

Using Artificial Intelligence to Detect Crisis Related to Events: Decision-Making Support for Businesses

Abstract

Artificial Intelligence (AI) could be an important foundation of competitive advantage in the market for firms. As such, firms use AI to achieve deep market engagement when the firm's data are employed to make informed decisions. This study examines the role of computer-mediated AI agents in detecting crises related to events in a firm. A crisis threatens organizational performance; therefore, a data-driven strategy will result in an efficient and timely reflection, which increases the success of crisis management. The study extends the situational crisis communication theory (SCCT) and Attribution theory frameworks built on big data and machine learning capabilities for early detection of crises in the market. This research proposes a structural model composed of a statistical and sentimental big data analytics approach. The findings of our empirical research suggest that knowledge extracted from day-to-day data communications such as email communications of a firm can lead to the sensing of critical events related to business activities. To test our model, we use a publicly available dataset containing 517,401 items belonging to 150 users, mostly senior managers of Enron during 1999 through the 2001 crisis. The findings suggest that the model is plausible in the early detection of Enron's critical events, which can support decision making in the market.

Keywords: Big Data, Artificial Intelligence, Machine Learning, Data Mining, Sentiment Analytics

1. Introduction

The critical goal of collecting and analyzing data is to make better and informed decisions. Data-driven organizations are expanding their competitive edge with better, faster, and yet more accurate decisions. The digital networks within organizations, as well as social media networks, contribute to a large amount of data production and carry tremendous value for organizations. They contain historical/archival and real-time communication data that are exchanged among the participants. The term "network data" includes messages sent or received in any online medium platform. Network data can range from chats or emails sent as correspondence via organizations' internal network (Aggarwal & Subbian, 2012) to blogs or tweets communicated via networks that are external to organizations. Online media has become pervasive in recent years. People are using social media networks as a communication channel to voice their opinions. Ki and Nekmat (2014) argue that an organization's success in crisis management depends, among others, on its speed of response through social media. These platforms serve as a vital tool for organizations to respond in the fastest and most direct manner and also to disseminate information to audiences globally. Network data presents both challenges and opportunities to organizations in crises (Fischer et al., 2016).

Important events tend to increase messaging activities in networks. For example, critical events such as natural disasters, important news, or even an exciting topic can create a large volume of data in social media. The surge in communication can represent an ongoing situation, and it can be tracked and analyzed to draw meaningful trends and patterns (Kavanaugh et al., 2012; Zhu et al., 2017; Candi et al., 2018).

Newsworthy events often create closely related messages, and they flow in the form of bursts (Aggarwal & Subbian, 2012). Situational crisis communication theory (SCCT) helps organizations to use network data to improve their management. SCCT debates the importance of considering past crises for managing an organizational crisis (Coombs, 2004). Based on the SCCT, to preserve an organization's reputation, crisis managers should formulate their communication to their audiences based on their past crises and particularly crises that their audiences are aware of. SCCT suggests and emphasizes the usage of communication to maintain and withhold the reputation of an organization (Coombs 2004, 2007). The effectiveness of actions taken in a recovery process is directly related to the quality of meaningful insights extracted from collected data. In many cases, there are stakeholders other than managers who can benefit from the knowledge obtained from a situational assessment. For example, stakeholders have a vested interest in understanding the impact of strategies implemented (Ki & Nekmat, 2014).

By using real-time data, management can keep the situation under control from becoming a full-fledged, blown up crisis. This is important for two reasons. Firstly, sensing a crisis in its early stages will help the management team to improve an organization's preparedness of a crisis. Secondly, during a crisis, it is crucial to have effective and productive communication. Comprehensive knowledge and a good understanding of the nature of a crisis will help in planning, controlling, and leading the situation.

This pioneering study is among the first studies that endeavour to use email data and sentiment analysis for extracting meaningful information that helps early detection of a

crisis in an organization. Our framework is designed based on cognitive architecture through the implementation of artificial agents. We developed a critical event detection analysis model (CEDA) that extends SCCT and attribution theories based on AI and big data analytics.

To expand on the proposed methodology, the next section of this paper is an overview of the current literature for existing methods developed on popular networks. Facebook, Twitter, RSS Feeds, Email, and others might have very different functionalities; however, knowledge built on one is fairly applicable to all, particularly in textual analysis. Sections 3 and 4 of this study describe our methodology for discovering the change in trends in Enron emails and provides an overview of its results. Section 3 focuses on big data and data mining, while Section 4 presents our approach to language-based sentiment analysis. In Section 5, we discuss textual and sentimental analyses, whereas Section 6 underlines the theory of Artificial Intelligence Rational Agents. In Section 7, we discuss the hypotheses and methodology used in this study, while Section 8 examines the combined effect of frequency analysis and sentiment analysis in detecting Enron's crises. Section 9 concludes this study.

2. Related Works

Faulkner (2001) defines crisis or disaster as "a triggering event, which is so significant that it challenges the existing structure, routine operation, or survival of the organization" (p. 138). In this context, an organizational crisis, according to Coombs (2007), is defined as the perception of an unpredictable event that threatens important expectancies of stakeholders that can severely impact an organization's performance and generate adverse outcomes. Such outcomes, according to Faulkner (2001), can be

considered as a shock at both the individual and collective levels, where the severity of the unexpected nature of the event may cause not only stress in the community but also a sense of helplessness and disorientation among others (Faulkner, 2001).

Our emotional response and confidence may affect our behaviour in assisting and aiding others (Willner & Smith, 2007). Willner and Smith (2007) claim that Weiner's attribution theory (1985, 1986) indicates that our emotional response to any behaviour is directly related to our attributions to the source of the individual's behaviour and our confidence in whether the behaviour can be changed. Jeong (2009) claims that, according to the Weiner's attribution-action model, the tendency of the actor being punished by others increases if the actor who caused the problem was perceived to hold a responsibility to a dilemma (higher internal and lower external attributions), as opposed to when the higher external and lower internal attributions are made.

SCCT, along with the attribution theory, offer guidelines to assess the reputational threat based on different crisis clusters and stakeholders' perceptions. Thus, they provide frameworks for crisis communication while taking into account the organization's situation and the publics' emotions (Ott & Theunissen, 2015). SCCT specifies ten crisis types or frames namely: natural disaster, rumour, product tampering, workplace violence, challenges, technical error product recall, technical-error accident, human-error product recall, human error accident, and organizational misdeed, while the attributions of crisis responsibility have been used to group the various crisis types into three main clusters of (a) victim, (b) accidental, and (c) intentional (Coombs, 2007). The victim cluster, for example, contains crisis types that produce very low attributions of crisis responsibility (e.g. natural disasters) and represents a mild reputational threat,

while the intentional cluster yields to strong attributions of crisis responsibility and represents a severe reputational threat (Coombs, 2007).

Anderson and Schram (2011) describe "crisis informatics" and "disaster-informatics" as a field of research that focuses on the use of information and communication technologies during emergencies.

The adoption and application of data science to address the managerial issues of business are still developing, yet the results have already been seen to be transformative for the organizations that have adopted it. In corporate finance, data science is widely used to help management handle tasks such as fraud detection and credit risk assessment (Wu, Chen, & Olson, 2014).

Inputs from internal and external events increase a firm's agility and help top management to make more informed decisions and mitigate risks involved (Vosoughi et al., 2018). Big data and the capability of its analytics in interpreting real-time events benefit management (Baesens et al., 2014). As an example, the report released by Towers Watson in 2014 reveals the importance of extracted knowledge in the supervision of the energy and enablement of employees for effective management (Global Workforce Study, 2014). Situational awareness is the knowledge that can be integrated from accessible data and used to assess a situation to manage it (Sarter & Woods, 1991).

In fast-paced business environments, improving situational awareness helps both managers and other stakeholders to improve performance through their early engagement (Nofi, 2000). Regarding crises, the content created and shared on an

organization's data network, either authored by the organization's actors or external participants, becomes crucial.

The first step to analyze the situation is to collect the organization's network data. For large organizations, the main concerns with the data are scale (volume), streaming (velocity), forms (variety), and uncertainty (veracity). For example, in social media, users share information to establish connections with others (Treem & Leonardi, 2013). Content generated by users in social media has surpassed 35 zeta bytes of data (Reinsel, Gantz, & Rydning, 2017).

Social media, web analytics, and media semantics have been effective marketing tools to increase brand awareness, loyalty, engagement, sales, influencing customer satisfaction, and conversation related to business-to-business (B2B) and business-to-customer (B2C) interactions (Agnihotri et al., 2016; Järvinen & Taiminen, 2016; Mehmet & Clarke, 2016; Siamagka et al., 2015; Swani et al., 2014;).

Even though using social media to increase situational awareness is not new (Watson & Rodrigues, 2018), yet, organizational and technical changes must happen before social media can be fully embraced (Plotnick & Hiltz, 2016).

3. Data

3.1 Data mining

Data are essential inputs to make better and informed decisions (Waller & Fawcett, 2013). Data mining is the process of finding meaningful patterns in data to extract valuable knowledge that leads to making informed decisions (Witten, Frank, & Hall, 2016). During the development of a crisis, data stored in structured and unstructured datasets in conjunction with various real-time data streams (feeds from social media or

sensors) can empower management and stakeholders to understand its severity and intensity. Some of these data are streaming data, and analyzing them requires processing a sheer volume of data. Storing massive data is costly, and, in many cases, the data itself may not have the same value in the future. For example, the processing of detected earthquake signals at a later point in time might not be useful for detecting an earthquake.

In the past, an organization's primary data were captured through business transactions and processes. Resources such as enterprise resource planning (ERP), Human Resource, Financial and Audit Reporting, Performance Monitoring, customer relationship management (CRM), and supply chain management (SCM) commonly used for sourcing Internal data. Recently, data from social networks and other external sources are considered new sources of data. Data from external sources can be categorized into two groups. The first category includes data that is directly related to companies, such as online social media content and mobile devices. The volume of capturing business and personal interaction data (such as social media and mobile data) is increasing tremendously. The second category includes data that may not be directly related to an organization; however, it can affect the organization's performance. For example, collecting socio-cultural data can help to improve business processes by making decisions more aligned with the current cultural changes. Also, knowledge derived from arbitrary data resources can be equally valuable to organizations. For instance, internet-connected devices form a massively connected network of things called the "Internet-of-Things" (IoT), which produces tremendous amounts of data that

are used for planning and managing smart cities. Likewise, public data from data lakes or governments can be harvested (Baesens et al., 2014) and used for data aggregation.

