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When Emotions Rule Knowledge:
A Text-Mining Study of Emotions in Knowledge Management Research

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ABSTRACT

Although emotions play an important role in human behavior and knowledge studies, knowledge management (KM) research considers them from specific angles and, to date, has lacked a comprehensive understanding of the emotions dominating KM. To offer a holistic view, this study investigates the presence of emotions in KM publications by applying a sentiment analysis. The authors present a sentiment dictionary tailored to KM, apply it to KM publications to determine where and how emotions occur, and categorize them on an emotion scale. The considerable amount of positive and negative emotions expressed in KM studies prove their relevance to and dominance in KM. There is high term diversity but also a need to consolidate terms and emotion categories in KM. This study's results provide new insights into the relevance of emotions in KM research, while practitioners can use this method to detect emotion-laden language and successfully implement KM initiatives.

KEYWORDS

Comparison Clouds, Emotion Scales, Emotion Taxonomy, Emotions, Knowledge, Knowledge Management Research, Sentiment Analysis, Sentiment Dictionaries, Text Mining

INTRODUCTION

Emotions are as much a part of human behavior as reason and play an important role in intelligence and knowledge (Martínez-Miranda & Aldea, 2005). Managing knowledge in organizations has proved to be very useful since successful knowledge management (KM) leads to significant improvements in their scientific, economic, and social aspects (Cao et al., 2012). Nonetheless, knowledge is often viewed merely as just another manageable organizational resource (Alavi & Leidner, 2001). Owing to its context-specificity and boundedness to human beings (Nonaka, 1994), however, it cannot be separated from human emotions and, thus, has to be approached differently than other organizational resources (Kuo et al., 2003). Consequently, the role played by emotions, which help to both express and understand knowledge (Davenport & Prusak, 1998), requires attention from within the information systems (IS) domain in general and from KM researchers in particular.

IS researchers have started to pay attention to the presence and role of emotions (Chau et al., 2020; Beaudry & Pinsonneault, 2010; Gregor et al., 2014). Likewise, KM studies on emotion-related topics are critical to acknowledging emotions and the role emotional concepts play in KM (Scherer & Tran, 2003; van den Hooff et al., 2012). Nonetheless, these studies also show how compartmentalized KM research on emotions is. It only focuses on single emotions and limited subtopics from emotion

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research while neglecting an overall and holistic perspective that would help to develop common ground in this area. For instance, concerning KM processes, the roles of emotional intelligence (Decker et al., 2009; Peng, 2013; Trong Tuan, 2013) and emotional obstacles (Lin et al., 2006; Pemberton et al., 2007) have been investigated. However, an integrated and comprehensive overview of emotions, unbiased by any particular single topic, is still lacking, and it is necessary to consolidate research on single emotions and emotional concepts (Hornung & Smolnik, 2018), and in which nexus they are displayed in KM research – with a taxonomy of emotions in KM research as the ultimate goal. To arrive at a comprehensive taxonomy of emotions in KM and close the aforementioned gap, it is crucial to understand which emotions are prevalent in and dominate KM research. Sentiment analyses, which have often been used to detect words associated with either positive or negative emotions in the context of politics, finance, and (social media) marketing (Matthies, 2016; Yassine & Hajj, 2010), are a useful instrument to gain a broader understanding of emotions. As a special type of text mining, sentiment analyses support the authors' goal of analyzing the underlying sentiment of a text that "can encompass investigating both the opinion and the emotion behind that unit" (Yadollahi et al., 2017, p. 2). Sentiment analyses also enable the exploration of vast amounts of data. They are also effective at revealing which emotions prevail in written KM publications and can, therefore, help to answer the following research questions:

RQ1: Which emotions dominate research on KM?
RQ2: How can these emotions be categorized according to emotion scales?

The sentiment analysis in this study relies on a dictionary-based approach in which KM-specific dictionaries 1) are created based on Hu and Liu (2004) and 2) applied to a comprehensive sample of 6,017 scientific KM publications to detect existing emotions. The analysis results are then 3) categorized and structured using an appropriate emotion scale.

