		Providing psychological care
Answer questions		Communicating with patients, family, and staff
Advise patients		Giving patients and family advice
Assist eating		Assisting at intake of food
Medical waste		Preparing and disposing of materials
Mucus		Operating the technical equipment
Medical material Disinfect material		Processing instruments

Order medications Order material Restock material Restock medication	Organizing the orders of material
Tablet system	Preparing and disposing of materials
Expire dates Fridge temperature Closed medication	Realising interventions of quality assurance
Prepare documentation Documentation general	Providing nursing documentation
Check documentation	Keeping the data up to date Auditing medicial transcriptions
Insurance memo Administration	Documenting of services
Schedule	Creating shift schedules
Work division Dividing patients Scheduling beds Plan operations Scheduling appointments	Organizing the work on the ward
Prepare documentation new patients	Prodiving nursing documentation
Take-over patient Welcome new patients Admittance new patients	Admissioning and discharging patients
Prepare tests Documentation new patients	Collecting patients' data
Inform patients	Giving patients and family advice
Hand out prescriptions and medications	Working on doctors' prescriptions
End documentation	Prodiving nursing documentation
Arrange transfer Arrange transport	Transitioning of patients into home care
Transfer patients	Accompanying patients
Family	Giving patients and family advice
Host visits Host head doctor	Participating in visits Assisting at examination
Inform doctor Answer telephone	Communicating with patients, family, and staff
Unscheduled meetings Cross-team meeting Team meeting	Participating in meetings
Supervise students Show students	Training and advising students
Education session	Participating in training programs Participating in hygiene training

Unique Tasks		
Task Inventory Task	≠	**Text Mining Task**
Lumbar puncture		Caring for patients with windpipe
Temperature		Assisting and conducting special therapies
Stiches		Conducting ECG
Catheter		Assisting at surgical interventions
Diabetics		Preparing and assisting at transfusions
Blood pressure		Caring for the blind
Drainages		Assisting at endoscopic tests
Stoma		Caring for patients with neurological diseases
Prepare patients		Taking care of unconfined ventilation
Care for isolation patients		Checking and documenting vital signs at operations
Deceased patients		Caring for patients with spine surgery
Deal with confused or aggressive patients		Conducting sterile dressings
Deal with accidents		Caring for patients with orthopaedic diseases
Prepare examination		Care for patients with vascular disease
Turning patients		Caring for mentally ill patients
Other requests		Caring for children
Last round		Providing holistic care
Washing patients		Caring for the elderly
Change patients		Providing palliative care
Toilet request		Realising the nursing process
Change beds		Improving interdisciplinary cooperation and collaboration
Order meals		Working on improvements
Prepare meals		Working in groups
Check meals		Considering the latest results of nursing research
Hand out meals		
Food/drink request		
Clean general		
Clean food		
Prepare bed		
Clean isolation room		
Laundry		
Order bed		
Plan visits (after stay)		
Revalidation		
International patients		
Goodbye		
Handle visitors		
Prepare visits		
Consult (head) doctor		
Report		
Break		
Socialize		
Make coffee		

in sub-sets of vacancies. In other words, the specificity of the text mining tasks in the medical care and to some extent the basic care clusters appears to be higher as compared to the task inventory tasks.

Third, a closer look at unique tasks of the task inventory method showed more tasks that may be characterized as mundane nursing tasks (e.g., washing patients, changing patients, cleaning beds, checking temperature). Compared to the basic care tasks from the text mining method (N = 10), the task inventory included a larger number of basic care tasks (N = 28) and different ones. In other words, the task inventory and text mining method are not equally suitable in collecting mundane or basic care tasks.

Comparison between inclusion, frequency, and importance ratings

We conducted a series of ANOVAs to justify the analysis of one combined rather than three subsamples before we compared our two methods. These analyses indicated that there were indeed no significant differences between the average ratings in the three questionnaires with the exception of the average frequency ratings of text mining tasks (F (2, 62) = 8.43, p = .001), which indicated that the average frequency of automatically extracted tasks was not equally distributed despite random assignment to the three questionnaires. Since there were no further significant differences between the questionnaires in terms of job satisfaction, work overload, or emotional exhaustion, there was sufficient evidence that the questionnaire version did not significantly affect the results and we therefore report the combined results below.

First, we compared the inclusion, frequency, and importance ratings for the task inventory, text mining, and bogus tasks with a repeated measures ANOVA (see Table 2). There was no difference between the mean inclusion ratings of the task inventory tasks and text mining tasks ($M_{task\ inventory}$ = 0.79, SD = 0.19; $M_{text\ mining}$ = 0.81, SD = 0.15), whereas in line with expectations the mean inclusion ratings of both methods were significantly higher than the inclusion ratings for the bogus tasks (M_{bogus} = 0.70, SD = 0.32). There was also no difference between the mean frequency ratings of the task inventory and text mining tasks ($M_{task\ inventory}$ = 3.73, SD = 0.36; Mtext mining = 3.64, SD = 0.41), whereas the mean frequency ratings of both methods again were significantly higher than the frequency ratings for the bogus tasks (Mbogus = 2.80, SD = 1.17). There was a significant difference between the mean importance ratings of the task inventory and text mining tasks ($M_{task\ inventory}$ = 3.43, SD = 0.65;

Table 2: Repeated Measures ANOVA and Contrasts Comparing Mean Values of Inclusion, Frequency, and Importance Ratings for Tasks Inventory, Text Mining, and Bogus Tasks

	df(*df*R)	*N*	*F*	Δ	*Dominant Method*	η^2	*p*
Inclusion rating	1.14(73.21)[1]	65	140.62**			.68	.000
Tasks Inventory vs. Text Mining			2.76	-0.02	TM	.04	.101
Tasks Inventory vs. Bogus Tasks			139.56**	0.49	TI	.69	.000
Text Mining vs. Bogus Tasks			154.82**	0.51	TM	.71	.000
Frequency rating	1.89(45.18)[2]	39	19.57**			.34	.000
Tasks Inventory vs. Text Mining			1.80	0.09	TI	.05	.187
Tasks Inventory vs. Bogus Tasks			23.81**	0.94	TI	.39	.000
Text Mining vs. Bogus Tasks			17.80**	0.84	TM	.32	.000
Importance rating	1.23(75.93)[3]	63	151.42**			.74	.000
Tasks Inventory vs. Text Mining			20.23**	-0.21	TM	.25	.000
Tasks Inventory vs. Bogus Tasks			144.95**	1.47	TI	.70	.000
Text Mining vs. Bogus Tasks			176.09**	1.68	TM	.74	.000

Note: Inclusion rating means of scale rated as 1 = *included in job* or 0 = *not included in job*. Frequency and Importance rating means of a 5-point scale. Δ = difference between mean scores. Dominant method is the highest mean score for Task Inventory (TI) or Text Mining (TM). ** $p < .01$. [1]Df Greenhouse-Geisser corrected ($\varepsilon = .57$), because Mauchly's test of Sphericity was violated $\chi^2(2) = 86.940$, $p < .05$. [2]Df Greenhouse-Geisser corrected ($\varepsilon = .59$), because Mauchly's test of Sphericity was violated $\chi^2(2) = 42.411$, $p < .05$. [3]Df Greenhouse-Geisser corrected ($\varepsilon = .61$), because Mauchly's test of Sphericity was violated $\chi^2(2) = 61.165$, $p < .05$.

$M_{text\ mining}$ = 3.64, *SD* = 0.58), in addition to the significant differences of both methods with the bogus tasks (M_{bogus} = 1.96, *SD* = 0.98). These results indicate that our methods performed similarly when it comes to inclusion and frequency ratings, but that the tasks from the text mining method elicited slightly higher importance ratings. In addition, both methods were superior compared to the bogus tasks, which is necessary to establish the discriminant validity of our two methods.