3.2 Big Data

Big data refers to datasets with colossal volume, variety, and velocity (Witten, Frank, & Hall, 2016). Big data has been around since early 2000 and has become a powerful resource for many businesses (White, 2015). Business analytical tools are evolving, and they can now produce real business value (Jans, Lybaert, & Vanhoof, 2010). Decision-making and forecasting models are the main areas of any business analytics (Wu, Chen, & Olson, 2014; Candi et al., 2018). Data harvested from multiple sources are fed into sophisticated algorithms equipped with advanced statistics, econometrics, and machine learning sciences (Hiebert, 2003). These data will be used to uncover useful hidden patterns and relations that would help to make informed decisions (Holton, 2009; Dubey et al., 2019).

In the event of a crisis, bad decisions are often costly and result in the misappropriation of resources, which hurts both organizations and society. A scientific analysis of the crisis based on the knowledge obtained from the event helps to carefully craft a strategy to manage the situation (Baesens et al., 2014).

In business settings, email can be a very important source of data for crisis management. Over and above recorded messages, it exceptionally contains rich data such as timestamps, details of the sequence of interactions, and users' intention that emerge in the organizational context (Bülow, Lee, & Panteli, 2019).

Closely related to email source, RSS feeds are the next source of data for crisis management. Thelwall and Stuart (2007) collected web feeds from RSS databases, and

Google searches to build a database of daily lists of postings. Then they generated a time-series graph of frequently used words that show a significant increase in usage during the monitoring period. For example, RSS web feeds are effective in extracting words with a sudden increase in usage in posts relevant to crises.

Facebook is another effective communication platform, with more than one billion active users. A positive or negative message about an organization can spread in a matter of a minute. The observation showed that all social media (blogs, Twitter, Facebook, and others) influence individual perceptions of an organization more than the transported messages. In other words, the medium is more important than the message itself (Ki & Nekmat, 2014).

Regarding the effectiveness of collecting real-time data, Baesens et al. (2014), points out a well-known Japanese barbershop chain that has sensors in all its stores' chairs. Sensors detect available seats for a haircut, duration of each haircut, and its total processing time. The collected information is used for the firm's online appointment system, performance analyses, and resource allocations.

Another prominent source of online network data is blogs, which a verity of topics including social, technical, political, and so forth are covered from the bloggers' perspectives. Generally, blogs are entirely personal and typically reflect bloggers' perceptions of the conversed topic (Thelwall & Stuart, 2007). Blogs can be influential based on what has been reported, the way it has been reported, the source that reports it, and the politics of the event. Table 1 shows a summary of the data sources described above and the related studies.

Table 1: Summary of the data sources

Data Sources	Previous Research	Crises Event
Email	Bülow, Lee, & Panteli (2019)	Explores email affordances in strategic inter-organizational relationships that experience conflict.
RSS feeds	Thelwall and Stuart (2007)	Shows RSS web feeds are effective in extracting words with a sudden increase in usage in posts relevant to crises.
Facebook	Ki & Nekmat (2014)	The medium is more important than the message itself, in influencing an individual's perceptions of an organization.
Blogs	Thelwall and Stuart (2007)	Covers verity of topics including social, technical, and political perspectives from the bloggers

Digital media, such as social media networks, websites, and blogs, are used as one of the popular platforms for managing crises in organizations. The social network facilitates real-time communication between individuals and groups, and they become a common platform for engaging stakeholders in communication discourse (Coombs, 2008).

Despite the availability of cloud collaboration platforms and increased popularity of social media, by far, email remains the most common medium used for communication in work settings (Bülow et al., 2019; Jung & Lyytinen, 2014).

One of the drawbacks of social media data analysis is that a large number of messages must be monitored from the social network to find quantitative evidence during a crisis (Thelwall & Stuart, 2007). Extracting accurate data from the mining of unstructured data is not feasible; however, one of the important features in big data, triangulation, allows validating data. As such, the majority of human interaction data offers an opportunity to generate new insights (Baesens et al., 2014). Investing in data quality at first may be

considered difficult and expensive, yet the economic return of high-quality data is substantial. According to Baesens et al. (2014), even small gains in data quality improve analytical performance.

During the crisis, big data can be used by organizations to create a favourable impression or to lead a selected group or audience towards a corrective action (Hiebert, 2003).

4. Factors Impacting on Messaging's Volume —Virality and Stickiness of Communicated Messages

Obtaining relevant data is an integral part of predictive analysis modelling, which requires extra attention. Therefore, it becomes a challenging process. One way to target the relevant data is through the detection of frequently occurring items shared in the communication network (Baesens et al., 2014).

Kavanaugh et al. (2012) grouped posted messages in three categories. The first group consists of people who appear to be complaining at first; however, they represent opportunities for organizations. These messages that are mostly posted directly on an organization's Facebook or Twitter pages ask for improvement in a product or service. Also, in this group, positive messages can be spread through online media channels to praise how well the organization resolved the problem. The second group is commentators. They are not asking for resolution; instead, they are venting to spread negative words on an organization's online media channels. They might go even further by posting complaint messages on other organization's blogs or newsletters. The third group is the ugly one. This group intends to harm the organization's reputation by spreading harmful content. The goal is to spread negative word-of-mouth.

Competitors can further harm an organization's reputation by taking advantage of these negative contents by greatly exaggerating the flaws (Kavanaugh et al., 2012). In 2013, British Airways' customer paid for a promoted tweet to maximize spreading his complaint about his lost luggage. His tweet got over 25,000 impressions in the first six hours of its posting (Grégoire, Salle, & Tripp, 2015). In online networks, comments charged by anger spread out quickly (Fan et al., 2014). In "spite-driven" comments, in which a customer may go beyond negating the organization's reputation, going viral is more likely. (Grégoire, Salle, & Tripp, 2015).

4.1 Novelty

Novelty encourages information sharing. Since novelty provides more information to understand events better, it becomes more valuable to have and to share. Therefore, novel news tends to be shared more often (Vosoughi et al., 2018). However, there are differences in why and how widely the true or false news spreads. True stories stimulate feelings of joy or sadness and are more likely to be anticipated. False stories, on the other hand, cause fear, disgust, and stronger emotional feelings. The empirical study of Vosoughi et al. (2018) shows that people tend to react and reflect on false stories with higher rates. A list of 32,000 Twitter hashtags' emotion weighted and classified into eight distinctive groups. The original classification of emotions to anger, fear, anticipation, trust, surprise, sadness, joy, and disgust is Plutchik's (2001) work, and it is based on the National Research Council Canada (NRC) lexicon, which contains approximately 140,000 English words.

There are differences between news and rumours. News is an asserted claim, and rumours are shared claims among people. On platforms such as Twitter, a rumour can

easily be started by a topic being shared, and since it triggers emotions (fear or disgust), it might be retweeted many times. Fake news also falls in this category. It is defined as a willful distortion of the truth. A study by Vosoughi et al. (2018) showed that even though people who had spread false news had fewer followers and spent less time on Twitter, their false news spread farther, faster, deeper, and more broadly than the active users who share the truth. In this regard, false news and rumours are overwhelmingly more novel than real news. To measure the novelty degree of true and false tweets, they compared the distributions of the experimental guided tweets for 60 days. False news can create many disadvantages for businesses, including misallocation of resources, misalignment of business strategies, and even loss of reputation (Vosoughi et al., 2018).

4.2 Going Viral

Each developing crisis scenario is unique; however, high profile crises usually get more attention and are contingent. This is due to users' comments and replies that facilitate and accelerate the news to go viral (Ki & Nekmat, 2014). The contingency starts when participants start responding to one another's replies. For a message to be contingent, the role of participants needs to be interchangeable (Sundar et al., 2003). Contributors' perception of closeness to the subject heightens their engagement during crisis communication (Ki & Nekmat, 2014). Another reason for people's participation in conversations is their desire to connect to a community that shares similar opinions. This provides them with the opportunity to express their views about a crisis. It has been consistently seen that people would rather re-publish another user's message than start a new, stand-alone message. For example, in retweeting, users build upon another's

commentary and opinion to develop their credibility on communicating their insights on a subject. Ki and Nekmat's (2014) research indicated that the majority of messages posted on an organization's Facebook wall during crises consisted of individual responses built upon the messages of others.

The impact of the internet in delivering news of crisis events is significant (Bucher, 2002). For example, in January 2012, a group of young people in France used a YouTube channel to express their reason for switching from the Orange cell provider to Free. The video went viral, and it was viewed more than 1.5 million times, almost overnight. In another case, FedEx suffered from negative publicity from someone posting a YouTube video showing a FedEx driver throwing a package containing a fragile item. This video was viewed over half a million times by the time FedEx had responded on the third day of its posting. Still, three years after its posting, the video was viewed over nine million times (Grégoire et al., 2015). In another example, Grégoire et al. (2015) reported on a young girl who was offended when she received a t-shirt as a gift in 2013, and she decided to share her opinion on the company's Facebook page. The page at the time had 1.7 million followers. Her comment received hundreds of responses and then hit Twitter.

One of the goals of managing a crisis event is to communicate information effectively to the relevant audience in time. This helps to lessen the adversarial impact on business performance and hopefully promote a positive image. Some social media channels, such as Instagram, Pinterest, and Flickr, might be more effective in spreading word-of-mouth than traditional communication channels. In many instances, it is more convenient for customers to reach directly into organizations through online media

channels (tweeting or sending an email) as opposed to buying a newspaper to read an article about the company or sending paper mails (Grégoire et al., 2015).

5. Textual and Sentimental Analyses

It is not always easy to understand the intention behind the communicated messages since the people on the other side of the crisis communication may have a different agenda (Thelwall & Stuart, 2007).

Statistical methods have been used and are still being used for identifying and classifying text. Antweiler and Frank (2004) used statistical algorithms to code the messages collected through Yahoo Finance as bullish, bearish, or neither (Antweiler & Frank, 2004); however, language-based analysis has recently become more predominant to use (Li, 2010). Araque et al. (2017) argue that with the increasing power of social networks, many Natural Language Processing (NLP) tasks and applications are being used in order to analyze this massive information processing. One of the domains in which language-based analysis has been employed is in examining the content of corporate financial reports and executive conference calls (Larcker & Zakolyukina, 2012). Fraud-monitoring software sifts through employees' emails or documents to detect corporate misconduct (Purda & Skillicorn, 2015).

The text analytics-based sentiment analysis involves a very large-scale data collection, filtering, classification, and clustering aspects of data mining technologies that handle the application of text analytics (Sharda et al., 2013). By tapping into data sources, such as tweets, Facebook posts, online communities, emails, weblogs, chat rooms, and other search engines, sentiment analytics offers marketers, decision-makers, and other stakeholders, insights about the opinions in the text collection (Sharda et al., 2013).