RESEARCH BACKGROUND

Emotion Theories

Emotions are the primary motivational system for human beings (Leeper, 1948; Mowrer, 1960). Thus, an emotional component drives human actions and interactions, which also display emotions in communication through IS (Rice & Love, 1987). Psychology researchers have focused heavily on emotions as a research object, which has led to not one universal but many different definitions and conceptualizations (Chaplin & Krawiec, 1979; English & English, 1958). Definitions range from broad views, such as emotions directing cognitive activities (Clark & Fiske, 1982; Mandler, 1975), to specifically seeing emotion as the complex reaction to a stimulus (Plutchik, 1984). In this study, an emotion is considered a chronologically unfolding sequence: After exposure to a stimulus, a human perceives a state of "feeling" and, consequently, displays externally visible behaviors or emotional outputs (Elfenbein, 2007).

The ambiguity of definitions in various disciplines has also led to emotions often being blended with strongly related but different concepts, such as mood or feeling (Rottenberg, 2005) – two terms that are often used interchangeably in extant research (Beedie et al., 2005). Therefore, the authors of this study initially include what they classify as emotions, feelings, moods, and sentiments to grasp the full extent of emotion-related words in KM research before assigning each of these words an appropriate emotion.

To firmly embed this research in existing emotion theory, the authors apply a comprehensive model to classify emotions. While there are several well-established models in research, some – like Plutchik's wheel of emotion (1980), which includes emotions such as *terror* and *grief*, and Richins's consumption-related emotions (1997), including emotions such as *envy* or *loneliness* – encompass too many other emotions that are not relevant to the KM context. Other models, such as the computer emotion scale by Kay and Loverock (2008), have a strong focus on negative emotions like *anger*, *anxiety*, and *sadness*, with only *happiness* as a positive counterpart, and are inappropriate for exploratory studies because it is essential to clearly distinguish and focus on both positive and negative emotions (Aviezer et al., 2012). Thus, the authors of this study decided to apply the well-established model by Izard (1977), called the differential emotion scale (DES), which involves the following 10 emotions: *interest, joy, surprise, sadness, anger, disgust, contempt, fear, shame*, and *guilt*. The DES includes not only a comprehensive yet manageable number of emotions but also universal emotions, for example, those expressed in a similar manner across different cultures (Izard, 1977).

Emotions and Sentiment Analysis In KM Research

KM is a well-established discipline with many journals and conference tracks dedicated to investigating and advancing academic KM research (Serenko & Bontis, 2017). Between 1993, when the KM discipline emerged, and 2012, there were 12,925 KM-related publications (Qiu & Lv, 2014) – a number that has since continued to rise. Besides this theoretical significance, KM and its success are critical to any organization's advancement (Jennex & Olfman, 2010). To achieve goals, add value, and improve an organization's situation, KM comprises all conscious and organized efforts to develop, preserve, and utilize knowledge (Holsapple & Joshi, 2004).

KM researchers within the IS domain have used a vast array of research methods and approaches (Ioannis & Belias, 2020) to examine KM theories, processes, technologies (Fteimi & Lehner, 2016), and successes (Jennex & Olfman, 2005). To date, KM research on emotions has been insightful but without a holistic view. Previous studies on single emotions have revealed the significance of *trust* (Kauffmann & Carmi, 2017; Song & Teng, 2008; Swift & Hwang, 2013), *pride* (van den Hooff et al., 2012), and *fear* (Khalil & Shea, 2012) in KM or shown how related concepts such as *emotional intelligence* can improve KM (Decker et al., 2009; Geofroy & Evans, 2017; Tuan, 2016). More studies have investigated positive emotions as a contributor to successful KM (Aarrestad et al., 2015; Marshall, 2000; Tenório et al., 2017; Trenck et al., 2015) than negative emotions as a hindrance to successful KM use and outcomes (Lin et al., 2006; Peng, 2013), which is one the main drivers to conduct a comprehensive investigation and classify both positive and negative emotions.

Text-mining analysis in KM has previously not been applied to uncover emotions but rather to uncover different KM topics (Qiu & Lv, 2014). For instance, the mechanics behind text analysis for organizational KM have been analyzed (Ur-Rahman & Harding, 2012), and Fteimi and Basten (2015) developed a KM-specific dictionary using text-mining approaches. While it is popular to analyze social media data and research (Bojja et al., 2020; Yassine & Hajj, 2010), a domain that is connected to KM, applying sentiment dictionaries to KM research is still in its early stages.

RESEARCH PROCESS AND METHODS

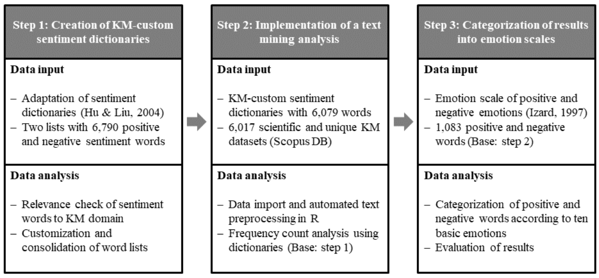
In a multistep research process (cf. Figure 1), a sentiment analysis was applied using a dictionary-based approach (also known as a bag-of-words model).