With another repeated measures ANOVA (see Table 3), we compared the task inventory and text mining methods by comparing the mean scores for inclusion, frequency, and importance at the cluster level. The medical care tasks from the task inventory exhibited significantly higher inclusion ratings compared to the text mining method. Whereas the basic care tasks, internal management tasks, and teamwork tasks from the text mining method were all significantly more often rated to be part of the job compared to the task inventory method. There was no significant difference in the average inclusion ratings for the patient management tasks. These results indicate that for most clusters (i.e., basic care, internal management, and teamwork) nurses, on average,

Table 3: Repeated Measures ANOVA Comparing Mean Values of Inclusion, Frequency, and Importance Ratings per Task Cluster between Tasks Analysis and Text Mining

	df	*N*	*F*	μ_{ti} (SD)	μ_{tm} (SD)	Δ	*Dominant Method*	η^2	*p*
Inclusion rating[1]									
Medical Care	1	65	11.21**	.82 (.21)	.76 (.21)	.05	TI	.15	.001
Basic Care	1	65	5.17*	.82 (.23)	.87 (.24)	-.05	TM	.08	.026
Internal Management	1	65	5.44*	.71 (.25)	.78 (.25)	-.07	TM	.08	.023
Patient Management	1	65	1.88	.80 (.27)	. 83 (.28)	-.05	TM	.03	.175
Team Work	1	64	21.29**	.79 (.22)	.93 (.15)	-.14	TM	.25	.000
Frequency rating[2]									
Medical Care	1	63	.03	3.53 (.70)	3.54 (.71)	-.01	TM	.00	.854
Basic Care	1	63	3.91	4.04 (.63)	3.84 (.88)	.20	TI	.06	.052
Internal Management	1	61	12.56**	3.66 (.58)	3.98 (.62)	-.31	TM	.17	.001
Patient Management	1	61	20.45**	3.58 (1.02)	4.25 (.78)	-.66	TM	.25	.000
Team Work	1	64	19.31**	2.92 (.78)	3.35 (.71)	.52	TI	.24	.000
Importance rating[2]									
Medical Care	1	65	11.15**	3.73 (.83)	3.53 (.82)	.20	TI	.15	.001
Basic Care	1	64	10.86**	3.41 (.81)	3.73 (.93)	-.32	TM	.15	.002
Internal Management	1	65	17.80**	3.11 (.79)	3.52 (.95)	-.41	TM	.22	.000
Patient Management	1	64	33.04**	3.19 (.90)	3.82 (.98)	-.63	TM	.34	.000
Team Work	1	63	17.95**	3.56 (.71)	3.97 (.70)	-.41	TM	.22	.000

Note: [1]Rated as 1 = *included in job,* and 0 = *not included in job*. [2]Ratings based on a 5-point scale. Δ = difference between mean scores. Dominant method is highest mean score for Task Inventory (TI) or Text Mining (TM). * $p < .05$, ** $p < .01$.

provided higher ratings for tasks that were automatically extracted from online vacancies. This implies that the text mining method, on average, yielded fewer tasks that were only part of some jobs or not part of the nursing profession at all compared to the task inventory. This can be explained based on the higher level of abstraction of the text mining tasks because less specific tasks are more likely to be acknowledged to be part of one's job. However, for the medical care tasks, the text mining method elicited more tasks that were only part of some nursing jobs as is reflected in the significantly lower average inclusion rating. This is in line with the qualitative observation that text mining tasks from the medical care cluster were more contextualized and thus likely not performed by all nurses across contexts.

The patient and internal management tasks, both most likely linked to the organizational context, from the text mining method received significantly higher frequency ratings as compared to those provided for the task inventory tasks. However, the teamwork tasks from the task inventory method received

significantly higher frequency ratings compared to the text mining method. There were no significant differences between the average frequency ratings of the medical care and basic care tasks of both methods. These mixed results indicate that there is no clear difference in how nurses rated the frequency of clusters between the task inventory and the text mining methods.

The basic care, patient management, and internal management tasks from the text mining method received significantly higher importance ratings on average compared to those from the task inventory. The medical care tasks from the task inventory method, however, were rated as significantly more important compared to those from the text mining method. These results indicate that for most clusters nurses rated the relative importance for tasks that were automatically extracted from online vacancies significantly higher. This implies that the text mining method included more tasks on average that were seen as important by our sample compared to those obtained through the task inventory, which again can be explained on the basis of the higher level of abstraction of the text mining tasks (in other words the text mining tasks were more generally worded and contained fewer specific details). Less specific tasks are more likely to be more comprehensive and thus more important than specific components. However, for the medical care tasks, the task inventory elicited more tasks that were seen as important, because the automatically extracted tasks were more contextualized.

We checked these results for robustness by conservatively only including the importance ratings of the nurses who indicated that the task was included in their job. All the results of the repeated measures ANOVA remained the same. In addition, we excluded all participants who scored higher than average on the inclusion of bogus items (M_{bogus} = 0.70) to check whether the results would change with relatively careless responses being excluded. All results again remained the same with the exception of the comparison of the inclusion ratings between the task analysis, text mining, and bogus tasks since the average inclusion rating of the text mining tasks ($M_{text\ mining}$ = 0.22, SD = 0.17; $M_{task\ inventory}$ = 0.25, SD = 0.22) was now significantly lower than the task inventory tasks (F (1, 33) = 4.39, p = .044). These results indicate that the comparison is relatively robust and not influenced by unrealistic ratings of nurses who do not perform a task.

Table 4: Correlations between Inclusion, Frequency, and Importance Ratings per Cluster, Employee Well-being, and Demographics

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Inclusion MC[1]	0.79	0.20																					
2. Inclusion BC[1]	0.83	0.22	.774**																				
3. Inclusion IM[1]	0.73	0.22	.346**	.480**																			
4. Inclusion PM[1]	0.80	0.24	.571**	.748**	.570**																		
5. Inclusion TW[1]	0.85	0.16	.421**	.458**	.342**	.598**																	
6. Frequency MC[2]	3.53	0.64	.574**	.340**	.005	.231	.215																
7. Frequency BC[2]	3.99	0.63	.287*	.322**	.315*	.280*	.085	.311*															
8. Frequency IM[2]	3.71	0.54	.197	.095	.223	.251*	.119	.113	.279*														
9. Frequency PM[2]	3.78	0.75	.239	-.094	.048	.182	.068	.136	.299*	.486**													
10. Frequency TW[2]	3.26	0.57	.135	-.079	-.115	.027	.120	.397**	.185	.218	.408**												
11. Importance MC[2]	3.64	0.79	.612**	.406**	.746	.270*	.220	.741**	.215	.071	.177	.185											
12. Importance BC[2]	3.49	0.77	.439**	.538**	.442**	.442**	.417**	.461**	.350**	.064	-.020	-.017	.630**										
13. Importance IM[2]	3.25	0.75	.147	.215	.470**	.284*	.240	.121	.293*	.344**	.235	.046	.292*	.654**									
14. Importance PM[2]	3.36	0.84	.308*	.381**	.327**	.615**	.509**	.174	.290*	.227	.292*	.062	.346**	.621**	.604**								
15. Importance TW[2]	3.72	0.60	.125	.036	-.071	.124	.279*	.294*	.042	.151	.080	.366**	.351**	.285*	.352**	.469**							
16. Job Satisfaction[2]	3.92	0.72	-.083	-.264*	.094	-.214	-.051	-.000	-.025	.091	.096	.090	-.053	.050	.253*	.093	.145	(.74)					
17. Work Overload[2]	3.42	0.99	.168	.240	-.040	.082	-.079	.339**	.251*	.057	-.132	.032	.317*	.146	-.114	-.029	-.060	-.557**	(.84)				
18. Emotional Exhaustion[2]	2.85	0.60	.255*	.280*	-.036	.093	-.029	.230	.216	-.026	-.166	-.032	.332**	.191	-.071	.048	-.021	-.512**	.675**	(.79)			
19. Age	37.52	12.45	-.148	-.198	-.008	-.055	.075	.019	-.357**	-.120	-.175	-.094	-.061	-.098	-.063	.039	.120	.297*	-.141	-.225			
20. Gender[3]	1.81	0.39	-.056	.125	-.002	.144	.117	.102	-.046	-.304*	-.204	-.129	.113	.183	.031	.007	.103	-.239	-.025	.046	-.130		
21. Work Hours	31.05	8.95	.041	-.005	.050	.004	.017	-.062	.022	.218	.367**	.036	-.087	-.012	.036	-.186	-.315*	-.060	-.043	-.119	-.047	-.205	
22. Job tenure	15.31	11.62	-.103	-.189	-.073	-.092	.017	.044	-.412**	-.168	-.215	-.113	-.075	-.171	-.155	-.081	.063	.201	-.027	-.167	.912**	-.084	.061

Note: $N = 65$. * $p < .05$, ** $p < .01$. [1]Rated as 1 = *included in job,* and 0 = *not included in job*. [2]Ratings based on a 5-point scale. [3]Rated as 1 = *male,* and 2 = *female*. Cronbach's alphas reported diagonally. Tasks are clustered in medical care (MC), basic care (BC), patient management (PM), internal management (IM), and teamwork (TW).