Essentially, the language-based analysis approach is based on earlier psychology and linguistic work. This approach has resulted in building lists of words ("bags of words") in which each group of words is associated with a particular sentiment. For example, it can examine a text for an indication of anger, anxiety, and negation (Larcker & Zakolyukina, 2012) or negativity, optimism, and deceptiveness (Li, 2010).

The sender's psychological state of mind is affected by the individual's assessment of the surroundings. The individuals' reflection of their surroundings can be seen in their writings and shared information patterns (Yates & Paquette, 2011).

Sentiment analysis is the process of classifying texts (Araque et al., 2017) into positive, negative, or neutral. The process is designed to detect the underlying hidden expression in the text. In business, sentiment analysis is used in various domains, including customer need to change analysis, marketing, and performance enhancement (Ragini et al., 2018). In this context, sentiment analysis is used to determine a text's subjectivity and its polarity (Ragini et al., 2018).

Various studies have used language-based analysis to assess situations during times of disasters; however, this study found it more useful when the language-based analysis was combined with statistical analysis.

5.1 Privacy

Privacy is a major for the current digital age (Hajli, Shirazi, Tajvidi, & Huda, 2020). Individuals' social background, cultural expectations, and norms shape their privacy expectations (Nissenbaum, 2009). Xu et al. (2014) argue that although the information discovered by data mining can be precious to many applications, there is an increasing concern about the other side of the coin, namely the privacy threats posed by data

mining. Previous research argues social media platforms, such as Facebook, Twitter, and apps location services to track their users, may pose major privacy concerns (Nadeem, Juntunen, Shirazi, & Hajli, 2020; Wang, Tajvidi, Lin, & Hajli, 2019). Another example is related to mobile devices in which some systems allow the installed apps to track and use the contextual information of users in order to adapt to the new conditions in an automated fashion. Privacy protection in contextually aware processes relies on procedures that address the anonymity and confidentiality of personal information (Shirazi & Iqbal, 2017). Shirazi and Iqbal (2017) studied privacy concerns with communicated messages in the context of both internal and external organizational networks. Shin and Choi (2015) argue that despite the fact that big data technology has the potential to provide powerful competitive advantages, private and public organizations are struggling to establish effective governance and privacy in connection with big data initiatives. In the distributed privacy preservation model, as noted by Aggarwal and Yu (2008), a new aggregated dataset that does not include any personally identifiable information can be obtained from the source records. Aggregating extracted anonymous data from organizations' employees' emails, for example, provides the required personal information privacy protection for all parties. In one behavioural aspect of organizational data usage, the management and employees tend to change their attitudes towards using an organization's data when they understand what data are accessed during the data collection process and what it has been used for (Díaz et al., 2018). Díaz et al. (2018) argue that building a data-driven culture in organizations will ease and enhance the actual data analytical efforts. Building awareness among the employees has to be a part of an organization's data

privacy strategy while holding them accountable and responsible for protecting all organizational data, especially private personal information. As such, before we generated a table of text extracted from emails, the dataset was anonymized in such a way that identifiers (e.g., name, employee ID, and phone number), quasi-identifiers (attributes that can be linked to external data), and other sensitive attributes were removed from the dataset (Ghinita et al., 2008; Dias et al., 2016).

6. Artificial Intelligence and the Rational Agents Theory

Roux-Dufort (2007) argues that the traditional perception of crises used to narrow down and only include exceptional circumstances. The scandal of financial domains (Enron, Worldcom), significant terrorist attacks (9/11), supernatural events, such as hurricanes and so forth are only a handful of examples of those events. As such, research and studies in the field of crisis management gain their legitimacy through the process of investigation and from the potency of the investigated incidents. Therefore, the more important the incident, the more licit the investigation will be because the ambiguity of the content urges the need to obtain knowledge (Roux-Dufort, 2007).

This study aims to develop a big data analytics framework by deploying artificial intelligence rational agents generated by R/Python programming language capable of collecting data from different sources, such as emails, Tweets, Facebook, weblogs, online communities, databases, and documents, among others (structured, semi-structured, and unstructured data). R/Python programming with their extensive libraries, frameworks and extensions offers excellent tools and capabilities for solving complex projects involving artificial intelligence and big data. These capabilities include

but are not limited to Artificial Intelligence, Machine Learning, Data Science, Natural Language Processing and Object detection and Tracking (Joshi, 2017).

To test our model, we focused on existing emails extracted during the Enron crisis. As a consequence, this pioneering project is, in fact, among the first studies that endeavour to use sentiment analysis for extracting meaningful information that helps early detection of a crisis in an organization. Our framework is designed based on cognitive architecture through the implementation of artificial agents.

Research on artificial intelligence (AI) agents has long focused on developing mechanisms to enhance how agents sense, keep a record of and interact with their environment (Castelfranchi, 1998; Elliott & Brzezinski, 1998; Rousseau & Hayes-Roth, 1998), the so-called “intelligent systems” (Russell, 1997). Recent studies of cognitive architectures indicate both abstract models of cognition, in natural and artificial agents, and the software-based models (Lieto et al., 2018) for designing systems that do the right things intelligently (Russell, 1997).

This approach encompasses considering the intelligent entity as an *agent*, that is to say, a system that senses its environment and acts upon it. In this context, an agent is defined by the mapping from percept sequences to actions that the agent instantiates. We define rational agents as agents whose actions make sense for the information possessed by the agent and its goals. Augier and Keriner (2000) argue that rationality refers to the purposefulness and forward-looking character of an agent.

The theoretical foundation of perfect rationality within AI is well defined by Newell’s paper on “knowledge level” (Newell, A., 1982). Knowledge-level analysis of AI systems relies on an assumption of perfect rationality. It can be used to establish an upper

bound on the performance of any possible system by establishing what a perfectly rational agent would do given the same knowledge (Russell, 1997).

Within the context of AI, Russell (1997) argues that intelligence is strongly related to the capacity for successful behaviour—the so-called “agent-based” view of AI. The candidates for formal definitions of intelligence (Dean et al., 1995; Russell, 1997; Russell & Norvig, 1995; Simon, 1958; Wellman, 1993) of a system *S* are *Perfect rationality* (the capacity to generate maximally successful behaviour); *Calculative rationality* (the capacity to compute the perfectly rational decision); *Metalevel rationality* (the capacity to select the optimal combination of computation sequence-plus-action); and *Bounded optimality* (the capacity to generate maximally successful behaviour given the available information and resources).

The metalevel rationality applied in this study is, in fact, a knowledge-level analysis or perfect rationality associated with computing action. In other words, while perfect rationality is difficult to achieve, considering the limitation of computing settings, the metalevel rationality of AI has been deployed in this study (see Fig. 2).

6.1 Metalevel Rationality

Russell (1997) is the capacity to select the optimal combination of computation sequence-plus-action under the constraint that the computation must select the action. Metalevel architecture splits the agent into two (or more) notional parts. The *object-level* carries out computations concerned with the application domain, such as projecting the results of physical actions, computing the utility of certain security states, and so on. The *metalevel* is a type of decision-making process whose application domain consists

of the object-level computations themselves, the computational objects, and the states that they affect.

The sheer volume of corporate archival and real-time data requires a change in traditional crisis analysis approaches that use static, archival data and manual analysis. As mentioned by Vera-Baquero et al. (2016), real-time access to business performance information is critical for corporations to run a competitive business and respond to the ever-changing business environment. With machine learning, AI automation and big data analysis, as deployed in our critical event detection analysis (CEDA) method depicted in Fig. 2, can build patterns of positive and negative (abnormal) words to monitor emerging trends proactively before a potential crisis occurs. In this context, the machine learning algorithms help us anticipate when employees (or stakeholders) are experiencing issues, and allow crisis managers to potentially address the problem and control how incidents are communicated and presented to the world (Coombs, 2007).

7. Methodology and Hypotheses of the Research

Previous studies have considered the use of network data for situational awareness; however, to the authors' knowledge, none have specifically investigated or analyzed the use of email communication by major organizations for situational assessment of a developing crisis. In our method, we used email data to detect critical events. Email usage is fairly well distributed across all types of organizations in developed nations. In a conducted survey, it has been shown that the two most used channels for communication in organizations are an intranet (93 percent) and email (90 percent). By and large, email is the most common channel for communication in organizations (Moynihan & Hathi, 2018). This study further examines trends in email communication

displayed by the organizations' email users to provide a more comprehensive examination of the effectiveness of Email meta-data for organizational crisis detection by asking the following question:

RQ1: What are the impacts of the sudden change in email communication trends and sentiment of the day on identifying a developing crisis in an organization?

RQ2: How an artificial agent's meta rationality can identify a sudden change in the email communication trend? (capacity to select the optimal combination of computation sequence-plus-action under the constraint that the computation must select the action)

Our approach seeks to improve detecting a crisis in organizations in its early stages. Emails, when analyzed effectively, can allow management to make informed decisions to avoid a potential crisis.

As argued by (Ulmera et al., 2007), crisis communication is growing as a field of study. The unpredictable events or crises can disrupt an organization's operations, threaten to damage organizational reputations (Coombs & Holladay, 2002). In particular, we are interested in the analysis of text and its relationship with the contexts in which it was used. In this context, early detection of crisis through analysis of patterns of communication context is particularly an important step in tackling crises in its early stage. If critical events are not detected in the early stages, they may develop to potentially unmanageable crises. Building on our discussion covered in sections 3, 3.1, 3.2, 4, 4.1, and 4.2, we propose:

H1: A sudden increase in the frequency of communicated emails positively correlates with a developing situation in an organization.

People's behaviour is shaped by the response to factors such as feelings, attitudes, beliefs, abilities, consequences of action, and accepted social norms. Human responses to internal or external stimuli are also evident in online communication channels. For example, the swearing-in social network promotes retaliatory responses (Turel & Qahri-Saremi, 2018). Linguistic analysis can effectively be used in detecting financial frauds. Purda and Skillicorn (2015) showed when a company is committing fraud, the employed writing style and presentation style in communicating financial information changes. Studying organizations' management's discussion and analysis (MD&A) report showed that the companies who have been associated with fraudulent activity in the past, have pushed to write an MD&A section in the 10-k report without referring to words relating to merger activity or potential legal problems (Words such as settlement, legal, and judgments). Combining the above discussion and our argument from section 5, we propose:

H2: Overall daily sentiment of communicated emails, when is negative, correlates with a developing crisis in an organization.

