Journal of Safety Research xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

An investigation into online videos as a source of safety hazard reports

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ARTICLE INFO

Article history:
Received 24 August 2017
Received in revised form 31 December 2017
Accepted 7 March 2018
Available online xxxx

Keywords:
Safety hazard
Online video sharing
Product recall
Text mining
Smoke words

ABSTRACT

Introduction: Despite the advantages of video-based product reviews relative to text-based reviews in detecting possible safety hazard issues, video-based product reviews have received no attention in prior literature. This study focuses on online video-based product reviews as possible sources to detect safety hazards. *Methods*: We use two common text mining methods – sentiment and smoke words – to detect safety issues mentioned in videos on the world's most popular video sharing platform, YouTube. *Results*: 15,402 product review videos from YouTube were identified as containing either negative sentiment or smoke words, and were carefully manually viewed to verify whether hazards were indeed mentioned. 496 true safety issues (3.2%) were found. Out of 9,453 videos that contained smoke words, 322 (3.4%) mentioned safety issues, vs. only 174 (2.9%) of the 5,949 videos with negative sentiment words. Only 1% of randomly-selected videos mentioned safety hazards. *Conclusions*: Comparing the number of videos with true safety issues that contain sentiment words vs. smoke words in their title or description, we show that smoke words are a more accurate predictor of safety hazards in video-based product reviews than sentiment words. This research also discovers words that are indicative of true hazards versus false positives in online video-based product reviews. *Practical applications*: The smoke words lists and word sub-groups generated in this paper can be used by manufacturers and consumer product safety organizations to more efficiently identify product safety issues from online videos. This project also provides realistic baselines for resource estimates for future projects that aim to discover safety issues from online videos or reviews.

1. Introduction

Products play an important role in our daily life. Indeed, our lives depend on the safe functioning of available products. Most producers are striving to produce their products with a high level of safety, however, there are still some products that cause harm to humans, the environment, and financial assets (Rausand & Utne, 2009). The process of retrieving, repairing or replacing hazardous or defective products that are already in consumers' hands or in the distribution chain is called a product recall (The CPSC recall hand book, 2012). Reasons for product recalls include issues such as design flaws, production faults, inadequate instructions, not maintaining specific standards, and lack of safety (Beamish & Bapuji, 2008; Berman, 1999). The United States Consumer Product Safety Commission (CPSC) is an independent agency of the United States government obligated to protect the United States public from unreasonable risk of injury and death associated with the use of hazardous or defective products. According to the CPSC, incidents associated with defective or dangerous products cost the United States more than $1 trillion annually (CPSC, 2017). Yet, recent studies show that the number of defective or dangerous products that have been recalled from the market in the last few years has increased substantially (Dawar & Lei, 2009; Dawar & Pillutla, 2000). As of October of 2017, the CPSC had 159 employees directed at hazard identification and reduction. While many companies test products in their own labs, there remain a significant number of products that are not tested before they enter the marketplace. With over 20,000 new products released each year (Tanner & Raymond, 2011), the CPSC is unable to test every product and often responds to safety issues after they have already occurred. The result is a tragic and preventable loss of life.

Product recalls also have significant external failure costs for manufacturers directly and indirectly (Hora, Bapuji, & Roth, 2011; Juran, 1988). Investigation costs, communication costs, physical distribution costs, litigation costs, products replacement, disposal costs, and restitution cost are examples of direct external costs that manufactures may face during a product recall (Berman, 1999; Dawar & Pillutla, 2000; Hora et al., 2011). Indirect costs of product recalls include damage to the firm's reputation, brand integrity, and loss of stock market value

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https://doi.org/10.1016/j.jsr.2018.03.004
0022-4375/

Please cite this article as: Nasri, L., et al., An investigation into online videos as a source of safety hazard reports, *Journal of Safety Research* (2018), https://doi.org/10.1016/j.jsr.2018.03.004

(Hora et al., 2011; Juran, 1988). Any delay in detecting and announcing product recalls can result in greater injuries and deaths, increasing costs, and irrecoverable problems, such as greater litigation costs and reputational damage (Cheah, Chan, & Chieng, 2007). For example, in a recent event, Ikea recalled around 29 million dressers and chests after at least six children died and 36 had been injured (McPhate, 2016). Ikea's recall was issued in June 2016 (Ikea.com, 2016); however, the first death was reported in February 2014 (Kerley, Dooley, & Steinberger, 2016) which suggests that injuries and deaths could have been prevented.

In recent years, technology, research, and innovation, have been employed to detect defective products on the market more effectively (Ahsan & Gunawan, 2014). One new approach to identify defective products is using large volumes of consumer feedback available in online reviews (Goldberg & Abrahams, 2018; Winkler, Abrahams, Gruss, & Ehsani, 2016). Online reviews are becoming more popular for consumers; according to Nielsen (2012), 70% of global consumers trust online reviews, a 15% increase in four years. Amazon, for example, has collected around 143 million reviews from 1996 to 2014 (McAuley & Yang, 2015), and 121 million reviews were submitted to Yelp from 2009 to 2016 (Statista, 2017). These online reviews can be valuable for manufacturers to understand consumer experiences of their products and provide individual consumers with valuable information about a product they may be purchasing. The online reviews can also be used by both manufactures and the responsible agencies, such as CPSC, to detect defective products in the market. The large volume of reviews, however, makes it very difficult for firms or individuals to manually identify and analyze the reviews.