Exploring the use of task data to understand employee well-being

Table 4 shows the means, standard deviations, and bivariate correlations between the inclusion, frequency, and importance ratings of the five clusters combining the task data from the task inventory and the text mining method. There were significant correlations between job satisfaction, work overload (r = -.56, p < .001), and emotional exhaustion (r = -.51, p < .001), and between work overload and emotional exhaustion (r = .68, p < .001).

For the five tasks clusters, there was a significant, negative correlation between the average inclusion of basic care tasks and job satisfaction (r = -.26, p = .035). Job satisfaction was also positively related to the importance ascribed to the internal management tasks (r = .25, p = .044). Work overload was significantly correlated with the average frequency with which nurses reported performing medical care tasks (r = .34, p = .007) and to a lesser extent with the frequency with which nurses reported performing basic care tasks (r = .25, p = .047). Higher inclusion of medical care (r = .26, p = .041) and basic care tasks (r = .28, p = .024) were both significantly correlated with emotional exhaustion. In addition, the extent to which nurses rated the medical care tasks as important was also moderately and significantly related to emotional exhaustion (r = .33, p = .007) and work overload (r = .32, p = .011). The results indicate that three out of five clusters are related to nurses' well-being, namely medical care, basic care, and internal management. The results also indicate that the frequency with which tasks were performed was not related to satisfaction and that a higher number of tasks (i.e., inclusion) was not related to emotional exhaustion, whereas the importance ascribed to some of the clusters was related to all three well-being indicators.

Table 5 presents the results of regression analyses for job satisfaction, work overload, and emotional exhaustion conducted separately for each rating type without any control variables that could obscure any explained variance (Bernerth & Aguinis, 2016). A higher average amount of basic care tasks was negatively related to lower job satisfaction of nurses, whereas a higher average inclusion rating on internal management tasks was related to higher job satisfaction. A higher average amount of basic care tasks was related to higher sense of work overload. The inclusion ratings explained 20.5% of the variance in job satisfaction (p = .023). A higher average frequency of basic care tasks was significantly related to higher work overload (r = .33, p = .006) and to higher emotional exhaustion of nurses (r = .28, p = .023).

Table 5: Standardized Regression Analyses of Inclusion, Frequency, and Importance ratings per Cluster on Job Satisfaction, Work Overload and Emotional Exhaustion

	Job Satisfaction			*Work Overload*			*Emotional Exhaustion*		
	β	*S.E.*	*p*	*B*	*S.E.*	*p*	*β*	*S.E.*	*p*
Inclusion rating									
Medical Care	.322	.174	.065	-.021	.186	.908	.109	.183	.550
Basic Care	-.506*	.211	.016	.444*	.221	.045	.410	.218	.060
Internal Management	.366*	.132	.006	-.162	.143	.257	-.170	.140	.224
Patient Management	.105	.140	.455	-.203	.146	.164	-.155	.143	.281
Teamwork	-.304	.202	.131	-.024	.213	.910	-.084	.201	.678
R^2	.205*	.090	.023	.123	.076	.108	.145	.081	.072
Frequency rating									
Medical Care	.023	.144	.872	.220	.128	.087	.187	.132	.158
Basic Care	-.118	.136	.386	.327**	.119	.006	.281*	.124	.023
Internal Management	.088	.146	.548	.063	.133	.638	.030	.136	.829
Patient Management	.048	.156	.757	-.250	.139	.073	-.256	.142	.072
Teamwork	.054	.147	.713	-.020	.134	.884	-.041	.137	.766
R^2	.025	.039	.524	.194*	.090	.031	.155	.084	.067
Importance rating									
Medical Care	-.106	.163	.514	.352*	.152	.021	.337*	.153	.027
Basic Care	-.094	.212	.656	.141	.204	.489	.149	.204	.465
Internal Management	.352*	.166	.034	-.240	.163	.140	-.254	.163	.119
Patient Management	-.085	.173	.622	-.042	.166	.802	.045	.164	.782
Teamwork	.127	.142	.373	-.112	.137	.413	-.114	.136	.401
R^2	.100	.071	.158	.166*	.084	.049	.163	.084	.052

Note: $N = 63$. * $p < .05$, ** $p < .01$. Regression were executed per rating type and included the correlations between job satisfaction, work overload, and emotional exhaustion. Regressions per outcome including the three different rating types simultaneously were not possible due to multicollinearity.

The frequency ratings significantly explained 19.4% of the variance for work overload ($p = .031$) and marginally 15.5% of the variance for emotional exhaustion ($p = .067$). A higher average importance of medical care tasks was both positively related to work overload ($r = .35$, $p = .021$) and emotional exhaustion ($r = .34$, $p = .027$). In addition, a higher average importance of internal management tasks was positively related to job satisfaction ($r = .35$, $p = .034$). The importance ratings significantly explained 16.6% of the variance in work overload ($p = .049$) and marginally 16.3% of the variance in emotional exhaustion ($p = .052$). These results indicate that in particular the inclusion or the frequency of basic care tasks is associated with less satisfaction and more overload. In addition, these results show that what one does mainly explains

one's satisfaction with the job, whereas the frequency with which one performs certain tasks or the relative importance one places on certain tasks helps to explain work overload.

Finally, we looked at the frequency and importance of individual tasks in order to explore which tasks might be either enjoyable, unpleasant, stress reductive, or burdensome for nurses to perform (see Table 6 and 7). First, these exploratory results indicate that some tasks are more enjoyable or unpleasant than other tasks. On the one hand, a higher frequency of some tasks was highly positively related to job satisfaction, such as assisting in special therapies (r = .78, p = .002) or collecting blood (r = .78, p = .005), whereas other tasks were negatively related to job satisfaction, such as participating in resuscitations (r = -.47, p = .019). Similarly, a higher importance of some tasks was positively related to job satisfaction, for example providing psychological care (r = .70, p = .009), negatively related for other tasks, such as showing students how to execute work (r = -.46, p = .038).

Second, the exploratory results indicate that some tasks may offer nurses resources (e.g., autonomy or knowledge) which help in dealing with workload and stress, whereas other tasks are burdensome and may require a lot of (emotional) resources. On the one hand, a higher frequency of some tasks was negatively related to work overload, including consulting the (head) doctor (r = -.61, p = .006), or to emotional exhaustion, such as creating shift schedules (r = -.59, p = .001), general documentation (r = -.76, p = .002), or participating in training (r = .59, p = .006). On the other hand, a higher frequency or importance of some tasks was positively related to work overload, such as ordering beds (r = .55, p = .002), handling visitors (r = .52, p = .005), and supervising students (r = .40, p = .041), or to emotional exhaustion, for example dealing with deceased patients (r = .40, p = .044) or preparing meals (r = .57, p = .008). All in all, these results indicate that it is potentially worthwhile to distinguish between tasks in order to understand well-being outcomes, because not all tasks are equal.