Fig. 1 shows the relationships among the indicators in our proposed integrated model. We suggest a sudden change in email communication trends, sudden increases in the frequency of communicated emails taken together with the day's overall sentiment, and predicts public behavioral intention

Fig. 1. Theoretical model: integration of SCCT and the CEDA

To capture the information, we developed a methodology that captures the sudden change in email communication patterns in an organization. For our study, we worked

on publicly available Enron email dataset. This dataset was initially collected and prepared for the CALO Project. It contains 517,401 items belonging to 150 users, mostly senior management of Enron. The email data are organized in the form of files and folders. Originally, the email dataset was made public by the Federal Energy Regulatory Commission during its investigation. It turned out to have many integrity problems, and later on, Melinda Gervasio, at SRI, corrected the problems. To our knowledge, this is the best available substantial dataset that relates to an organizational crisis and concerns the public interest.

Fig. 2 illustrates our critical event detection analysis method (CEDA), which consists of four stages. In the first stage, data preparation, we developed a python script that crawls in the dataset's folders and builds a corpus of data, including some initial statistical data relevant to each item set, and distinguishes sent emails, received the email, or non-email items. In total, we recognized 210,344 sent emails and 286,597 received emails. The numbers have factored in the CCs and BCCs. We developed an automatic method in order to extend and examine other email datasets if they become available. The advantage of an automatic method is that it can provide convenient and standardized access to extract relevant information and is not intrusive. Each item in the Enron mail directory list contains the header of the email, the subject, the date, the correspondence to the sender and receiver, and the email body sections. To work with data, we built a new corpus of data where each line became our new line for the data frame in R. In the second stage, we identified and compared communications from different periods of the last three years of Enron before its bankruptcy.

In CEDA, situational events are detected by inferring from trend changes in communication patterns in the existing dataset. In near real-time processing, continuous massive streaming of content is processed in a single instant since the streaming data may not be available for reprocessing again, or it does not have the same value at a later time.

To process and analyze semi-structured data, we first studied some available tools that could perform pattern discovery on text files. As an aggregation tool for semi-structured data, we deployed Nvivo software version 11. Nvivo allows importing, managing, and analyzing text and has advanced visualization tools. A common issue with using the existing analytical tools is that most of them are designed to perform predefined tasks. After some preliminary assessment, we found them to be very limited for this study. Our input data was scattered widely in irregular patterns under several folders and subfolders. Also, the volume and number of records in our dataset were beyond the practical functionality of these tools.

Initially, it was difficult to infer from the email counts whether they were crisis-related. For instance, sent/received email frequency on its own would not be conclusive enough to indicate an emerging crisis. However, including other external environmental factors, such as historical news events from reputable news outlets and market reflection on Enron's stock price, increased our method's predictive capability.

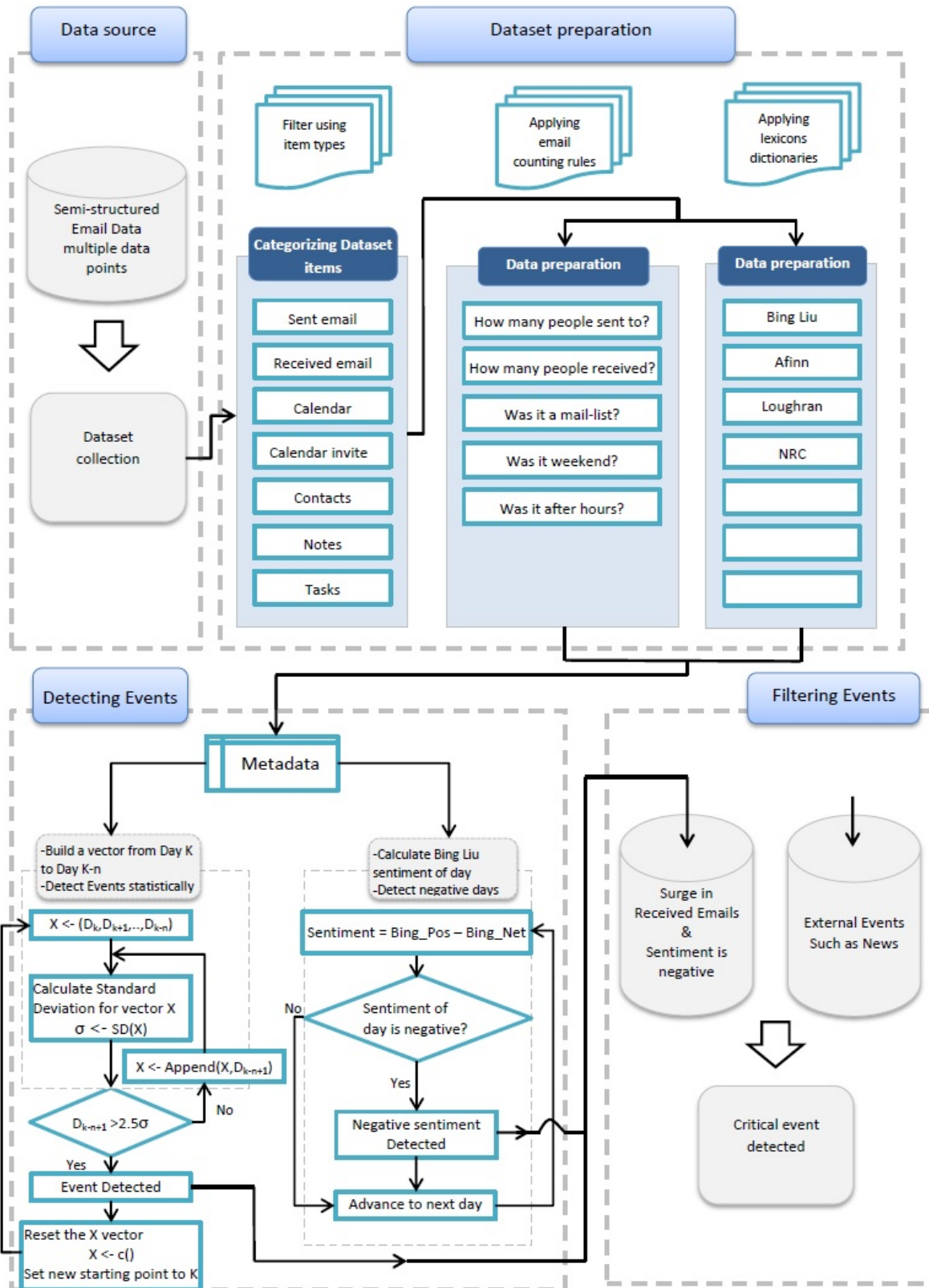


Fig. 2. Our proposed critical event detection analysis method—CEDA

Fig. 3 illustrates the summary count of the resulting calculation of sent and received emails using our method of inspecting the Enron dataset. For example, to calculate the number of sent emails, we included all the recipient addresses that were in the To:, CC:, and BCC: sections of the header of that email as with. We calculated the number of received emails by counting how many other people received the same email by looking at the detailed information available in the metadata of each email. We also detected mailing lists and tagged them separately.

Our preliminary examination of Enron's email suggested that the frequency change in sent and received emails could provide valuable information.

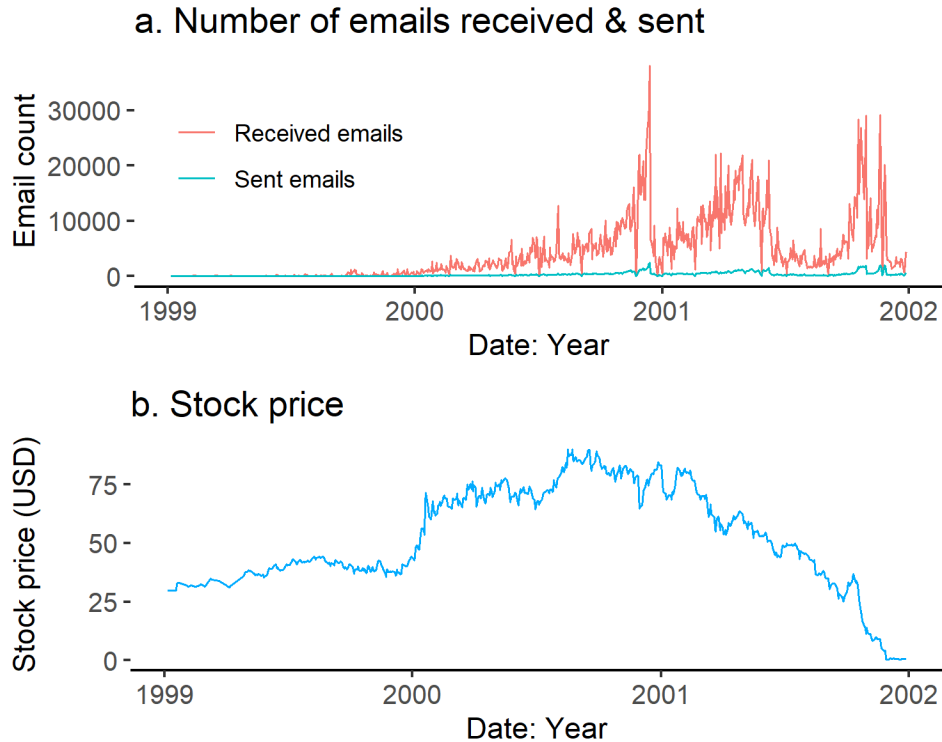


Fig. 3. (a) Number of emails received and sent (b) The closing stock price for Enron by day— January 1999 to December 2001

7.1 Sudden change in email communication frequency

To detect ongoing crisis events at Enron, we defined a statistical model that raises red flags for suspicious instances. To explain our statistical model, suppose we knew event 1 (E_1) was occurring on May 22, 2000 (Fig. 4). Let us consider the line L_{avr} represents the average number of emails received per day from May 1 through May 21. In the same way, let us consider L_6 and L_{2_6} to represent one standard deviation and two standard deviations, respectively, of the number of emails received per day for the same period. The threshold in our model is defined as any day in which the total number of emails received falls out of 2.5 standard deviations of the mean of its

previous days' number of emails received. This may indicate that an important message has triggered a sudden increase in the number of emails received for that day. In other words, the message has gone viral. In Fig. 4, the regular repeating low points in the sent or received curves are weekends. Including them unnecessarily widens the standard deviations of the past days (the days before the event day), and this would negatively impact our model's detection assessment.