The authors customized sentiment dictionaries (step 1) and used them as input for step 2 to implement a matching algorithm that maps the dictionary's contents against those of the dataset (Li, 2010). Subsequently, in step 3, the authors categorized the results of step 2 into 10 basic emotions according to Izard's emotion scale (Izard, 1977).

CREATION OF KM-CUSTOM SENTIMENT DICTIONARIES

The authors referred to the dictionaries of Hu and Liu (2004) to create customized KM sentiment dictionaries that initially contained two separate lists containing 2,007 positively and 4,783 negatively connoted sentiment words. Following the recommendation that the application of dictionaries always

Figure 1. Multistep sentiment analysis



take into account the respective application domain (Krippendorff, 2013; Matthies, 2016), two of the co-authors first performed a manual relevance check of all the words on both dictionary lists for the KM domain. Consequently, 147 positive words and 691 negative words that both coders deemed irrelevant (e.g., colloquial slang words) were removed. The respective intercoder-reliability values of 0.7 for the positive words list and 0.68 for the negative words list indicate strong reliability in the agreement of both coders (Landis & Koch, 1977). Furthermore, the lists were extended by the respective British spelling variants of 127 words (e.g., *dishonour* vs. *dishonor*), since the datasets in the subsequent text-mining analysis include texts using either American or British spelling. The result of this overall customization led to a positively connoted dictionary list of 1,911 words and a negatively connoted dictionary list of 4,168 words. The overall customization process resulted in a reduction rate of 5% for the positive-word list and 13% for the negative-word list.

IMPLEMENTATION OF A TEXT-MINING ANALYSIS

The sentiment dictionaries developed in the previous step served as input for the text-mining analysis. Following the process-oriented understanding of text mining as a holistic approach to knowledge discovery, the analysis was performed over several main phases, starting with data selection and proceeding to its analysis and subsequent interpretation (cf. Figure 2). This results in interfaces to steps 1 and 3 of the overarching research process depicted in Figure 1 as the developed dictionaries and subsequent categorization according to emotions are linked to the text-mining process.

The analysis was conducted using the top 10 KM journals as ranked by Serenko and Bontis (2017). All datasets consisting of available titles and abstracts representing a comprehensive summary of a paper's main findings were obtained from the Scopus database (by December 2018). Editorials, duplicates, and datasets where no abstract was available were excluded. The subsequent analysis included 6,017 unique datasets. Table 1 provides a detailed overview of the journals included and the corresponding number of datasets considered, which vary because of different publication frequencies.

The analysis was performed using *R*, a statistical data analysis software with a variety of packages and functionalities to implement text mining, among others (Venables et al., 2014).

In any textual analysis, different preprocessing steps are necessary to handle data effectively (Elder et al., 2012). First, to ensure a consistent analysis of similar words (e.g., *Fear* vs. *fear*), cases were harmonized by transforming all the letters to lower case. Second, punctuation marks, special characters (e.g., copyright symbols), and numbers were removed from the corpus as they do not add value to the textual analysis. Third, effective sentiment analyses also require considering negation. Since negation shifts the meaning of a word or even a whole sentence in the opposite direction, it leads to biased results. For example, adjectives with positive (e.g., *good*, *relevant*, *happy*) or negative (e.g., *bad*, *obsolete*, *frustrated*) connotations typically indicate the opposite sentiment. Words in the corpus that had been preceded by a negation word (e.g., *not, no, neither, never*) were identified