Table 6: Correlations between the Frequency of Individual Tasks and Employee Well-being

	Source	Cluster	Dependent variable		
			Job Satisfaction	*Work Overload*	*Emotional Exhaustion*
Deceased patients	TI	MC	-.254	-.065	.399*
Emergency case	TI	MC	.199	-.141	-.473*
Collecting blood	TM	MC	.776**	-.481	-.542
Doing laboratory tests	TM	MC	.707*	-.470	-.212
Participating in resuscitations	TM	MC	-.467*	.476*	.334
Assisting at diagnostical interventions	TM	MC	-.045	.575*	.301
Assisting at examination	TM	MC	-.423	.562*	.265
Providing medication on demand	TM	MC	-.040	.497*	.366
Taking care of unconfined ventilation	TM	MC	.597**	-.304	-.354
Assisting and conducting special therapies	TM	MC	.783**	-.441	-.648*
Toilet requests	TI	BC	-.004	.416*	.317
Prepare meals	TI	BC	-.256	.590**	.573**
Food/drink request	TI	BC	.041	.461*	.040
Caring for children	TM	BC	.048	.583*	.349
Supporting of rehabilitation	TM	BC	-.134	.401*	.214
Providing holistic care	TM	BC	.166	.562*	.208
Monitoring the patients' therapy	TM	BC	.260	.568*	.510
Caring for the elderly	TM	BC	-.116	.437*	.367
Check documentation	TI	IM	.098	-.545*	-.462*
Order bed	TI	IM	-.131	.553**	.303
Plan visits (after stay)	TI	IM	-.377*	.044	.002
Auditing medical transcriptions	TM	IM	-.307	.452*	.327
Organizing the work on the ward	TM	IM	.013	.502	.533*
Creating shift schedules	TM	IM	.374	-.449*	-.589**
Family	TI	PM	-.136	.471*	.374*
Handle visitors	TI	PM	-.105	.520**	.377*
Realizing the nursing process	TM	PM	-.334	.441*	.352
Host head doctor	TI	TW	-.195	.458*	.395*
Consult (head) doctor	TI	TW	-.085	-.601*	-.473
Cross-team meeting	TI	TW	.263	-.464*	-.295
Working on improvements	TM	TW	.411*	-.120	-.144
Working in groups	TM	TW	-.803**	.069	.113
Participating in meetings	TM	TW	.434*	-.086	-.203
Participating in training programs	TM	TW	.293	-.274	-.388*
Considering nursing research	TM	TW	.564**	-.256	-.590**

Note: * $p < .05$, ** $p < .01$. TI = Task inventory, and TM = Text mining. Tasks are clustered in medical care (MC), basic care (BC), patient management (PM), internal management (IM), and teamwork (TW).

Table 7: Correlations between the Importance of Individual Tasks and Employee Well-being

Task	Source	Cluster	Dependent variable		
			Job Satisfaction	*Work Overload*	*Emotional Exhaustion*
Check medication	TI	MC	-.262	.235	.410*
Injections	TI	MC	-.382	.267	.539**
Blood pressure	TI	MC	-.088	.486**	.418*
Drainages	TI	MC	.575*	.288	.300
Gavage	TI	MC	-.192	.504**	.409*
Monitor patients	TI	MC	-.055	.461*	.442*
Care for isolation patients	TI	MC	-.035	.393*	.260
Deal with emergencies	TI	MC	-.022	.385*	.370*
Assisting and monitoring anesthesia	TM	MC	-.226	.149	.465*
Conducting ECG	TM	MC	-.072	.289	.484*
Collecting blood	TM	MC	-.079	.497**	.351
Doing laboratory tests	TM	MC	-.084	.373	.538**
Assisting at endoscopic tests	TM	MC	.673**	-.153	-.389
Caring for patients post OP	TM	MC	-.468*	.085	.461*
Providing medication on demand	TM	MC	-.280	.456*	.466*
Preparing and administering of injections	TM	MC	-.146	.533**	.394*
Providing psychological care	TM	MC	.695**	-.087	-.153
Care for patients with vascular disease	TM	MC	-.215	.565**	.459*
Washing patients	TI	BC	.255	-.459	.586*
Toilet requests	TI	BC	-.015	.380	.375*
Order material	TI	IM	.505*	-.520*	-.378
Restock medication	TI	IM	.330	-.438*	-.229
Documentation general	TI	IM	.374	-.537*	-.757**
Check documentation	TI	IM	.033	-.496*	-.376
Insurance memo	TI	IM	.147	-.058	.399*
Administration	TI	IM	-.116	.611*	.436
Goodbye	TI	PM	.254	-.537	-.615*
Unscheduled meetings	TI	TW	.566**	-.304	-.404*
Supervise students	TI	TW	-.048	.185	.4003*
Show students	TI	TW	-.456*	.366	.399
Break	TI	TW	-.116	.413*	.414*
Participating in training programs	TM	TW	.416*	-.355	-.264

Note: * $p < .05$, ** $p < .01$. TI = Task inventory, and TM = Text mining. Tasks are clustered in medical care (MC), basic care (BC), patient management (PM), internal management (IM), and teamwork (TW).

DISCUSSION

The first aim of this study was to examine whether text mining can inform researchers and practitioners about what employees do in ways that are comparable and/or complementary to a task inventory. We showed that it is possible to automatically extract valid tasks from online vacancies using text mining (in the sense that these were recognized as such by SMEs), and that they showed a relatively high correspondence with tasks collected using an interview and observation based task inventory. The differences between the results from the methods also show they are complementary. As such, our study answers the call to apply new technologies and add a big data based approach to the field of job analysis (McEntire et al., 2006; Sanchez & Levine, 2001). Job analysis has remained relatively impervious to developments in big data and machine learning, and has continued instead to rely on interviews, observations, and surveys among SMEs to gather information about jobs (Sanchez & Levine, 2012). This study showed that text mining might be a suitable method to gather task information in a relatively quick, inexpensive, and potentially reliable way as compared to task inventories.

It is noteworthy that our comparison showed that text mining generally yielded higher inclusion and importance ratings, whereas the results were less clear for the frequency ratings. This finding can be attributed to the lower level of detail of the automatically extracted tasks compared to the richly detailed tasks collected through interviews and observations in one organization (e.g., one simplified task versus five detailed tasks about medication). The automatically extracted tasks were thus more likely to be part of most nursing jobs in our sample (i.e., higher average inclusion ratings). Although this may be due to the aggregated nature of these tasks, text mining draws from a larger, representative sample of the population than current methods, which could help to overcome the issue in job analysis that some tasks are wrongly included or excluded because they are only executed in a particular context (Morgeson & Campion, 2000; Sanchez & Levine, 2000). Moreover, the large number of vacancies that were automatically analyzed resulted in a variety of specialized nursing tasks (e.g., taking care of blind patients, dealing with aggressive patients) that did not surface in our interviews and observations executed at one particular hospital with a specific subset of nurses. Current job analysis methods often overlook these idiosyncrasies (Sanchez & Levine, 2012), because it is impossible to interview, observe, and/or survey all nurses, or even to collect data in varying

contexts. However, it is rarely the case that employees even within the same job do the same tasks across contexts (Fine, 1996), and text mining might thus be more suitable to address the nonstandard nature of work and as such could complement current forms of job analysis.

Text mining complements rather than substitutes current job analysis methods, because either method has its pros and cons. For purposes of conducting a job analysis that require all (detailed) information about what employees do within one organization, task inventories may be preferred over the use of text mining. The qualitative comparison between the two methods showed that a task inventory provided a more thorough understanding of one job within a particular context. Especially the mundane and less positive, but still very frequently occurring tasks in the nursing profession (e.g., washing patients, cleaning) did not surface in the text mining method. This could be explained by our use of online vacancies, which are aimed at recruiting employees and thus may include information aimed at advertising and/or signaling mainly the positive or enjoyable aspects of the job. Moreover, mundane tasks may not be mentioned explicitly, because they may be assumed to be known to nurses who apply to those jobs. It thus remains important to assess the purpose of conducting a job analysis prior to deciding what type of information and what method to use (Peterson et al., 2001).

Our findings contribute to the debate in the job analysis literature on the suitability of job information types. On the one hand, the overwhelming amount and variety of job information (Berkers, Mol, Kismihók, & Den Hartog, 2015; Levine, Ash, Hall, & Sistrunk, 1983; Prien et al., 2004) resulted in a standstill in the debate about the usefulness of these information types (Clifford, 1994; Peterson et al., 2001; Voskuijl, 2005). On the other hand, job analysis as a field has moved towards the use of more abstract, less detailed, and less context-specific forms of job information over the past decades (Dierdorff & Morgeson, 2009; Lievens et al., 2004; Sanchez & Levine, 2001). Abstract and general forms of job information, however, insufficiently capture the nuance and complexity in work that are part of reality (Uhl-Bien, Marion, & McKelvey, 2007), especially considering the changing nature of work. Based on the specificity, observability, and understandability of tasks (Cucina et al., 2012; Morgeson & Campion, 1997, 2000; Sackett & Laczo, 2003), we argued for focusing more on detailed rather than abstract, and contextualized rather than generic job information. The finding that tasks are not equal in their impact on employee well-being

and performance added evidence for the usability of tasks. The automatically extracted tasks were generally more abstract and less detailed than the tasks from the task inventory, but were still understandable enough for nurses in our sample to rate them, arguably provided a sufficient overview of what nurses do, and could individually be related to employee well-being.