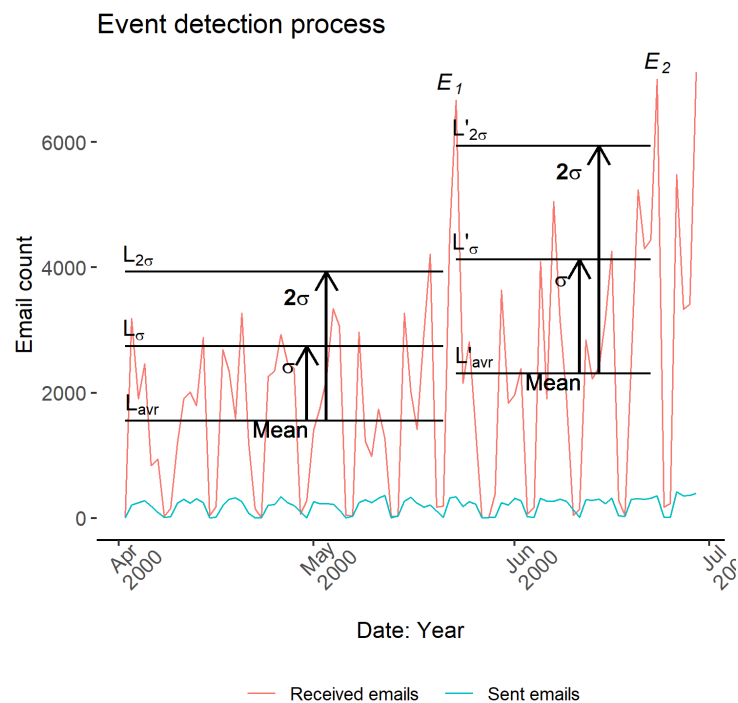


Fig. 4. Event detection process– Enron emails from April 2000 to July 2000

The model detects E_2 event the same way as E_1 , except the reference point for calculating the average line, L'_{avr} starts from the event E_1 . We are expecting some residual effect from the previous events, including E_1 , which may impact the number of received emails in the days coming after E_1 . Since we set a new start point for

calculating event E_2 , the model implicitly includes the residual effects of all the previous events, but more so of the last event since some of the old events' effects may have already tapered off. Therefore, we always calculated the most recent effects to add to the accuracy of our method.

This way, we detected all the days where the total number of emails received was significantly higher than the mean of the total number of emails received for the period they accounted for. This covered 98.76 percent of the population of all past days where the total number of received emails varies to be less than 2.5σ deviation from the period's average.

7.2 Overall sentiment of the day

We added sentiment analysis to our study to measure whether the sudden surges in the total number of received emails were due to a positive or negative sentiment fact of the day. It is essential to analyze the organization's emotional load of the day to understand the true meaning of the surges in the number of emails. Our sentiment analysis consists of two stages, namely, individual email-based polarity analysis and day-based polarity analysis. Each email has information about its sentiment. To avoid a washout effect, we avoided working with combined emails' text. In order to categorize the emails, we customized publicly available tools to score the sentiment of each email based on the Bing Liu lexicon. The lexicons are a dictionary of words that are used for calculating the polarity of the text. Bing Liu's opinion-mining lexicon contains 2006 positive words and 4,683 negative words that include misspelled and slang terms of words as well (Lui, 2012). Opinion words or phrases in a text play a key role in carrying the sentiment of the

text as a whole (Ragini, Rubesh, & Bhaskar, 2018). Fig. 5 shows the output of CEDA's sentiment analysis of Enron's received emails (see also Figures 1 and 2 in Appendix B).

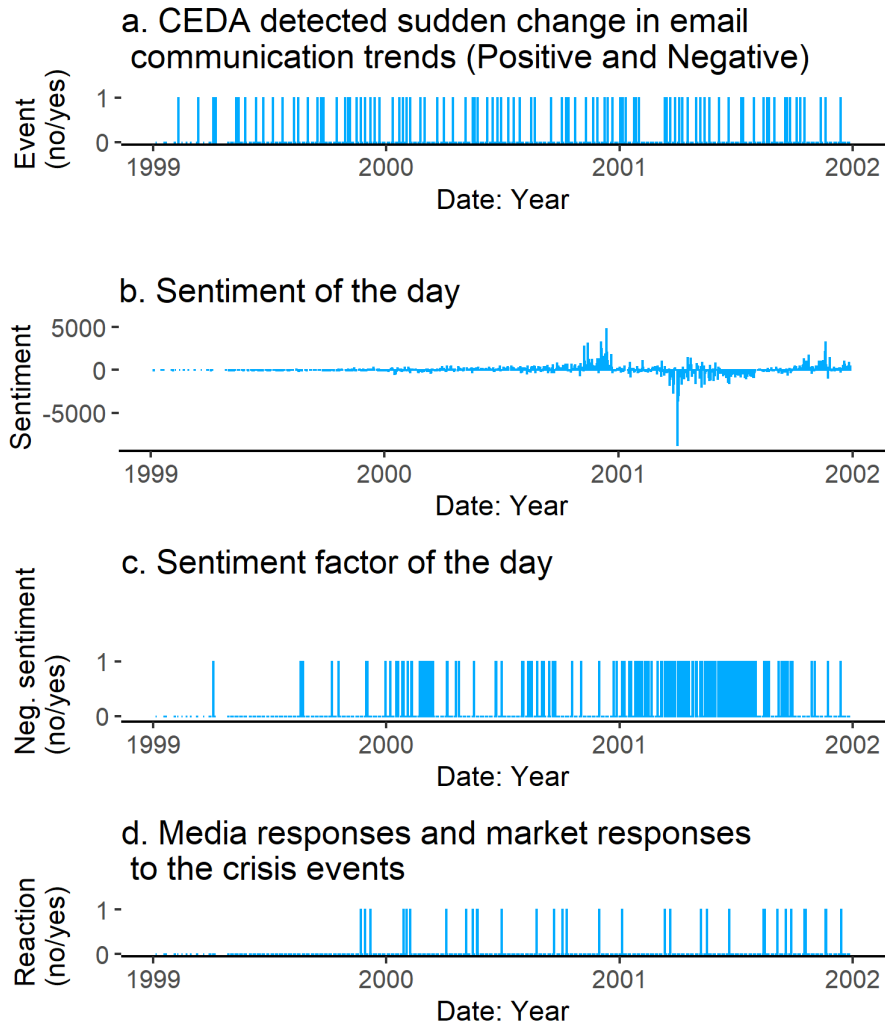


Fig. 5. (a) Detect events by the CEDA method, (b) Sentiment of the day, (c) Sentiment factor of the day, (d) Media and market reaction to the Enron crisis events by year—January 1999 to December 2001

7.3 External Crisis Events Construct

We used mixed market responses and media responses as a proxy to indicate the firm's real crisis events.

7.3.1 Market response (sudden drop in the firm's stock price)

The average daily percent movement of the stock market is used as a basis to detect crises in Enron's financials. Looking at the S&P 500 stock market over the last ten years, the average daily move in the stock price is between -1% and +1% (Financial, 2020). Therefore, for our study, any change beyond two percent is considered as an important market reaction event. CEDA compares Enron's every day's closing price to up to five past consecutive closing prices. If the stock price for the day is less than the n days ago stock price minus two percent accumulated loss for the past n days, that is considered as a market's negative reaction to a possible crisis event.

7.3.2 Media response (bad news in media)

We searched the public news outlet and academic sources to retrieve the list of important events that hit Enron during the sample period. The events are taken from *The New York Times*¹, *Washington Posts*¹ dailies and AGSM¹ (Australian Graduate School of Management) UNSW Sydney. Table 2 shows a partial news events timeline taken from data collected by the University of New South Wales—Sydney (UNSW Business School). The table represents examples of how the news was coded. The variable is set to 1 if an event translated to a crisis event, 0 otherwise. A complete list of all chronological news events is presented in Appendix A.

Table 2: Example of Enron Corp chronological news timeline. from May 2000 to June 2000

05/05/2000	agsm.edu.au	- Enron trader, in an email to colleagues, announces "Death Star," a new strategy to game the California market.	0
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¹ <https://www.nytimes.com/2006/01/18/business/worldbusiness/timeline-a-chronology-of-enron-corp.html> Accessed on June 16, 2018

¹ http://www.washingtonpost.com/wp-dyn/articles/A25624-2002Jan10_5.html Accessed on June 16, 2018

¹ <http://www.agsm.edu.au/bobm/teaching/BE/Enron/timeline.html> Accessed on Aug 08, 2018

12/05/2000	agsm.edu.au	- Timothy Belden (chief trader for Enron's West Coast power desk) sends email to Enron headquarters in Houston confirming his strategy is working. "So far so good: pricing keeps going up." Belden has made a massive bet that California's energy prices will increase. His email confirms that prices are rising.	0
22/05/2000	agsm.edu.au	- The California ISO (Independent System Operator), the organization in charge of California's electricity supply and demand, declares a Stage One Emergency warning of low power reserves.	1
12/06/2000	agsm.edu.au	- Skilling makes joke at Las Vegas conference, comparing California to the Titanic.	1

7.4 Hypothesis Testing

Hypothesis 1 examines the correlations between sudden increases in daily communicated email trends and developing situations in an organization. Hypothesis 2 examines the correlations between the overall sentiment of the days and developing situations in an organization.

We used logistic regression analysis as an appropriate inferential statistic for three reasons. First, our research questions are relational questions seeking information about the relationships between detected events by CEDA and crisis events; we are interested in determining whether there is an association among these variables. Second, we considered the level of measurements; all four variables in this study are dichotomous: sudden change in email communication trends detected (yes/no), the overall sentiment of the day (negative/positive), the sudden drop in the firm's stock price (yes/no), and bad news in media (yes/no). Third, logistic regression allows testing the probability of falling a given case into one of two categories on the dependent variable.

8. Experimental Results and Statistical Analysis

them, our comparison cloud analysis suggested an excellent insight of ongoing issues for the day in question (Fig. 6).

Table 3 represents a sample output from dataset preparation of our proposed critical event detection analysis model (Fig. 2 CEDA, Apply filtering base on item types and Apply email counting rules). At this stage, the unstructured Enron dataset's email data, which were in the form of files and folders, categorized and filtered based on item types (sent, received, calendar, contact, note) and transformed into our numerical version of Enron's corpus data. Each row in our dataset represents statistics wherein "Date" represents the day in which the data extraction and calculations were made for, "Email counts" accounts for the total number of emails that have been sent and received in that day, "Total word count" is the total word count for all emails all together for that day, "To" represent the total number of email addresses where the emails were sent to using "To" box, "Ext email address/To count" represents the number of email addresses that were external users (non-Enron email addresses) using "To" box, same explanation of "To" applies to "CC" and "BCC", "Reply chain" represents the total number of times that the emails were forwarded, "All To" represents the total number of email addresses that emails have been sent to all together (To + CC + BCC). A similar definition of "Ext email address" goes for "All Ext To addresses".