Figure 2. Phases of text-mining process with links to steps 1 and 3

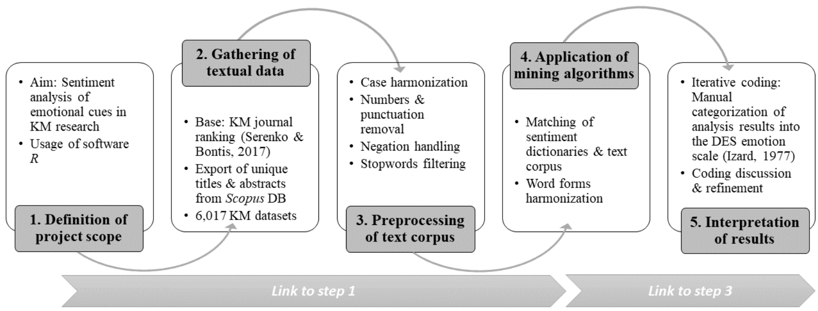


Table 1. Corpus description

Journal Title	Ranking	Period	# items
Journal of Knowledge Management	A+	1997–2018	1,262
Journal of Intellectual Capital	A+	2000–2018	664
The Learning Organization	A	1994–2018	704
Knowledge Management Research & Practice	A	2006–2018	461
Knowledge and Process Management	A	1997–2018	421
VINE: The Journal of Information and Knowledge Management Systems	A	1985–2018	1,040
International Journal of Knowledge Management	A	2005–2018	275
Journal of Information and Knowledge Management	B	2002–2018	543
International Journal of Learning and Intellectual Capital	B	2004–2018	366
International Journal of Knowledge and Learning	B	2005–2018	281
Σ			**6,017**

and excluded from further analysis. Fourth, words that were not particularly relevant to the analysis because they were expletives or stop words were also filtered out. In addition to these stop words, a domain-specific corpus like the scientific KM corpus in this study might include specific words or word sequences that occur frequently. This affects the results of frequency counts and other analyses. For instance, many abstracts include the term sequence *research limitation*. Considering that the word *limitation* is also a negatively connoted sentiment word, this word and other similar specific words (sequences) were excluded from the corpus.

Before applying the dictionaries from step 1 to the corpus, some of the aforementioned preprocessing steps were also applied to the dictionaries to prevent the matching algorithm from leading to incorrect results. This concerned, in particular, spelling harmonization and the elimination of punctuation. Subsequently, the authors ran the sentiment analysis by applying the matching algorithm to examine and accumulate all occurrences of sentiment words in the corpus. Each dictionary entry was matched to the corpus, and the corresponding concept was stored once there was a match. Equal entries were automatically accumulated into a frequency count list. Finally, inflected word forms were harmonized by consolidating singular and plural word forms or merging degrees of comparison or derivatives into a single word form (e.g., *limitation* and *limitations* were consolidated to *limitation*; *good*, *better*, and *best* were consolidated to *good*; *enjoy*, *enjoyable*, and *enjoyment* were consolidated to *enjoy*).

CATEGORIZATION OF RESULTS INTO EMOTION SCALES

To identify the dominant emotions in KM research, the results of the preceding text-mining analysis were categorized in the final step according to the DES emotion scale (Izard, 1977). Based on the DES, sentiment words can be assigned to one of the following basic emotions: *interest*, *joy*, and *surprise* for the positively connoted emotions, and *anger, contempt, disgust, fear, guilt, sadness,* and *shame* for the negatively connoted emotions. All remaining emotions are assumed to be gradations of these 10 basic ones. As with the coding process undertaken in step 1 during the dictionary creation, two of the co-authors performed an independent categorization of the text-mining analysis results to assign each word to a basic sentiment category. To achieve a high degree of reliability, the individual main emotions' definitions and meanings were taken from The Oxford English Dictionary (2007) and used as coding guidelines. As the word lists also include synonyms, two thesauruses (http://www.thesaurus.com and https://www.dict.cc) were used to identify corresponding words, which helped avoid possible misinterpretation. After a first partial coding and subsequent discussion with both coders, the categorization continued for the remainder of the word list. All results were documented and compared, resulting in a significant intercoder-reliability value of 0.5 for the categorization of positive words and a weak value of 0.3 for the categorization of negative words. Where categorizations were ambiguous, a third person did additional coding, and the coders discussed these cases in more detail. Furthermore, the authors observed that some words, despite occurring in the corpus and the dictionaries, had no meaningful emotional connotation; thus, no categorization into an emotion scale could be made. Therefore, the category (N/A) was introduced. After several iterations, the results were consolidated and interpreted.

Sentiment analysis of knowledge management research

Applying the sentiment analysis to the corpus led to the identification of all occurring positive and negative sentiment words from the customized dictionaries, together with their corresponding frequencies. This revealed which emotions dominate KM research (RQ1). Next, these results were assigned to emotion scales (RQ2), thus moving the authors a step closer to a KM emotion taxonomy.