The second aim of this study was to investigate the value of task data for understanding employee well-being and to see whether the different tasks clusters and individual tasks were related to job satisfaction, work overload, and emotional exhaustion. Higher general inclusion and frequency ratings of basic care tasks, for example, were found to be related to higher work overload and emotional exhaustion. This could be explained by the time, energy, and physical effort some of these tasks require, such as helping patients eat or wash. At a task level, these tasks (e.g., washing patients and helping them go to the toilet) were indeed significantly related to work overload and emotional exhaustion, whereas other basic care tasks were not. The explorative task-level analyses thus showed that not all nursing tasks are equal (not even within a single cluster) supporting similar claims made in task level studies of well-being (cf. Gabriel, Diefendorff, & Erickson, 2011; Semmer et al., 2007; Taber & Alliger, 1995). More detailed and nuanced insight about employee well-being can be derived from a higher degree of specificity compared to a general, "one measure fits all", approach, because they capture the nuance and complexity of reality (Tett et al., 2000). A higher degree of specificity in research on employee well-being (i.e., task rather than cluster, and cluster rather than whole job) may facilitate the development of theory and targeted interventions. For example, interventions aimed at decreasing experienced work overload, and thus preventing burnout, among nurses could target the problematic tasks and alleviate these instead of focusing on all basic care tasks.

Practical implications

There are several ways in which our text mining alternative for job analysis can be used in practice. First, automatically extracting tasks using text mining could be used in several industries to assess which tasks might be suitable to computerize or robotize. Better insights into what employees do could help ensure that the most burdensome, boring, or dangerous tasks are outsourced to computers or robots and that the most meaningful and motivating tasks are kept intact (Bresnahan, 1999; Frey & Osborne, 2013). Currently,

efforts at automation and/or robotization of work are often technology-driven rather than employee- or task-driven, implying that tasks that can be computer- or robotized are. Organizations could start to make more strategic choices that benefit employees as well by selectively looking at potential tasks and assessing their relationship with employee well-being before deciding which tasks ought to be robotized or computerized. This would prevent situations as described in the case of the metro drivers in Paris, in which unknowingly important and valued parts of the job, such as responding to emergency situations, were lost with the introduction of self-driving metros (Anteby & Nishani, 2016). Based on our study among nurses, some of the basic care tasks might be prioritized for robotizitation, such as adding robotized arms to reduce the physical effort and energy spent on assisting and carrying patients during washing and visits to the toilet.

Second, automatically extracting tasks using text mining could also be used in different industries to improve work (re)design based on the tasks that are performed by employees. In our study, basic care tasks proved to be the most problematic due to their positive relationship with work overload and emotional exhaustion and some of those tasks such as preparing meals are not included in all jobs, because many hospitals have dedicated kitchen services that take care of them. Hospitals can thus redesign nursing work by outsourcing, changing, or at least decreasing the frequency of tasks that exhibit a negative relationship with nurses' well-being when possible. Organizations are argued to have a responsibility in ensuring that employees have meaningful work (Michaelson et al., 2014), and insights about what employees do offers opportunities for enrichment following the principles of job design (Hackman & Oldham, 1975).

Limitations and directions for future research

This study was subject to some limitations. First, the results of our comparison between a task inventory and text mining method is limited to the data used, namely online vacancies. Despite the clear advantages of using vacancy data, being readily available, easy to obtain, and the existing experience with automatically analyzing this type of text (Sodhi & Son, 2007), its quality is sometimes questionable. The quality and level of detail of task data in vacancies posted by organizations, for example, was higher than those posted by recruitment agencies. Although text mining vacancies allows a larger sample of jobs to be analyzed than current job analysis methods, not all jobs

might be advertised online (Sodhi & Son, 2007). We suggest that alternative data sources are investigated in future research to complement or substitute the online vacancies. There is still a vast amount of potentially rich sources of job information contained in other 'big' data, including electronic records of performance monitoring that could be exploited using state-of-the-art technology (Sanchez & Levine, 2001). Another alternative may be to supplement online vacancies with existing job descriptions, for example, retrieved from O*Net (Campion et al., 1999). The higher the quality level of the data, the better the results using text mining method (or stated conversely "garbage in is garbage out").

Another limitation of our study is the small sample that was used to estimate the relationships between task clusters, specific tasks, and employee well-being. Due to the large number of tasks and the cognitive burden this would place on respondents, each respondent only rated a third of the total number of tasks. As a result, only a limited sample remained to assess the impact of a particular task on job satisfaction, work overload, or emotional exhaustion. The exploratory analyses of which task clusters and which specific tasks nurses experienced to be most burdensome (i.e., positively related to overload and exhaustion) or more enjoyable (i.e., positively related to satisfaction) should therefore be interpreted with caution, since some were bound to turn out significant (Hollenbeck & Wright, 2017). We suggest that future research includes a priori hypotheses about relationships between tasks and well-being and presents all tasks to all respondents. Letting those participating rate only frequency or importance might be an alternative way to reduce the cognitive burden placed on participants, which could negatively affect the reliability of the results (Morgeson & Campion, 1997). In addition, our study is limited by its cross-sectional design and thus does not clarify the direction of the relationship between specific task ratings and employee well-being. The significant positive relationship between the relative importance nurses placed on taking a break and work overload ($r = .41$, $p = .036$) and emotional exhaustion ($r = .41$, $p = .032$), for example, is more likely explained by revered causality in which higher work overload and exhaustion make that nurses perceive a break as more important than the other way around.

Another potential avenue for future research is to not only look at the impact of several tasks on employee well-being, but to also include the balance between those tasks. Aiken and colleagues (2001), for example, found that

nurses' well-being decreased when they needed to perform tasks that directly require nurse-patient interaction. On the contrary, our results showed that by themselves some medical or basic care tasks were related to work overload and emotional exhaustion of nurses, whereas others were not or were even related to job satisfaction. It would be interesting to research whether an inverted-u might explain the relationship between specific tasks and well-being better. Both spending no time at all or too much time on certain tasks may negatively affect nurses' well-being, either not allowing them to express their professional identity by performing congruent tasks (Pratt et al., 2006; Shamir, 1991) or draining their resources.

APPENDIX A: Examples Interviews and Observations[5]

Interview Protocol (shortened)

Thank you for your time. We conduct these interviews as part of the Pro-Nursing project, aimed at understanding which tasks nurses perform. This interview will around half an hour. Is it okay if I record the interview? We will store the information from this interview strictly anonymously. The interview is about your job and the tasks you perform, so there are not wrong or right answers. Please try to use your own words and describe your work in such a way that we or someone else that is unfamiliar with your work can understand it as well.

1. Could you please describe in detail the work you do?
2. Could you describe a regular day at your work? What do you do on a daily basis?
3. What are tasks that you perform daily? And which tasks not?
4. What responsibilities do you have?
5. Which tools and equipment do you use in your job?
6. Do you have any questions? About the content of the study or the procedure?

Transcription and coding example [marked area is coded as task #48 toilet requests]

What else happens on a day?

The patients also have a 'bell' that they can use and they ring, ring, ring this bell. This is additional to all the other work. Requests about going to the toilet, helping with washing, somebody who forgot something. In between all this points that has to be done there are the patients who ring the bell and need something and that must be done directly. This is very much interruption.