Table 3: Sample output for stage 1– Collecting and building statistical data - Received emails for Enron for the period of 6 April 2001 to 17 April 2001 (Weekends are excluded)

Date	Email count	Total word count	To	Ext email address	CC	Ext Emil address	BCC	Ext email address BCC	Reply chain	All To	All Ext To address
			count	To count	Count	CC count	count	count	FW/RE	count	count
06/04/2001	583	136694	7797	1376	1361	95	1361	95	106	10519	1566
09/04/2001	926	220313	15598	3021	2246	244	2246	244	217	20090	3509
10/04/2001	817	144981	5407	1691	2838	386	2838	386	147	11083	2463
11/04/2001	911	92509	6444	999	3272	412	3272	412	263	12988	1823
12/04/2001	794	128299	4960	901	2548	184	2548	184	150	10056	1269
13/04/2001	577	54385	4485	504	2385	74	2385	74	138	9255	652
16/04/2001	911	163297	6661	1201	3496	44	3496	44	201	13653	1289
17/04/2001	976	124034	10086	1211	3691	174	3691	174	181	17468	1559

Table 4 and Table 5 show examples of resulting output from assessing the sentiments of the day extracted from the Enron emails. The texts from the body and subject lines of all received emails for each day were analyzed using publicly available sentiment-based lexicons. We calculated the sentiment of email data, Bing Liu, AFFIN, Loughran, and NRC lexicons to increase the reliability of our findings.

Table 4: Sample output for stage 2.2, Building sentiment data from received emails for Enron for the period of 6 April 2001 to 17 April 2001 (Weekends are excluded)

Date	Trust	Joy	Fear	Sadness	Anger	Surprise	Disgust	Anticipation	NRC	NRC
									POS	NEG
06/04/2001	8812	3609	3259	2785	2380	2138	1263	8016	14571	6255
09/04/2001	14488	5590	7674	5665	6414	3201	4146	11016	23427	12705
10/04/2001	9430	3674	4243	3389	2998	2257	1906	6764	15001	7215
11/04/2001	5766	2062	1615	1080	1155	790	799	3492	7894	3639
12/04/2001	9171	2960	3169	2402	2810	1864	1381	6476	13240	5813
13/04/2001	2918	928	667	1289	562	490	206	2146	4107	2315
16/04/2001	10796	3329	3140	2335	2898	1908	1424	6894	15596	6641
17/04/2001	7103	2307	3189	2747	3036	1155	1753	5164	10400	5378

Table 5: Collecting and building sentiment data from received emails for Enron for the period of 6 April 2001 to 17 April 2001 (stage 2.2 continued)

Date	Uncertainty	Litigious	Constraining	Superfluous	Bin	Bing	Bing	Afinn	Lough	Lough
					POS	NEG	Pos-Ne	score	POS	NEG
06/04/2001	1105	1781	551	1	3866	4472	-606	1291	1309	1309
09/04/2001	1496	3892	874	2	6668	8229	-1561	427	2083	2083
10/04/2001	1372	2441	792	4	4121	4900	-779	-248	1112	1112
11/04/2001	1020	1099	403	2	2616	2284	332	1671	640	640
12/04/2001	1079	2358	454	5	3653	3793	-140	1575	1179	1179
13/04/2001	674	686	210	2	1090	2068	-978	363	311	311
16/04/2001	1286	1806	787	4	4508	4787	-279	1731	1117	1117

17/04/2001	801	1878	419	1	308 0	380 6	-726	-623	863	863
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Enron’s news events (Appendix A, Table 1) were manually collected and classified. In order to have a better classification of the crisis news, the table was presented to six MBA students, three Ph.D. students, and two information system professors and asked them to rate the news based on whether the news relates to a crisis event or not. Table 1 in Appendix A is the outcome of consensually agreed results. The variable is set to 1 if a news event translated to a crisis event, 0 otherwise. In Table 6, the critical event information is reflected in the fourth column. The second and third columns in Table 6 is the output of our CEDA model. Similarly, when there was a surge in the number of received emails detected or the sentiment of the day was negative, the variable is set to 1.

Table 6: Sample output stage 3– Critical Event Detection - Received emails for Enron for the period of 6 April 2001 to 17 April 2001 (Weekends are excluded)

Date	Was any surge in received emails detected?	Was the overall sentiment of the day for Enron emails negative?	Critical event detected by CEDA	Crisis events (market responses and media responses)
06/04/2001	0	1	0	0
09/04/2001	1	1	1	0
10/04/2001	0	1	0	0
11/04/2001	0	0	0	0
12/04/2001	0	1	0	0
13/04/2001	0	1	0	0
16/04/2001	0	1	0	0

17/04/200				
1	1	1	1	1

We ran a series of logistic regression analyses to test the relation between hypothesized constructs. The binary logistic regression analysis result showed that our model is a good fit ($-2 \times \text{Log likelihood} = 244.43$) (Appendix B, Table 1). Referred to as model deviance, $-2 \times \text{Log likelihood}$ is the most useful test to compare competing models in binary logistic regression analysis (Stevens & Pituch, 2016). The Omnibus Tests of Model Coefficients test results also confirm that our model includes the set of predictors that fits the data significantly better than a null model ($\chi^2(3) = 218.41, p < .001$) (Appendix B, Table 2).

In Table 7, each predictor's regression slope (B) represents the change in the log odds of falling detected crisis events by CEDA (EEvWithin3days) into the market and media reactions to real crisis events (News&NSE). The model's positive regression ($B=4.23$) indicates the detected event by our predictor variable (detected events within three days) has a high probability of falling into the target group (News&NSE). In this test, it is important that Odds Ratio ($\text{Exp}(B)$) does not include 1.0 (not zero) between the lower and upper confidence bound for a 95% confidence interval.

Table 7: The predicted change in the probability of target group membership per unit increase on the predictor

Variables in the Equation							95% C.I. for EXP(B)	
	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
EEvWithin3days	4.225	0.643	43.110	1	0.000	68.367	19.370	241.305

Step	EEventDetected	0.000	0.000	1.303	1	0.254	1.000	0.999	1.000
1 ^a	NSEdetected	0.005	0.003	2.810	1	0.094	1.005	0.999	1.010
	Constant	3.095	0.201	236.428	1	0.000	0.045		

a. Variable(s) entered on step 1: EEvWithin3days, EEventDetected, NSEdetected.

Table 8 provides the accuracy of the model. The overall classification accuracy based on the model is 95.5%.

Table 8: Accuracy of the model in predicting target group membership

Classification Table^a

Observed			Predicted		
			News&NSE		Percentage Correct
			0	1	
Step	News&NSE		639	5	99.2
1		1	27	44	62.0
	Overall Percentage				95.5

a. The cut value is .500

Our method for detecting the sudden change in the number of received emails trend combined with the sentiment of the day is conclusive and predicted 62 percent (table 8) of the news event published in major news outlets and market response when a crisis event hit Enron for the period of our study. The results support our hypotheses. Detection of critical events by finding the change in the pattern of the number of

received emails in combination with the use of the sentiment analysis method is statistically significant.

9. Discussion and Conclusion

New technological advancements such as artificial intelligence have become an important foundation of competitive advantage in the market for firms. Therefore, in this research, we examine the role of computer-mediated Artificial Intelligence agents in detecting crisis related to events in a firm. The findings of our empirical research suggest that knowledge extracted from day-to-day data communications such as email communications of a firm can lead to the sensing of critical events related to business activities. Critical events, in general, if not detected in the early stages, are a threat to an organization, and can become unmanageable crises. The past crises or history of crises in an organization could help crisis managers evaluate whether a recent crisis is an exceptional event (unstable), or is part of a pattern of events (stable). As Coombs (2007) claims, reoccurrence of an event, or continuation of more than one event, may indicate that the recent event is not an exceptional incident. As such, it is crucial for organizations to have the ability to access real-time crisis information to be able to assess the situation. Technology provides a platform in which crisis-related information is acquired in the fastest and most direct manner. Computer-mediated communication platforms, such as an organization's internal communication channels and external social media channels, facilitate real-time dialogue between intended stakeholders and, therefore, become strategically important.

We performed analyses of the Enron email dataset to identify changes in patterns of emailing frequencies and used that information to detect critical events. We developed a big data tool to perform an initial email count and to calculate the number of “emails sent” and “emails received” for the last three years of Enron before its bankruptcy. Then, we used advanced analytical tools to visualize and represent the result of the email counts to make a greater sense of a large amount of data more quickly and easily. Pattern changes in the emails’ metadata showed greater importance in detecting and assessing situational events. Despite the simple psychological fact behind the change in the number of emails sent and received during crisis periods, the use of email metadata is a relatively underexplored area.

This study analyzed Enron users’ email communication effectiveness in detecting critical events. Through the mining of the organization’s semi-structured email data and using more in-depth content analysis, we developed a model called critical event detection analysis model (CEDA) for detecting critical events. The model analyzes the connection between the frequency change in the number of emails received and an ongoing situation communicated through an interactive, computer-mediated communication channel. To obtain a better result in the detection process, the model factors in the textual character of communicated messages (e.g., polarity, emotions).

Theoretical implications and practical implications

Our managerial contribution is to provide a tool to enhance decision-making in organizations by detecting crisis in its early stages. Our theoretical contribution is to build a framework to detect triggering events in an organization using email metadata.

This can serve as a foundation for other researchers to explore other social network data or metadata for assessing and predicting emerging critical events in organizations. Our main practical implication is that we develop and introduce a critical event detection analysis model (CEDA) for detecting critical events in this empirical study. We analyze Enron users' email communication effectiveness in detecting critical events. Our analysis helps us develop the model to a big data tool to perform an initial email count. The model helps the firms to calculate the number of "emails sent" and "emails received" for the last three years of Enron before its bankruptcy. We argue that critical events are a threat to an organization. Organizations can learn from past crises to empower crisis managers to evaluate whether a recent crisis is unstable or stable. Our findings provide the ability to access real-time crisis information to be able to assess the situation. This helps organizations to have better forecasting for the market, for example. Our research suggests to the managers that computer-mediated communication platforms, such as an organization's internal communication channels and external social media channels, are essential tools to enable real-time dialogue between intended stakeholders.

Limitation and future research direction

This study was limited to an organizational crisis and as such it did not cover the external crisis such as the Severe Acute Respiratory Syndrome pandemic, and the Swine Flu epidemic (Pan et al., 2012) and large scale supernatural disasters (e.g., Hurricane Katrina, Asian Tsunami) and/or significant events, such as the 9/11 terrorist attacks. Another limitation of this study is associated with sentiment analysis of English text; thus, languages other than English need to be explored. A possible extension to

the methodology would allow researchers to explore the domain to multinational corporations (MNC).