Most Dominant Positive and Negative Emotion Words In KM Research

Of the 1,911 positive terms listed in the developed KM dictionary, only 493 terms (26%) appear in the corpus after the merging of similar words. An even more drastic result can be seen concerning the negative words with 590 hits from the original 4,168 dictionary entries (14%). However, the frequency count analysis indicates that positively connoted words are used three times more frequently in scientific texts than those with negative connotations (78% vs. 22%). Table 2 provides a comparative list of the top 10 most frequent words from both the positive and the negative dictionary list, together with the corresponding frequency count. For each word, its original rank is shown according to its descending frequency count in the overall hit list (1,083 positive and negative words). For instance, the top 10 frequent words are all positively connoted words and followed by the first two negatively connoted words, *limit* and *critical*.

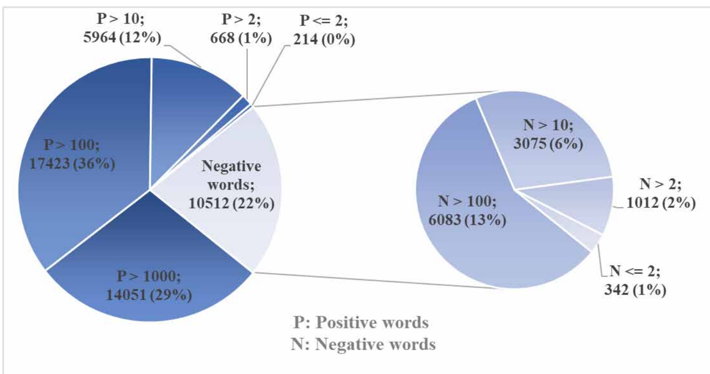
While the top 10 positively connoted words already account for 33% of the total frequency count, the 10 most frequently mentioned negatively connoted words account for only 9% of the total frequency count. It is also noteworthy that 39% of all positive and negative words are mentioned only once or twice in the whole corpus. Figure 3 depicts further statistical insights into the frequency count distributions of positively (left pie chart) and negatively (right pie chart) connoted sentiment words according to different frequency count categories.

For each category, the graph illustrates the absolute occurrence and, in brackets, relative frequency related to the total frequencies of all positive (or negative) words. For the positive words, the graph shows the most dominant category (36%) comprises words that were mentioned more than 100 but

Table 2. Comparative list of the top 10 most frequent positive and negative words in KM research

Rank	Positive Words	Frequency Count	Rank	Negative Words	Frequency Count
1	innovation	*3,115*	11	limit	*879*
2	originality	*2,271*	12	critical	*824*
3	support	*1,848*	14	problem	*808*
4	improve	*1,543*	24	risk	*516*
5	effective	*1,521*	28	complex	*464*
6	success	*1,444*	30	lack	*385*
7	good	*1,209*	35	regression	*292*
8	important	*1,100*	38	difficult	*283*
9	well	*976*	43	concern	*238*
10	competitive	*945*	44	exploitation	*232*

Figure 3. Frequency count share of positive words (left pie) and negative words (right pie)



fewer than 1,000 times. The same applies to negative words, where this category accounts for a relative share of 13%.

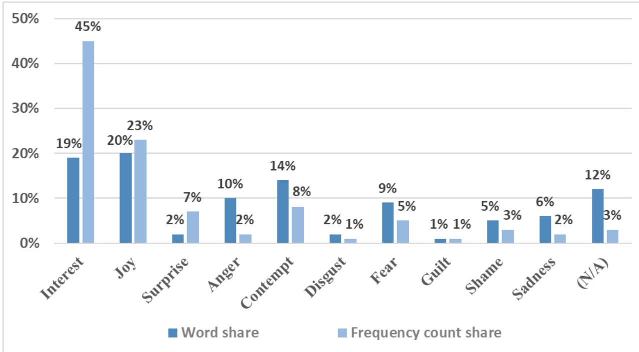
Emotion-Scale Categories of Positive and Negative Words

Based on the previous results, each of the 1,083 words was manually categorized according to one of the following 10 emotion categories: *interest, joy, surprise, anger, contempt, disgust, fear, guilt, sadness,* and *shame*. Additionally, the category *N/A* was introduced to account for ambiguous categorizations.

Figure 4 provides a meta-summary of the 11 emotion categories. For each category, the proportion of all its words out of the total number of all positive (or negative) words is specified as the word share. The frequency count bars indicate the relative occurrence frequencies of all words in a particular category compared with the sum of all positive (or negative) occurrence frequencies.