Text mining is becoming a popular method for analyzing large volumes of text data from customer reviews and drawing conclusion for improving product designs, marketing strategies, and finding product defects (Abrahams, Fan, Wang, Zhang, & Jiao, 2015; Abrahams, Jiao, Wang, & Fan, 2012; Law, Gruss, & Abrahams, 2017; Winkler et al., 2016). Besides online text-based review platforms such as Amazon, consumers may also share their experience about products in video-based social networks such as YouTube. In general, people prefer to get information by seeing rather than reading (Pavel, 2013). This perhaps explains why 10 times more people view TV and video than those who read magazines or newspapers (Media Partners, 2016). According to Points Group, every minute, 48 h of video are being uploaded to YouTube, and U.S. consumers watched 38.2 billion videos in just 3 months of 2014 (Hofstetter, 2016).

In the context of safety hazard detection, video-based product reviews may represent a richer and more informative alternative to text-based reviews. First, "A minute of video is worth 1.8 million words" (McQuivey, 2008) and the brain processes visual information 60,000 times faster than text (Becca Fieler & Fieler, 2016). Using video-based product reviews, manufacturers can observe the reviews related to safety hazards and identify the technical problems that consumers have difficulty describing correctly in text. Second, the video may be a more effective way of communication and may facilitate recall process decisions. Around 60% of executives agree that if both text and video are available for one specific subject, they are more likely to choose video (Chudleigh, 2015). Next, online review videos may have a lower chance of being fabricated since the manufacturer can watch the videos and determine whether the problem really happened or not. However, it is almost impossible to identify fake online text-based reviews from real ones.

Despite the advantages of video-based product reviews in detecting possible safety hazard issues, this type of review has received little attention in the prior literature. In this research project, we focused on online video-based product reviews as a possible tool for the identification of safety hazards. To this end, we collected and reviewed over 15,000 videos from YouTube that had one or more predefined potential safety hazard words in their title or description. Two lists of words were created using two common text mining methods to detect safety issues: negative sentiment words and smoke words. Negative sentiment words are *emotive* words used to show displeasing situations or qualities, such as poor, bad, and awful (Liu, 2012). In contrast, smoke words are words that are highly prevalent in postings mentioning defects compared with postings not mentioning defects (Abrahams et al., 2012). While some smoke words are emotive, smoke words may also include *non-emotive* words, such as words referring to product components (e.g. "airbag"), or product functions (e.g. "leakage"). A core difference between sentiment words and smoke words is the scores associated with each word:

- For *sentiment* words, word scores are a <u>subjective emotion score (emotion-valence)</u>, e.g. the AFINN sentiment word list assigns valences from −5 to +5 (Nielsen, 2011).
- For *smoke* words, word scores indicate their <u>relative frequency (prevalence) in safety-concerns versus non-concerns</u> (Winkler et al., 2016).

The rest of this paper is organized as follows. In Section 2, we review the literature on safety hazard detection through data mining. We describe our sample data and methodology in Section 3 and results are presented in Section 4. Section 5 summarizes this research, concludes with scholarly contributions, describes the limitations, and proposes future directions.

2. Literature review

With the growth of social media platforms in recent years, the volume of user-generated content – reviews, comments, blogs, rating, etc. – has increased enormously. As people become more dependent on user-generated content (Nielsen, 2012), reviews become a valuable repository of information for both retailers and injury prevention practitioners. However, user-generated content data are usually unstructured, which makes it difficult to extract useful information. In the following sections, we discuss two common methods for finding safety issues from user-generated content used in the literature (i.e., sentiment analysis and smoke words).

2.1. Sentiment analysis

Sentiment analysis, sometimes called opinion mining, is "*the field of study that analyzes people's opinions, sentiments, evaluations, attitudes, and emotions from written language*" (Liu, 2012). Sentiment analysis tools – such as AFINN (Nielsen, 2011) and Harvard General Inquirer (Stone, Dunphy, & Smith, 1966) – typically use a predetermined list of words to assign scores or categories to words in order to assess sentiment. Sentiment analysis has gained more attention with the popularity of social media and social networks (Liu, 2012) and it is having a major impact on different areas affected by opinion such as management sciences, political science, economics, and social sciences (Yuan, You, & Luo, 2015).

Sentiment analysis can potentially be used to detect safety hazard issues from products reviews, where reviews with higher negative ranking will indicate a potential safety issue (Abrahams et al., 2012; Pan et al., 2014). However, researchers have identified several issues in detecting safety issues from customer reviews using the sentiment analysis method (Goldberg & Abrahams, 2018). First, the sentiment dictionaries use emotive words, but a significant percentage of safety-related words – e.g. words such as "melt" and "flame" – are not emotive words. Second, basic single-word sentiment analysis methods uses the emotive valence of specific words to assess sentiment, but customer reviews are full of exceptions to this rule. For instance, although "it isn't a bad product" may receive a negative score, the sentence does not imply a negative meaning. Finally, while sentiment analysis methods typically capture performance-related information, they are not able to distinguish between safety and non-safety related complaints.

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