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Appendix A

Table 1: Enron News events for the period 1985-2002

Date	Publisher	News Event	
1985	NYT	- Houston Natural Gas merges with InterNorth to form Enron, HNG CEO Kenneth Lay becomes CEO of the combined company the following year.	0
1987-01	agsm.edu. au	- Enron discovers that oil traders in their Vahalla, NY, office have been diverting company funds to their personal accounts.	1
1987-04	agsm.edu. au	- The board--including Ken Lay--learns that Louis Borget and Tom Mastroeni, the men in charge of the Vahalla operation, were gambling beyond their limits, destroying trading reports, keeping two sets of books and manipulating accounting in order to give the appearance that Vahalla was earning steady profits. The board does not fire the Vahalla executives because Lay makes it clear that they are making too much money to let them go. Lay increases the trading limits of the Vahalla traders.	1
1987-10	agsm.edu. au	- Ken Lay professes shock at the actions of the traders. They are fired. Three years later, Borget and Mastroeni plead guilty to a number of felonies. Borget spends one year in jail; Mastroeni receives a suspended sentence.	1
1987-10	agsm.edu. au	- Borget and Mastroeni end up on the wrong side of a massive trade, threatening to bankrupt the company. Enron executive Mike Muckleroy manages to bluff the market and reduce the loss from \$1 billion to \$140 million, thus saving the company.	1
19/10/1987	agsm.edu. au	- Black Monday. The Dow Jones industrial plummets 508, points, dropping 20.4%. It's the greatest single-day loss in Wall Street history.	0
1989	NYT	- Enron begins trading natural gas commodities.	0
1990-06	agsm.edu. au	- Lay hires Jeffrey Skilling to lead the company's effort to focus on commodities trading in the deregulated markets. Andrew S. Fastow is one of Skilling's first hires later that year.	0
1991	NYT	- Richard Causey leaves Arthur Andersen LLP to join Enron as assistant controller.	0
1991	agsm.edu. au	- Enron asks SEC to approve mark-to-market accounting.	

1997	NYT	- Skilling named president and chief operating officer of Enron. Fastow creates Chewco, a partnership, to buy the University of California pension fund's stake in another joint venture dubbed JEDI, but Chewco doesn't meet requirements to be kept off Enron's balance sheet. First step toward similar financial moves to hide debt and inflate profits that fuel Enron's downfall.	1
1998	NYT	- Fastow named finance chief.	0
1999	NYT	- Causey named chief accounting officer. Fastow creates the first of two partnerships, LJM, purported to "buy" poorly performing Enron assets and hedge risky investments but really helps the company hide debt and inflate profits. Enron directors approve Fastow's plan that he run the partnerships that do deals with Enron while continuing as Enron's finance chief. Causey and former chief risk officer Rick Buy assigned to monitor such deals to protect Enron's interests.	1
19/01/2000	agsm.edu.au	- Annual Analysts Meeting. First day -- Skilling: "EES [Enron Energy Services] is just rockin' and rollin." Second Day: Enron rolls out its Broadband plan. Scott McNealy, of Sun Microsystems, shows up to offer his support. By end of day, stock rises 26% to new high of \$67.25.	0
2000-04	agsm.edu.au	- Conference call with stock analysts. Skilling: "we have been swamped with new opportunities"	0
05/05/2000	agsm.edu.au	- Enron trader, in an email to colleagues, announces "Death Star," a new strategy to game the California market.	0
12/05/2000	agsm.edu.au	- Timothy Belden (chief trader for Enron's West Coast power desk) sends email to Enron headquarters in Houston confirming his strategy is working. "So far so good: pricing keeps going up." Belden has made a massive bet that California energy prices will increase. His email confirms that prices are rising.	0
22/05/2000	agsm.edu.au	- The California ISO (Independent System Operator), the organization in charge of California's electricity supply and demand, declares a Stage One Emergency, warning of low power reserves.	1
12/06/2000	agsm.edu.au	- Skilling makes joke at Las Vegas conference, comparing California to the Titanic.	1
2000-07	agsm.edu.au	- Enron announces that its Broadband unit (EBS) has joined forces with Blockbuster to supply video-on-demand.	0
23/08/2000	NYT	- Enron shares reach high of \$90.	0

10/09/2000	WP	- Enron Chairman Kenneth Lay contributes more than \$290,000 to George W. Bush's election campaign.	0
20/09/2000	agsm.edu.au	- Jonathan Weil writes piece about mark-to-market and energy companies. Investment analyst James Chanos reads this in the Texas Journal, a regional supplement to the Wall Street Journal.	1
03/10/2000	agsm.edu.au	- Enron attorney Richard Sanders travels to Portland to discuss Timothy Belden's strategies.	1
10/10/2000	WP	-Enron hires Linda Robertson, from the Clinton administration, as vice president for federal government affairs to head its Washington office, infuriating Republican leaders who oppose business groups hiring Democratic lobbyists.	0
01/11/2000	agsm.edu.au	- FERC investigation exonerates Enron for any wrongdoing in California.	1
06/12/2000	agsm.edu.au	- Christian Yoder and Stephen Hall write internal memo detailing Belden's strategies.	1
13/12/2000	NYT	- Enron announces that Skilling, then president and chief operating officer, will succeed Kenneth Lay as CEO in February 2001. Lay will remain as chairman. Stock hits 52-week high of \$84.87.	1
2000-12	agsm.edu.au	- Enron uses "aggressive" accounting to declare \$53 million in earnings for Broadband on a collapsing deal that hadn't earned a penny in profit.	1
03/01/2001	WP	- Lay is one of the 474 people Bush names to advise his presidential transition team.	0
2001-01	agsm.edu.au	- Belden's West Coast power desk has its most profitable month ever -- \$254 million in gross profits.	0
17/01/2001	agsm.edu.au	- Rolling blackouts in Northern California.	1
22/01/2001	agsm.edu.au	- Quarterly Analyst Conference Call -- Skilling reports: "outstanding ... fantastic ... tremendous ..."	0
25/01/2001	agsm.edu.au	- Analyst Conference in Houston, Texas. Skilling bullish on the company. Analysts are all convinced. Ken Rice increases his estimates for value of Broadband.	1
2001-02	agsm.edu.au	- Tom White resigns from EES (Enron Energy Services, the retail division he headed since 1998) and becomes Secretary of the Army. He cashes out with \$14 million and begins to build a huge home in Naples, Florida. The purchase price for the property is \$6.5 million.	1
2001-02	agsm.edu.au	- Over the past year (while he presided over EBS, Enron Broadband Services), Ken Rice cashes in \$53 million in shares and options.	1
2001-02	agsm.edu.au	- Lay retires as CEO and is replaced by Skilling.	1

2001-02	WP	- Jeffrey Skilling takes over as chief executive. Kenneth Lay remains chairman	1
05/02/2001	agsm.edu.au	- Senior Andersen partners meet to discuss whether to retain Enron as a client. They call use of mark-to-market accounting "intelligent gambling."	1
15/02/2001	agsm.edu.au	- Mark Palmer, head of publicity for Enron, and Fastow go to Fortune to answer questions. Fastow to Bethany McLean: "I don't care what you say about the company. Just don't make me look bad."	1
19/02/2001	agsm.edu.au	- Fortune article, by Bethany McLean: "Is Enron Overpriced?"	1
2001-03	agsm.edu.au	- Enron transfers large portions of EES business into wholesale to hide EES losses.	1
2001-03	WP	- Karl Rove, President Bush's senior adviser, met privately with Intel officials, of which company he owned over \$100,000 worth of shares. At the time, Intel was concerned with government approval of a merger between a Dutch company and an Intel supplier. The merger was later approved.	1
2001-03	agsm.edu.au	- Arthur Andersen takes auditor Carl Bass off the Enron account.	1
23/03/2001	agsm.edu.au	- Enron schedules unusual analyst conference call to boost stock. It works.	1
17/04/2001	agsm.edu.au	- Quarterly Conference Call. The "asshole" call.	1
17/05/2001	agsm.edu.au	- "Secret" meeting at Peninsula Hotel in LA -- Schwarzenegger, Lay, Milken.	1
19/05/2001	WP	- Congress begin implementing President Bush's energy plan into legislation.	0
05/06/2001	WP	- Rove divested his stocks in energy, defense and pharmaceutical companies. Rove owned holdings worth more than \$100,000 in each Enron, Boeing, General Electric and Pfizer.	0
21/06/2001	agsm.edu.au	- Skilling hit in face with blueberry tofu cream pie by Francine Cavanaugh at The Commonwealth Club in San Francisco.	1
2001-06	agsm.edu.au	- FERC finally institutes price caps across the western states. The California energy crisis ends.	0
30/06/2001	WP	- The White House acknowledges Karl Rove was involved in shaping the administration's energy policy at a time when he owned equities in energy companies.	1
13/07/2001	agsm.edu.au	- Skilling announces desire to resign to Lay. Lay asks Skilling to take the weekend and think it over. There are two different views of what happened that day. According to Lay, he tried to talk Skilling out of resigning. Skilling says Lay didn't seem to care and that	1

		he offered to stay on for six months. Board member says he recommended the transition period to Lay. Lay claims Skilling wanted an immediate out.	
03/08/2001	agsm.edu.au	- Skilling makes a bullish speech on EES. That afternoon, he lays off 300 employees.	1
14/08/2001	NYT/WP	- Skilling resigns; Lay named CEO again.	1
15/08/2001	agsm.edu.au	- Jim Chanos thinks the stock is going through the floor and bets aggressively on that. Notes that Skilling's departure coincided with release of second quarter 10-Q. Enron's cash flow was a negative \$1.3 billion for the first six months. ; Sherron Watkins, an Enron vice president, writes to Lay expressing concerns about Enron's accounting practices.	1
22/08/2001	NYT	- Finance executive Sherron Watkins meets privately with Lay to discuss concerns of murky finance and accounting that could ruin the company.	1
2001-09	agsm.edu.au	- Skilling sells \$15.5 million of stock, bringing stock sales since May 2000 to over \$70 million.	1
12/10/2001	WP	- An in-house lawyer at Arthur Andersen emails the lead partner in the firm's Houston office to remind him of the firm's document-destruction policy.	1
15/10/2001	WP	- Lay talks to Commerce Secretary Donald L. Evans. Commerce officials say the call did not cover Enron's financial troubles.	1
16/10/2001	NYT/WP	- Enron announces \$638 million in third-quarter losses and a \$1.2 billion reduction in shareholder equity stemming from writeoffs related to failed broadband and water trading ventures as well as unwinding of so-called Raptors, or fragile entities backed by falling Enron stock created to hedge inflated asset values and keep hundreds of millions of dollars in debt off the energy company's books.	1
17/10/2001	WP	- SEC sends a letter to Enron asking for information after the company reported hundreds of millions of dollars in third-quarter losses.	1
19/10/2001	NYT	-Securities and Exchange Commission launches inquiry into Enron finances.	1
20/10/2001	WP	- A report filed with the Internal Revenue Service reveals that a political group allied with House Majority Whip Tom DeLay (R-Tex.) raised nearly \$500,000. The Republican Majority Issues Committee (RMIC) was required to show, for the first time, how it raises and spends its money. One of the committee's largest donations included Enron's \$50,000.	1