After inspecting the results, the authors opted to merge the *contempt* and *disgust* (as well as *shame* and *guilt*) categories. This decision was taken as the categorization process had revealed that corresponding words could often not be assigned to a single category but are associated with both emotions. Additionally, the word share of the *disgust* and *guilt* categories is below 2%, which justifies this approach.

Figure 4. Meta-summary of emotion scales



Positive Emotional Categories in KM Publications

Figure 5 shows a comparative word cloud for all three positive emotion categories (*interest, joy,* and *surprise*) and the words covered by these categories. The visualization also allows for a comparison concerning category size. For instance, the *surprise* category has the fewest words, while *interest* and *joy* are roughly equivalent. The illustration also makes it possible to show the relevance of a word in a particular category, based on its frequency count. For example, the word *originality* (2,271 counts) in the *surprise* category is mentioned less frequently over the whole corpus than the word *innovation* (3,115 counts) in the *interest* category. In relation to its own category, however, *originality* is more dominant, since the *surprise* category comprises a far smaller number of words than the *interest* category. Therefore, the weighting of the frequency count is considerably higher in the case of *originality* (69% vs. 14% for *innovation* in the *interest* category).

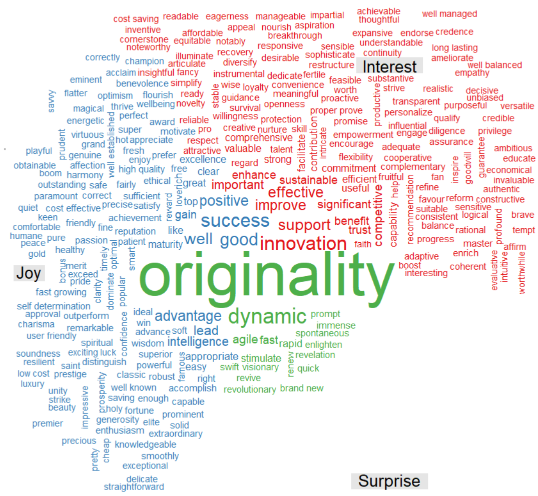
Regarding the individual categories, the results reveal that words in the *interest* category are mentioned twice as frequently as words in the *joy* category. *Interest* expresses an emotion associated with a helpful or important feeling and helps to draw particular attention: for instance, a c*ompetitive* and business-aligned KM solution that provides *benefit* and enhances *trust*, *supports* organizations in achieving their business goals and, therefore, evokes the emotion of *interest*. Accordingly, words in the *joy* category are associated with an emotion of *happiness* and *satisfaction* that results from achieving particular *positive* effects. Words that express *joy* include *success, good, positive, advantage, intelligence, reputation, harmony,* and *motivate*. For example, *motivated* employees and a *harmonious* KM culture *positively* influence working outcomes and lead to more *success* with *happy* employees and a *satisfied* management.

Negative Emotional Categories In KM Publications

Similar to the positive emotion categories, a comparative word cloud for the negative emotion categories was created from the *anger, contempt, fear, sadness*, and *shame* categories. Highly relevant negative words in their categories are *critical* (*shame* category), *difficult* (*anger* category), *problem* and *limit* (*contempt* category), *complex* and *risk* (*fear* category), and *weakness* and *crisis* (*shame* category). The category with the top word share is *contempt*, followed by *anger* and *fear*.

The most prominent negative emotion category is *contempt*, which the authors merged with *disgust*. With words from this category (e.g., *limit, problem, fuzzy, insufficient, poor, mistake, slow*), the emotion relates to something that is ignored or even despised and is, therefore, not worthwhile. Hence, *poorly* performing KM tools, *insufficient* KM activities, or frequently occurring *problems* in communication processes affect the quality of measures taken during KM implementation. Whereas *anger* is associated with annoyance and displeasure with a certain thing or situation, *fear* implies being

Figure 5. Comparative word cloud of positive emotion categories



scared or afraid because of an unwelcome event (*The Oxford English Dictionary*, 2007). Examples of words from the first category are *difficult, crime, hinder, bad, delay,* and *attack*, whereas fear is associated with words like *risk, error, radical, hard, chaos,* and *danger.* Applied to the KM context, *delays* in the delivery of project results or *attacks* on the KM system infrastructure can provoke *anger*, while *risks* or *dangers* arising from external environmental influences (e.g., job loss, knowledge gaps, introduction of new technologies) spread a feeling of *fear* unless suitable countermeasures are taken.