Observation Protocol and examples (shortened)

TASK	COUNT	COMMENT	WHO	SHIFT
Change/Prepare	2	Change into scrubs/shoes.	Nurse	Office
Report	2	Discuss overall issues, 1 is in charge, takes the lead. Discuss every patient one by one...	Nurse, Doctor	Office
Washing patients	1	Assist patient with taking a shower. Change bandages special for shower.	Nurse, Patient	Patient room
Basic check	0			
Prepare examination	2	Set up cart for doing rounds of patient consults. Get patient maps, medications, ...	Nurse	Hall, medical room
Check meals	0			
Prepare meals	10	Prepare meal for each patient based on requests. Precooked diners are heated ...	Nurse	Kitchen
Assist eating	0			
Check medications	5	Check which medications per patient are necessary at what time. Discuss or check ...	Nurse	Hall, patient room
Document (steps)	20	Everything is noted down in the patient files. Steps taken, state of the patient, ...	Nurse	Hall, office
Blood test	1	Draw samples of blood for testing.	Nurse	Patient room

[5] Representative examples provided here, but full transcriptions and observations are available upon request.

APPENDIX B: Task List from the Task Inventory Method

Cluster		Task description
Medical Care		
Medication	1	Collect the needed medications in the medical room and put on car to distribute during the patient rounds. Preparations are done the day before after all medications are taken by the patients.
	2	Arrange the medications for that day for newly admitted patients to ensure that they have all the medications they need for the rest of the day based on the information gathered during the intake.
	3	Check which medications per patient are necessary at what time and if everything is okay with the medication, check for example how much of the medication went through the IV. Discuss or check with patient what medications they took, brought, or need. Extra care is needed for some patients to make sure that they take all medication.
	4	Hand out medications to patients based on the documentation and preparations done earlier.
	5	Give the patient necessary injections with medications based on the decisions made by the doctor.
	6	Discuss the level of pain with the patient and decide with doctor or individual on additional pain medication. For small pains like headache, stomach ache, or problems sleeping, the nurse can decide independently. In case of doubt, consultation with a doctor is required. Come back later to check up for effects of the additional medication.
Diagnostics & Medical tests	7	Draw samples of blood for testing. Prepare bowl with materials for blood test, put patient in position and adjust pillow if necessary to make sure patient is comfortable, ready, and safe, add band on arm, look for a suitable vein, inject the needle, getting blood, making sure patient is okay, put on a bandage and give instructions after everything is done.
	8	Print labels and documentation for blood samples. Add information in computer about time that the blood was taken and add labels to the blood samples to make sure everything is administered and can be send to the lab.
	9	Take samples from patient's mouth or nose for testing. After getting the smear, package, and send to lab.
	10	Get urine sample of patient. Put urine stick in urine for first testing of the urine. In case something is wrong or requires more testing, package and send sample to the lab.
	11	Place the needle of the IV and attach the drip on the request of the doctor or based on scheduled medication. Remove drip from patient and from the room. Throw away material and provide bandage.
	12	Assist doctor with executing a lumbar puncture by preparing all material, putting the patient in place, holding the patient, and handing material during the procedure.
	13	Check the oxygen level in the blood of patients with special machine by entering blood and reading the results.
Special care patients	14	Check the temperature of the patient with a thermometer and document temperature.
	15	Check the state of the stiches while removing and checking bandages. Also remove stiches based on the doctor's request.
	16	Check the state of the catheter, clean, place, clean, and replace catheter if decided this is necessary by the doctor. Check the amount of urine in the catheder.
	17	Get the material for checking sugar and get patient ready. Puncture the skin on the finger of the patient to get a bit of blood for the test. Check the sugar results for diabetic patient and discuss results with the patient.
	18	Check blood pressure of patients, put band on patient's arm and listen through stethoscope while pumping air. Discuss results with patient and document afterwards.
	19	Check drainage in patient's head or back for fluid and blood.
	20	Take care of stoma.
	21	Provide patients food and nutrients by gavage. In case a patient cannot eat by themselves and needs nutrients in a different way, the nurse has to give food by a tube through the nose or stomach of the patient.
	22	Check the bandages to see if it looks okay and bandages are dry. Change bandages to clean and fresh ones. For more complex bandages and if doctor is there to visit, doctor performs the bandage change while nurse assists by handing material, holding the patient and cleaning up afterwards.

	23	Document all input, including food, liquid, and medication, of the patient compared to the output, urine, faeces, and fluids. Calculate the differences and document in patient folder.
	24	Check and monitor the state and progress of patients who require special care. Go to them to check, measure blood pressure, see if they are present and awake. Check monitors from a distance. Nurse is the closest one to monitor progress of the patient and the one to inform and check if patients are doing worse or better.
	25	Prepare the patients for their treatments of that day. Make sure that patients are prepared for surgery, for the visit of the doctor, special therapies, MRI scans etc.
	26	Prepare before going in the isolation room of special patients by putting on a mask, clothes cover, hair net, shoe covers, gloves before entering the room. After entering disinfect and remove mask, hair net, gloves, clothes cover, and shoe covers.
	27	Deal with the death of a patient after noticing that a patient has deceased.
	28	Monitor patients who are confused, because of neurological surgery or other conditions, to make sure they do not run away or hurt themselves. In extreme cases file an official request to fixate a patient and fixate the patient to the bed.
Surgery care	29	Help patients put on the special clothing for surgery including thrombosis stockings, put on name bracelet, check patients' medications, allergies, and diagnostics as a safety procedure, make sure that patient did not eat in preparation for the surgery, that the patient received a mark from the doctor, and put the patient in a special bed for transfer to make sure that the patient is ready for the scheduled surgery. This is done based on the information in the operation protocol and the operation schedule in the computer.
	30	Give patients anaesthesia medication in preparation for their operation based on the operation protocol.
	31	Monitor and checking post-operation patients continuously. Check for pain, their state, situation, medication, and progress. Special to post-op care is checking if patients are awake, if possible wounds are bleeding, and if they have feeling in their limbs and body after neurological surgery. Post-op care is additional to basic checks with the patient to ensure that the patient is doing well after surgery.
	32	Document additional information about the patient for patients who had surgery, or who need special care, for a couple of days. This includes blood tests, drainages, if the patient is awake, input and output, the size and state of a possible wound.
Emergencies	33	Start with providing the first aid in case of an emergency and get someone else to call the emergency number to get a special team to the location to provide specialized care such as reanimation.
	34	Provide first aid for accidents, for example patient who are experiencing an epileptic episode or who fell out of the bed, and then inform the doctor.
	35	Document additional information after an emergency about the emergency, how this could happen, what has been done, and what the results were.
	36	Check expire dates of the medication and material in the emergency case to make sure that everything in there is still valid and safe to use to guarantee quality.
Basic Care		
Patient rounds	37	Set up cart for doing rounds of patient consults with the doctor. Get patient folders, medication for each patient, and check documentation for each patient before entering the patient rooms.
	38	Ask patients about their current state and pain level. Ask how they are doing, what they are feeling, if and where they have pain to assess their state and decide on next steps based on needs of the patient. Also check their medication, wounds, bandages etc. Discuss what is next (possible surgery, physio, doctor consultations etc.) and what the patients might need. Involve the family if present. Do tests if necessary.
	39	Check if patients are mobile, help them walking around while checking their progress and state, help patients with getting up from bed or chair, get and adjust pillows for body and particular limbs. Put patient in wheel chair and back in bed.
	40	Turn patients in their bed from one side to the other who have difficulty moving by themselves or are immobile, because of paralysis or paraplegia, to make sure they do not get bedsores. Is done around every two hours preferably by two nurses. This also includes moving patients back to the top of the back, because they have the tendency to slide down in the bed.
	41	Interact with the patient and give them some attention to make them feel comfortable. Ask questions, list to them, and show interest. Be kind.
	42	Answer any questions or requests for information from the patients about their medical situation, such as their therapy or how to shower with bandage.