22/10/2001	WP	-Enron acknowledges a Securities and Exchange Commission inquiry into a possible conflict of interest related to the company's dealings with the partnerships. Shares of Enron sank more than 20 percent on the news.	1
23/10/2001	NYT	-Lay professes confidence in Fastow to analysts.	1
23/10/2001	agsm.edu.au	- In a massive shredding operation, Arthur Andersen destroys one ton of Enron documents.	1
24/10/2001	NYT/WP	-Enron ousted CFO Fastow.	1
31/10/2001	WP	-Enron announces that the SEC inquiry has been upgraded to a formal investigation.	1
05/11/2001	NYT	-Enron treasurer Ben Glisan Jr. and in-house attorney Kristina Mordaunt fired for investing in Fastow-run partnership.	1
		-partnership. Each invested \$5,800 in 2001 and received a \$1 million return a few weeks later.	
08/11/2001	NYT/WP	-Enron files documents with SEC revising its financial statements for previous five years to account for \$586 million in losses.	1
08/11/2001	WP	- Andersen receives a federal subpoena for documents related to Enron.	1
		- Enron begins talks to sell itself to rival Dynegy for about \$8 billion in stock and cash.	
09/11/2001	NYT	-Dynegy Inc. announces an agreement to buy Enron for more than \$8 billion in stock.	0
09/11/2001	WP	-The company discloses that it overstated its earnings by \$567 million since 1997. Two company officials are fired.	1
		- Dynegy announces an agreement to buy its much larger rival Enron for more than \$8 billion in stock and cash.	
13/11/2001	WP	-Kenneth Lay turns down a \$60.6 million severance payment that would be triggered at the completion of the Dynegy deal.	1
19/11/2001	NYT/WP	-Enron restates its third-quarter earnings and discloses a \$690 million debt is due Nov. 27.	1
28/11/2001	NYT	-Enron stock plunges below \$1 as Dynegy Inc. aborts its plan to buy its former rival.	1
28/11/2001	WP	- Dynegy seeks to abruptly cut the amount of it's buyout offer as Enron's credit rating is cut to junk-bond status.	1
29/11/2001	WP	-SEC investigation is expanded to include Arthur Andersen.	1
		-Dynegy deal collapses.	
02/12/2001	NYT/WP	-Enron goes bankrupt, thousands of workers laid off.	1

03/12/2001	WP	-Enron arranges up to \$1.5 billion debtor-in-possession financing to keep operating while in bankruptcy and announces 4,000 layoffs.	1
12/12/2001	WP	-Joseph F. Berardino, chief executive of Arthur Andersen, appears before Congress, testifying Enron might have violated securities laws.	1
10/01/2002	WP	- The Justice Department confirms that a criminal investigation of Enron's collapse has begun.	1
22/01/2002	WP	- A former Enron employee claims she saw documents being shredded after the announcement of the Securities Exchange Commission investigation in October	1

Note: The events are taken from The New York Times¹, Washington Posts¹ dailies and AGSM¹ (Australian Graduate School of Management) UNSW Sydney.

¹ <https://www.nytimes.com/2006/01/18/business/worldbusiness/timeline-a-chronology-of-enron-corp.html> Accessed on June 16, 2018

¹ http://www.washingtonpost.com/wp-dyn/articles/A25624-2002Jan10_5.html Accessed on June 16, 2018

¹ <http://www.agsm.edu.au/bobm/teaching/BE/Enron/timeline.html> Accessed on Aug 08, 2018

APENDIX B

Table 1: Theoretical model: integration of SCCT and the CEDA

Model Summary			
	-2 Log likelihood	Cox & Snell R Square	Nagelkerk e R Square
Step 1	244.426 ^a	0.263	0.552

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Table 2: Testing theoretical model's improvement in fit after including full set of predictors

Omnibus Tests of Model Coefficients				
Step 1	Step	Chi-square	df	Sig.
		218.241	3	0.000
	Block	218.241	3	0.000
	Model	218.241	3	0.000

Appendix C

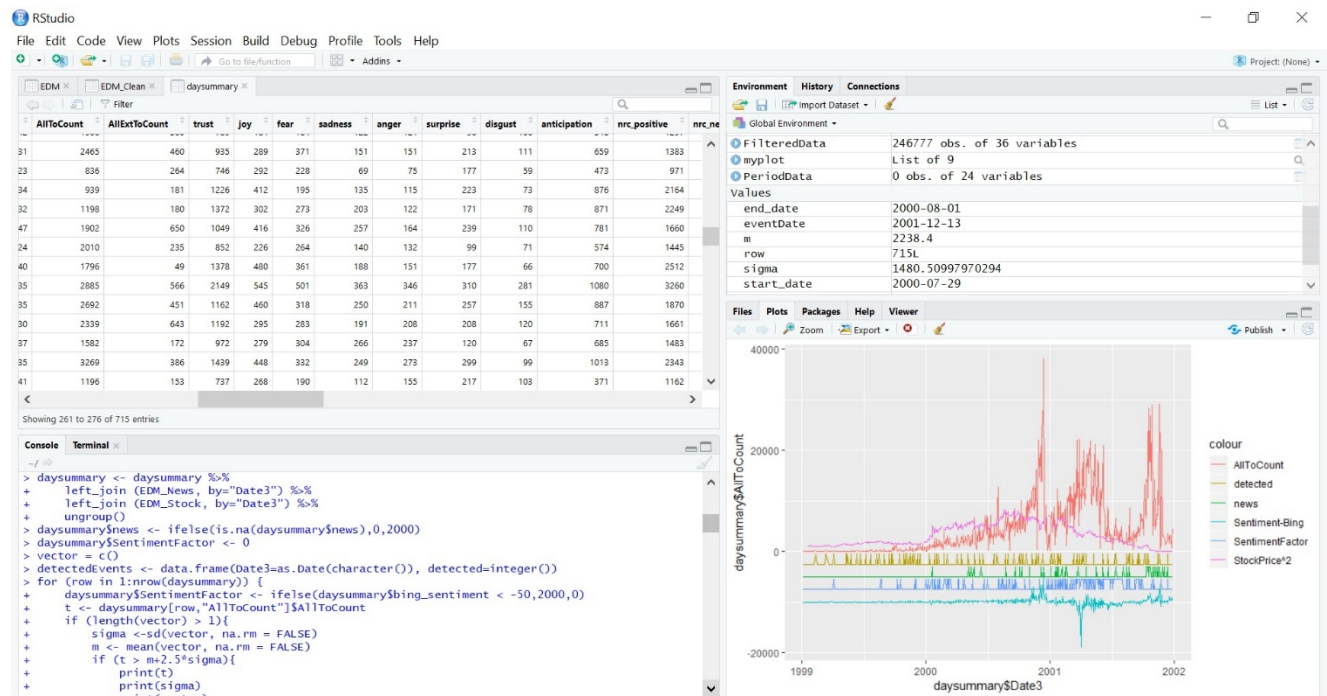


Fig. 1. A snapshot of our work – Using R for creating the final Visual presentation for critical event detection assessment.

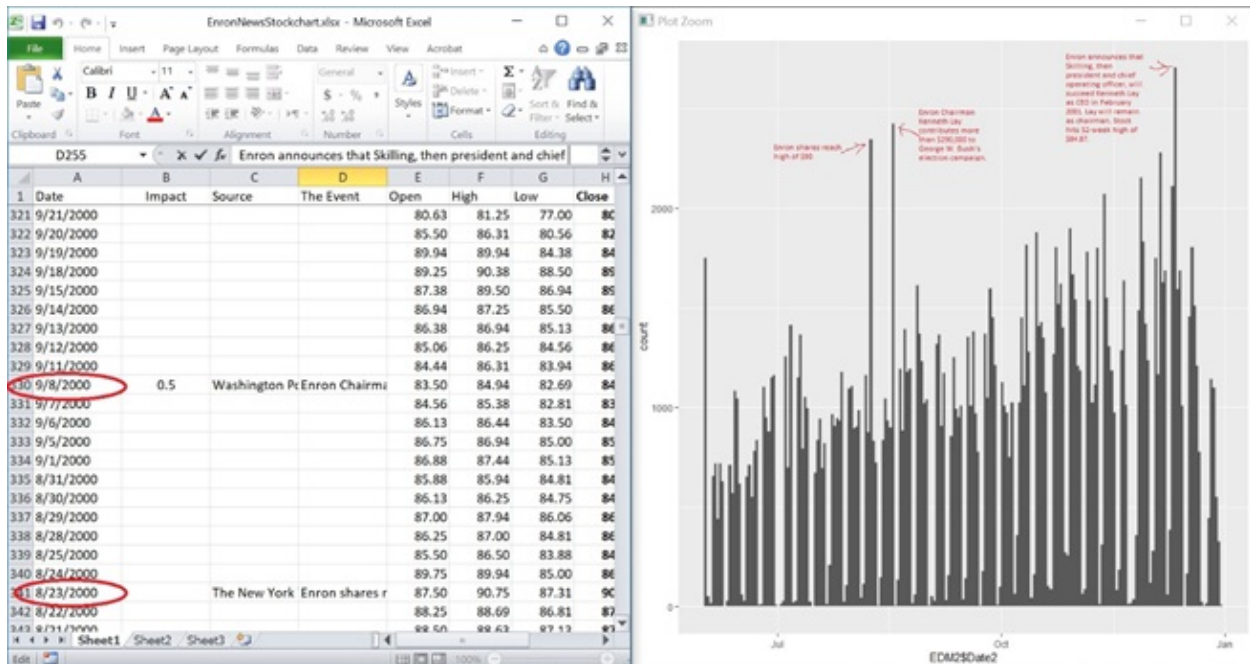


Fig. 2. A snapshot of our work for earlier stages of defining what would be considered a critical event