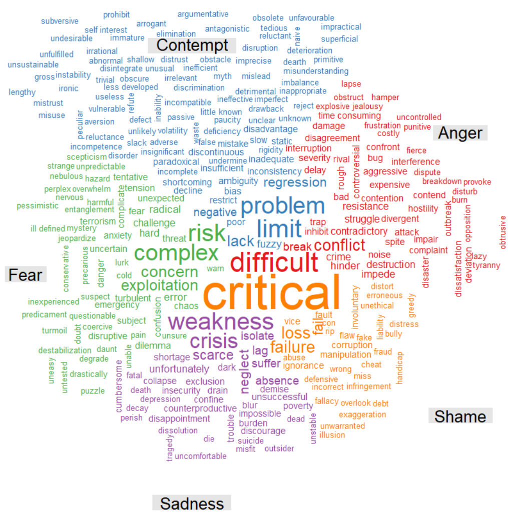
DISCUSSION

The authors find that emotions exist in KM research. While *joy* has the highest total word share of any emotion category, *interest* has the highest frequency count share, making the general emotional tone in KM a positive one. More specifically, particular terms (e.g., *success, innovation*, *trust* for the positive terms or *problem, risk*, *difficult* for the negative terms), which are highly associated with topics dealing with the successful or failed implementation of KM initiatives, processes, and systems, occur quite often in KM publications. Below is an example of a sentence from the corpus used in this study that contains three positive emotion categories, namely *joy* (represented by *genius*, *good/well*, *prosperity*, and *harmony*), *interest* (represented by *efficient*, *creative*, *value*, and *promote*), and *surprise* (represented by *spontaneous*):

*"**efficiency** on a par with nature's principle of least action; **spontaneous** and frictionless coordination; **creative** inspiration akin to artistic **genius**; doing **well** by doing good: **prosperity** and social **value**; **harmony** with the natural environment; **spontaneous** change in an evolutionary direction; and leadership which **promotes** full human development"* (Heaton & Harung, 2011)

To express negative emotions, the authors observed that KM researchers have primarily attempted to use words indicating an undesirable situation that, when related to KM, is associated with the deployment of technologies, the implementation of relating KM strategies, or the establishment of an organization-wide KM culture. Such feelings can occur when an unexpected outcome leads to disappointment, as shown in this sentence from the dataset used in the study, which displays *sadness* (represented by *traumatic*), *shame* (represented by *defenses*), *fear* (represented by *anxiety*), and a negative word assigned to no emotion category (*stress*):

Figure 6. Comparative word cloud of negative emotion categories



*"The influence of unconscious factors was paramount, rooted in the re-stimulation of collective pre-**traumatic**-**stress** disorder, and mediated via a set of social defenses against **anxiety**"* (Wasdell, 2011).

Additionally, some positive (e.g., *beneficial, helpful, useful*) and many negative words (e.g., *problem*, *error*, *mistake*) are identified as synonyms, which makes it possible to draw conclusions on term diversity and the need for term consolidation in KM. This ambivalence is visible in the study's findings, which not only show that the top 10 most frequent emotion-related terms are all positive but also suggest a much higher frequency of positive emotion terms (78%) than negative emotion terms (22%) in KM publications. Yet the negatively connoted sentiment dictionary (4,168 words) has more than twice as many expressions as its positively connoted counterpart. This imbalance also prevails in the chosen emotion scale, which offers more negative than positive basic emotions. Nonetheless, the DES (Izard, 1977) offers a good basis for emotion research in KM as many other emotion scales either provide an even stronger focus on negative sentiments (Kay & Loverock, 2008) or have many interpersonal emotions (Plutchik, 1980; Richins, 1997) unlikely to occur in scientific KM publications. However, positive basic emotions in the DES mostly occur in two categories, namely *interest* and *joy*, which suggests that KM ultimately needs its own taxonomy of emotions with more diverse and refined positive categories. Additionally, a KM-specific emotion taxonomy should encompass fewer negative categories than the DES suggests, as the authors merged *contempt* with *disgust* and *shame* with *guilt*. This may be the case because words describing *anger*, *fear*, and *sadness* are depicted less strongly in scientific texts, possibly because such emotions are more intense and expressive.