	43	Inform the patients during the patient rounds about their progress based on the information about their state received in the basic check. Advise patients about what to do, such as to take it slow. Also inform patients about the rest of the procedure and give quick check-ups about the day, for example "I will be back in 10 minutes to help you shower".
	44	Deal with requests from patients that are made during consults or at the initiative of the patients by pressing the button about technical issues such as Wi-Fi, television or laptops, the (usage of the) remote control, usage of the telephone etc. The goal of answering these requests is to ensure a pleasant stay of the patients.
	45	Check if patients are ready for the night by making a final round before turning off the lights.
Patient hygiene	46	Wash patients or assist patients with taking a shower or bathe and change bandages to special ones for showering during patient rounds in the morning shift to ensure patients are well and ready for the day.
	47	Change patients who cannot use the bathroom or who are incontinent. Take care of bedpan, urine bottle, and/or diapers to ensure patients are clean.
	48	Deal with requests from patients that are made at the initiative of the patients by pressing the button about visiting the toilet. Assist patients with going to the bathroom to ensure hygiene and health of patients in a safe way.
	49	Change bedlinen (partly or completely) based on request of the patient or by initiative nurse to ensure a clean and hygienic environment for the patient. Sometimes done with patient still in the bed if the patient is immobile.
Food & drinks	50	Ask patients about their meal preferences to write down what they want to eat and drink and at what time. Order the food from the kitchen through the computer system. Also order food, such as bread, coffee, and tea for use during the next day. Provide information to kitchen staff.
	51	Prepare meal for each patient based on their individual requests. Precooked diners are heated, put on plates with some fresh ingredients and then served. Cold dishes are made from scratch (such as read, salad). Everything is put on a tray per patient before handing it out. Also help prepare final steps of food or small meals, including making sandwiches or coffee.
	52	Check the meals prepared by the kitchen for the needs of each individual patient based on the patient documentation. Should match their needs (type of food, diabetes etc.), exclude patient who are not allowed to eat, and should be safe.
	53	Bring the prepared food to the patients. Everything is put on a tray and brought to the room, where the nurse decides together with the patient where they want to eat (bed or table). The food is put down for the patient at the discussed place.
	54	Deal with requests from patients that are made during consults or at the initiative of the patients by pressing the button for something to drink or eat. This is possible during the whole shift at every possible moment and interrupts the work flow. The goal of answering these requests is to ensure well-being of the patients.
	55	Help patients who require extra care with eating their food. Provide the food by hand or feed the patient. Watch patients who have difficulty swallowing.
Clean	56	Clean up in the rooms, do dishes, pick up dirty dishes, clean the kitchen, clean the hall way. Everything that is used needs to be cleaned and make sure the rooms look clean.
	57	Pick up plates and trays used for food. Clean up everything and bring back to the kitchen for cleaning.
	58	Remove old bedlinen, clean the bed with soap and disinfect, and put on new bedlinen for the new patients. Also clean complete room for new patients, disinfect all surfaces, dust room, clean the bathroom, and vacuum.
	59	Clean the isolation room with even more care based on safety regulations. Change the bed every day and disinfect everything in the room. Also order a special cleaner by phone to clean the isolation room after patient has left.
	60	Place laundry in the laundry basket after changes bed. Replace the laundry basket and make sure dirty laundry is ready for pick up by cleaners.
	61	Dispose of medical waste of the isolation patient, needles and medications in a safe manner.
	62	Take care of suctioning machines that deal with mucus in the nose and mouth. Clean and check.
	63	Clean all medical material and replace plastic of medical machines, including IV, every 24 hours.
	64	Disinfect all material that is used during the day, all surfaces, and medical equipment.
Internal Management		
Inventory	65	Check the inventory if any medications are needed and order new medications from the pharmacy. This is often done while preparing medication.

	66	Check inventory if material (medical or other) is needed and order new materials.
	67	Remove tablet on which medical materials, such as needles and gloves, are placed in order to make sure it is replaced by someone else with new material
	68	Place newly ordered material in stock room. Replenish cart with material and replenish closet in patient rooms with material for patient care. Make sure that everything that is needed is there at the right place. This is done late and at night to make sure everything is there for the busy morning shift.
	69	Place newly ordered medication delivered by the pharmacy in the medical stock room. Also replenish the cart with medication. This is done late and at night to make sure everything is there for the busy morning shift.
	70	Check the expire dates of the medication, if medications are expired or about to expire, to make sure that there are still valid and safe to consume and to guarantee the quality of medication used.
	71	Check the temperature of the fridge where the medications and blood are kept. Must be at the right temperature and working to ensure quality of the medications that are used by the nurses.
	72	Check expire dates of special, closed off, medication such as morphine. Check if medications are expired or about to expire, to make sure that there are still valid and safe to consume and to guarantee the quality of medication used.
Documentation	73	Prepare all documentations for new patients that are admitted the next day or the next shift. Print and bind documentation and print name labels for the rooms. This is done to make sure that the next shift can start well and transmission between two shifts is efficient.
	74	Note everything down in the patient files. Steps taken, state of the patient, if it goes better or worse, toilet visits, if they eat something, medication that the patient received, blood pressure, blood sugar, possible blood tests and all other test results to track progress of the patient. Everything that the nurse does is documented and signed to back up legal responsibility and for scheduling nurses and work load. Also execute and document all information that was discussed during the visit after the visitation with the doctor. This includes appointments, medications, and prescriptions. Documentation is done in time and often between all other activities. After actions and at the end of the whole shift.
	75	Double check all documentation. Go through all documentation of everything during the day to check if everything is written down, if anything is missing check that piece of information. . This is done to make sure no information gets lost which results in a good transition between shifts.
	76	Write down memo's for the patient that are used for their insurance claims about the treatment that they received at the hospital. Write down at the end of the day what is done for each patient which is later used to create an invoice for the insurance company of the patient.
	77	Administer the number of patients that the department has that day. Document the in and out flow of patient for the hospital.
Scheduling work	78	Discuss who is working which shift and make a work schedule for the different shifts.
	79	Discuss which task(s) need to be done and who does what. Give a specific request to colleague to perform task. Objective is to make sure the work is done efficiently and timely.
	80	Divide the patients over the nurses that are working that shift. Each nurse, if more nurses are working during that shift, will be made responsible for the care of a number of patients at the beginning of shift.
	81	Discuss the occupation of the rooms and beds for that day, check who is admitted that day and who is leaving to decide which patient will be placed in which bed and room. Take into account the planning of operations and scheduling of patient dismissals. Adjust information about the patient placement on the board in the nurses' office.
	82	Order a clean bed for the new patient.
	83	Schedule the surgery of the patient. Inform patient about the appointment and check with the doctor during consult or by phone. After the doctor visits, the planning of the appointments is done in the computer and everything is written down for administrative reasons.
	84	Organize the appointments of the patients for the next day. Plan the visits of the doctors, appointments for treatments, examinations, or tests. For example book a time slot at the MRI.
	85	Schedule and discuss the doctor appointments of the patients. Schedule for example the physiotherapy session of a patient for the next day or next week. Inform patient about the appointment and check with the doctor during consult or by phone. After the doctor visits, the planning of the appointments is done in the computer and everything is written down for administrative reasons.
	86	Request revalidation for patients by filling out forms and arranges everything between the patient and revalidation centre.