The findings reveal that some emotion categories, specifically those that are stronger and not typically researched but (as this study shows) are relevant to KM, are under-represented and provide examples for possible areas for future research. One example is the positive emotion category *surprise*, where few researchers have made attempts to research KM topics using surprise-connoted positive words such as *dynamic* leadership (Turner & Baker, 2017) or KM as an accelerator for *original* startup strategies (Bandera et al., 2018). To further investigate surprise in the context of KM, research regarding *dynamic*, *visionary*, or *original* KM initiatives and practices could be conducted. This could lead to important insights dealing with the emotion of surprise in a KM context since the negative counterpart emotion category *fear* has received such widespread attention through two of the top negative sentiment words, *complex* and *risk*. Such knowledge barriers, like the *risk* of losing power and appreciation, have been prominently researched by Khalil and Shea (2012), as well as Ardichvili et al. (2003). Furthermore, KM research on resistance to *radical* and *disruptive* change (Wasdell, 2011) has added the negative element of uncertainty to the framework of KM. Similarly, the relevance of holistic KM should be taken into account in future analyses by considering all the elements of KM systems and strategic initiatives, as well as a shared culture of knowledge exchange (Agrawal & Mukti, 2020) to build a bridge to an integrative relationship model for all the KM components involved. This aspect might, for instance, be covered by analyzing the context of the texts. In further studies, the authors of this paper intend to broaden their text-mining analysis to validate the manual results and develop a generalizable taxonomy of emotions in KM research. To this end, the authors will apply machine-learning techniques (e.g., classification algorithms) to their corpus and repeat the categorization for emotion scales. Aside from the comparison on a methodological level, machine learning can provide interesting insights and more reliable results than a manual classification technique in this context – for example, by building emotional topic categories that automatically group the related sentiment terms according to the documents' content.

CONCLUSION

As part of the overall research project to investigate the role of emotions in KM research and arrive at an overall taxonomy, this study aims to present the results of a KM-specific sentiment dictionary development process and its application to KM publications using text-mining methods. The first steps toward the intended emotions-in-KM taxonomy were taken by identifying positive and negative emotions in KM research and manually categorizing them according to the DES. In doing so, the study showed which emotions have dominated KM research and how they could be assigned to an emotion scale.

Lack of context during the text mining analysis is one of the limitations of this study. Some terms in the positive emotion categories can, depending on the context, also express a negative emotion or feeling (e.g., *enough, classic, simpler*), which can affect the interpretation and meaning of such terms. A statement like "*enough* liquid funds" may express *joy* but a feeling of *anger* or *contempt* in another context (e.g., "*enough* problems"). The same ambiguity applies to terms of the negative emotion categories, which, depending on the situation, may sometimes also be interpreted as a positive emotion ("*lower* costs" → *joy* vs. "*lower* motivation" → *anger*). Furthermore, well-established sentiment dictionaries with a predefined categorization of positively and negatively connoted words were used for this study. For future research, a further refinement of these dictionaries can take place by omitting words expressing a cognitive cue rather than an emotion (e.g., *intelligence* or *unclean*). However, the existing sentiment dictionaries that were applied are widely used and proven across different application domains (Matthies, 2016), making the modification inherently biased through the manual approach – and, therefore, requiring careful and extensive validation. Another of this study's limitations is its manual aspect, especially the consolidation and coding of terms, which is time-consuming and relies solely on the judgment and efforts of all the coders involved.

With this attempt to highlight emotions in KM research, the authors have contributed to several research streams in IS. Despite the knowledge's strong ties to emotions and sentiments, this study fosters early research in the field and gains a better understanding of emotions research in KM. By adapting the sentiment dictionaries to a KM context and classifying them according to the DES, this study is also the first attempt to apply the DES to KM research. A comparison with the analyses' results of the machine-learning approach is currently underway. The authors have also contributed to emotion-related research in KM by providing a comprehensive overview of emotions in KM research. The authors reveal the need to consolidate emotions and emotion categories in KM, as well as the need for an emotions-in-KM-taxonomy to show relations and connections, especially in the KM context. A key implication for organizations is that, in addition to the traditional themes of KM, employees' feelings and emotions need to be considered to successfully implement KM initiatives.

The presented text-mining approach constitutes a promising approach to analyze internal company text repositories such as discussion forums regarding employees' emotions.

As for the theoretical contribution in the general IS context, this study contributes to the analysis as described by Gregor's (2006) theory types in IS research. Developing a taxonomy and applying it to research objects generally serves the purpose of systematically describing how these research objects relate to specific common dimensions or attributes. In this context, the authors envision an emotions-in-KM taxonomy that is terminologically descriptive and allows for the classification of sentiment expressions. This study represents the first steps toward a comprehensive framework that will give causal explanations to make progress in said IS theory type taxonomy (Gregor, 2006).

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