Patient Management		
International patients	87	Make special arrangements concerning international patients, including their flight, stay at the hospital and city, and their transfer. This also includes patient management before and after their stay at the hospital, contact, and appointments. Also arrange tolk if necessary.
Intake patients	88	Prepare documentation of new patients coming in. Create a file and personal folder with the provided information. Make sure everything is ready for arrival of the patient. This is often done at night to release pressure from the busy morning shift to make sure all documents and checklists are ready. Also prepare documentation of patients for next days or next week by transferring information to new pages.
	89	Take-over patient from another (regular) hospital brought by ambulance or from another section in the hospital (IC or IMT). Discuss paper work with patient and ambulance or hospital personnel.
	90	Welcome new patients who arrive at the ward and take care of their arrival. Provided the patients with a room, show how everything works (phone, buzzer etc.) and provide them clothes. Give patients time to settle in and change in to their patient clothes before returning for the official admitting part.
	91	Gather information about the patient, this includes their medical condition, the treatment they will received or received, why they are there, their doctor's information, what medications they are on, if they require assistance, and personal information such as allergies. Create new personal patient map (if not ready yet). Go through all the information with the patient to check. Also answer questions from patients about their stay and treatment.
	92	Prepare test and handle administration before after receiving a request for a test from doctor by telephone or in person during consultations and when patient first arrives.
	93	Fill out forms with information about the new patient, including their medical condition, the treatment they will received or received, why they are there, their doctor's information, what medications they are on, if they require assistance, and personal information such as allergies. Add information in the computer by clicking boxes and answering additional questions about the patient, for example "is there a risk that the patient will fall in the hospital?". Write a patient note about the patient, why the patient is there, and what kind of help the patient requires. This last document is needed for reporting and sharing information between staff.
Dismiss patients	94	Inform leaving patients about their progress in recovering, the medications they need to take and how often they need to take their medication, any next steps that need to be made in their recovery, future appointments, what to do (in case of an emergency), how to apply bandages is necessary. Ask patients to call or come by if anything is problematic or not going well to make sure that they are okay continuing their recovery at home.
	95	Give prescriptions to patients for needed medications with instructions for usage. Also provide information about future appointments at the hospital on paper and bandages or medication for the coming few days to make sure that they are okay continuing their recovery at home.
	96	Say goodbye and give best wishes to leaving patients and their family.
	97	Clean up the patient folder by removing papers and binding together in another folder for administration. If there is a request to do so, take care of additional documentation for patients such as copies of medications, lab results, CT scan etc. for their own general practitioner. These requests are made during consults.
Transfer	98	Call the place of the appointment, examination, including MRI, CT-scan, and X-ray, or surgery to discuss the transfer or pick up of a patient.
	99	Call the transport service for patients who are leaving and cannot go home alone. Order transport specialized for the patient, bed or wheel chair, and write the protocol for the transport.
	100	Transfer patients to and from the operation room (OR), to and from appointments or examinations such as X-ray or CT scan. Put patient in bed or wheel chair and accompany them to their location.
Visitors	101	Interact with family members and visitors of the patient. Ask family members questions, talk with them, socialize, make them feel at ease. Also answer questions that family members might have about progress, state of the patient, and the next steps in the procedure. Nurse functions as the contact point between patient, family, and the doctor. Conversations form also input for consultations with the doctors.
	102	Handle visitors of patients by showing them the room after welcoming them. In case of visitors of an isolated patient, extra information has to be provided to visitors on how to behave and how to prepare. Assist with putting on gloves, masks, hair covers, shoe covers etc.
Doctor consultations	103	Quick check of the patient and the current state before the doctor has a consult with the patient to make sure they are there and not in too much pain. Also get patient maps with documentation and form with information for the patients that will be visited by the doctor to make sure the visits of the doctor go as efficient as possible.

	104	Visit patients per doctor (depends per doctor at what time) once a day to discuss patient's state, medication, and procedures. Nurse facilitates and provides information to both patients and doctor. Discuss with doctor per patient before entering the patient room. Provide information and get information during the consult with the doctor about state, medication, pain, steps, procedures, and appointments. Information should be documented afterwards.
	105	Visit patients with the head doctor to discuss the patient's state, medication, and procedures. One (head) nurse facilitates this visit and provides information about what happened to the patient and what will happen next.
	106	Check with doctor about how to proceed with patient or discuss patient request or question about medical treatment. Initiative can come from doctor and nurses. Objective of consulting is to ensure quality of treatment of the patients and to share responsibility.
Teamwork		
Information sharing	107	Report important information to close of one shift and hand over to the next one to ensure a smooth transition between shifts. Discuss per patient, led by one nurse taking the lead, so that every nurse knows about each patient what happened in the previous shift and what needs to happen in the next hours of the new shift. The current state of the patient is discussed in overall ("doing well") and by lab results and at medical level (blood pressure, wounds, sugar etc.), followed by the steps and actions that have been taking during the shift (therapy, surgery, doctor visits etc.) and the medication that the patient received and still needs to take. Also discuss which doctors are treating which patients. Discuss new patients and the patients that are leaving the clinic. This is done with the use of folders with documentation per patient. Each nurse takes own notes per patient on a form that they keep during their shift. This is important to make sure no information about the patient is lost for good continuation of the treatment of each patient.
	108	Inform the doctor by phone about patients who need acute help for example after an incident or because the patient is rapidly doing worse or a wound is not looking well.
	109	Answer internal (mainly) and external calls requesting information or about the pickup and transfer of patients. Also make quick calls to check by initiative of nurses about patients, information, and visiting times of doctors.
	110	Have quick, unscheduled meetings to share information with one or multiple colleagues considering the work. Discuss incidents and how to prevent, what is happening, updates of the content and execution of the work. This kind of meetings are only done when necessary to improve performance during that particular day.
	111	Discuss what is going on with each patient from the department with all involved personnel. This includes nurses, doctors, physiotherapists, psychologists, and assistant doctors. Everybody who is involved with that patient. Discuss the patients, who is coming in, who is going, what is going on, and what needs to be done next. For example if there is a patient who cannot sleep we discuss it there. This is done to make sure all information is shared and that there is an opportunity to share ideas between the occupations.
	112	Have and attend team meetings with whole nursing team to discuss the work, functioning of the team, how the week has gone, what went well, and what could be improved. This is done as a moment of evaluation. This can also be used as a moment to share new techniques and medications.
Student education & Training	113	Introduce themselves, the team, and hospital to new students and plan when student will come and what they will do. Match the students with a nurse who will be responsible for them during that day.
	114	Facilitate learning by doing of students who are doing an internship or traineeship at the hospital. Be responsible for that student during the shift and show them how everything works, supervise students practicing their skills, function as a point of contact, and provide guidance.
	115	Organize additional education for nurses around a topic (such as urology). Get a doctor involved who can share expertise, arrange a time and plan the education session in the schedule.
Work recovery	116	Have a break ranging from quick breaks for tea or water to a moment to eat.
	117	Talk about work to decompress emotions of the shift, work in total, share personal information (vacation plans) etc.
	118	Make coffee for the nurses who are starting their shift.

APPENDIX C: Task List from the Text Mining Method

Cluster		Task
Medical Care	1	Assisting and monitoring anesthesia
	2	Caring for patients with windpipe
	3	Checking vital signs
	4	Administrating of medication
	5	Realising the wound management
	6	Assisting and conducting special therapies
	7	Conducting ECG
	8	Collecting blood
	9	Preparing and administer intravenous drugs
	10	Assisting at surgical interventions
	11	Doing laboratory tests
	12	Participating in resuscitations
	13	Assisting at diagnostical interventions
	14	Preparing and assisting at transfusions
	15	Operating the technical equipment
	16	Caring for the blind
	17	Assisting at endoscopic tests
	18	Caring for patients with neurological diseases
	19	Assisting at examination
	20	Caring for critical care patients
	21	Caring for patients in the recovery room
	22	Identifying early emergency symptomes
	23	Caring for patients post OP
	24	Providing medication on demand
	25	Preparing and administering infusions
	26	Taking care of unconfined ventilation
	27	Checking and documenting vital signs at operations
	28	Caring for patients with spine surgery
	29	Conducting sterile dressings
	30	Preparing and administering of injections
	31	Providing psychological care
	32	Preparing patients for surgery
	33	Caring for patients with orthopaedic diseases
	34	Care for patients with vascular disease

Cluster		Task
Basic Care	35	Caring for mentally ill patients
	36	Caring for children
	37	Assisting at intake of food
	38	Supporting of rehabilitation
	39	Providing holistic care
	40	Accompanying patients
	41	Monitoring the patients' therapy
	42	Caring for the elderly
	43	Providing basic or general care
	44	Providing palliative care
Internal Management	45	Prodiving nursing documentation
	46	Auditing medicial transcriptions
	47	Organizing the work on the ward
	48	Processing instruments
	49	Organizing the orders of material
	50	Preparing and disposing of materials
	51	Keeping the data up to date
	52	Realising interventions of quality assurance
	53	Documenting of services
	54	Creating shift schedules
Patient Management	55	Giving patients and family advise
	56	Working on doctors' prescriptions
	57	Realising the nursing process
	58	Developing an individual care planning
	59	Collecting patients' data
	60	Transitioning of patients into home care
	61	Admissioning and discharging patients
Teamwork	62	Improving interdisciplinary cooperation and collaboration
	63	Communicating with patients, family, and staff
	64	Participating in visits
	65	Working on improvements
	66	Working in groups
	67	Participating in meetings
	68	Participating in training programs
	69	Participating in hygiene training
	70	Considering the latest results of nursing research
	71	Training and advising students