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Affective Computing for Managing Crisis Communication

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Abstract. With affective computing being used as a tool that enhances decision-making in fields other than computing, this article exploits the potential of its applications in crisis communication. The article reviews emotion representation in different crisis communication models, leading to the identification of a research gap in these models and proposes an initial version of a Conceptual Framework for Affective Computing Supported Crisis Communication. The proposed framework underscores the significance of emotions as a pivotal factor influencing attitudes and behaviours during crises and integrates affective computing solutions aimed at effectively monitoring crises and determining suitable crisis communication strategies.

Keywords: affective computing, crisis communication, emotions in crises, computational communication

Introduction

Affective computing is a sub-field of human-computer interaction research that focuses on recognizing, analyzing, and interpreting different emotional states (Tao and Tieniu, 2005). The concept of a machines' ability to recognize, interpret and respond to human affective states was proposed in 1995 and further developed by MIT computer science professor Rosalind W. Picard (Picard, 1995; Picard, 1997; Picard et al., 2001). She was the first to suggest that machine intelligence needs to include emotional intelligence, and that computers might be given the ability to "have emotions." Since then, affective computing has grown into an interdisciplinary research area that draws from cognitive science, psychology, physiology as well as computer science to ensure that computers can identify human emotions and respond intelligently to them. Thus, affective computing is often used interchangeably with the term emotion AI (Ho et al., 2021), as it is seen as a key to advancing the development of human-centric AI.

Given that affective computing is being used as a tool to enhance decision-making in fields other than computing, this article explores affective computing as a promising approach to crisis communication research and practice.

Coombs (2009) suggests that “a crisis can be viewed as the perception of an event that threatens important expectancies of stakeholders and can impact the organization’s performance. Crises are largely perceptual. If stakeholders believe there is a crisis, the organization is in a crisis unless it can successfully persuade stakeholders it is not. A crisis violates expectations; an organization has done something stakeholders feel is inappropriate.” Crisis communication researchers have established a common understanding of the role of emotions. During an organizational crisis — a sudden and unexpected event that threatens to disrupt an organization's operations and poses both a financial and a reputational threat (Coombs 2007) — emotions play a significant role in shaping and re-shaping publics' perception of the situation as the conflict between the public and the organization intensifies. Emotions serve as a strong influence in how events are interpreted, perceived, and responded to as they unfold and evolve (Jin et al., 2007). Emotions influence the publics' short and long-term attitudes towards the organization(s) that stand behind the crisis, endanger organizations' reputation (Coombs, 2010), drive negative word-of-mouth (Coombs, 2022), and impact purchase decisions (Stockmeyer, 1996), including for example, product boycotts (Choi and Lin, 2009). Even though crises create a unique stakeholder group for organizations — the victims, it represents a relatively small subset of stakeholders. Non-victims, which is the group primarily analyzed by this thesis, is at least as important as the victims, as it is significantly broader and also judge organizations on how they handle crises (Coombs and Holladay, 2005). The ability to anticipate and understand the emotional reactions of different stakeholders influences organizations' effectiveness in crisis management and communication. Understanding the emotional impact of a crisis is essential for dealing quickly and effectively with the negative consequences of a crisis, including making informed choices about crisis communication strategies. An organization's reputation can be better safeguarded by crisis communication that considers the emotional responses of stakeholders and incorporates these insights into its post-crisis response planning (Coombs Holladay, 2005). Moreover, this helps to protect organizations involved in the crisis, and enhances the ability to protect the public interest. Two of the three most dominant crisis communication theories — the Situational Crisis Communication Theory (SCCT) and Integrated Crisis Mapping (ICM) model (Bukar et al., 2020) — incorporate the role of emotions. Other crisis communication models that recognize the effect of emotion on crisis development have been proposed (e.g., Lu and Huang, 2018). However, nuanced knowledge of the impact of emotions on people's reactions in crises and the effect of response strategies still requires more research.

The article reviews the representation of emotion in different crisis communication models, leading to the identification of the research gap in these models and proposing the initial version of the Conceptual Framework for Affective Computing Supported Crisis Communication, integrating affective computing solutions aimed at effectively monitoring crises and determining suitable crisis communication strategies.

The article is structured as follows: the first section introduces the concept and applications of affective computing; the second section explains the potential of affective computing to support crisis communication research. The third section discusses in detail how emotion is represented in crisis communication research, while the fourth section proposes the conceptual framework for affective computing-supported crisis communication research and practice. Finally, the last section summarizes the underlying principles and discusses outlooks, future directions, as well as possible limitations and problems in the research of affective computing in the context of crisis communication.

1. Affective computing and its applications

At the core of affective computing research are technologies and applications that contribute to understanding the factors that influence human affective states and behavior, starting from text sentiment analysis to audio, and extending to visual and physiological-based emotion recognition (Wang et al., 2022). Research methods to measure and detect users' affective states include both laboratory and off-lab (Fortin-Cote et al., 2019), as well as mobile solutions (Politou et al., 2017), in both real and virtual environments (Marín-Morales, 2017). The rapid increase of online social media and e-commerce platforms, and vast amounts of textual data generated by users of these platforms, provide researchers with rich material for emotion analysis (Wang et al., 2022; Balaji et al., 2021). Facial expressions (Tsao and Livingstone, 2008), body gestures (Kapur et al., 2005), and speech (Batliner et al., 2011; Tuncer et al., 2020) are physical modalities, other than text, widely used to identify and analyze emotions. As the effectiveness of physical-based affect recognition may suffer from so-called social masking — a person's involuntary or deliberate concealment of their real emotions (Zhang et al., 2020), methods that are considered more objective but also more intrusive, measure physical modalities such as skin conductance, blood volume pulse, skin temperature, as well as physiological modalities such as electroencephalogram (EEG) (Alarcao and Fonseca, 2019) and electrocardiogram (ECG) (Sarkar and Etemad, 2020)).

Continuing to develop new methods, researchers have presented how parameters like mouse and keyboard inputs (Zimmermann et al., 2003), text input patterns on a smartphone (Lee et al., 2012; Ghosh et al., 2019), or steering wheel grip intensity (Oehl et al., 2007) are also reliable indicators of human emotions. The growth of affective computing has stimulated the creation of public benchmark databases, which mainly consist of unimodal (textual, audio, visual, and physiological) and multimodal databases. In turn, these commonly used databases have inspired the advancement of machine learning and deep learning techniques in the field of affective computing (Wang et al., 2022). Also, the analysis of large neurophysiological datasets is made easier with the use of machine learning techniques, and pattern classifiers can combine physiological characteristics gathered from various modalities (Yin et al., 2017).

Affective computing has grown into a fruitful area that aims to increase technological efficiency in fields such as robotics (Rattanyu et al., 2010), computer-assisted learning (Wu et al., 2015), human health, e.g., helping people with autism and facilitating their acquisition of social skills ((Blocher and Picard, 2002; Ward, 2018), depression detection (Deshpande and Rao, 2017), and telehealth (Lisetti and LeRouge, 2004). Affective computing is a useful approach for adding an emotional layer of human–environment relationships, thus enriching a variety of fields such as traffic planning, urban safety, human-centric tourism (Huang et al., 2020). In the fields of communication and marketing, affective computing has been applied to evaluate the effectiveness of communication narratives and materials (Valle-Cruz et al., 2021). A general challenge facing the field of affective computing is exploring more hybrid types of cognitive systems, where not only are computational resources and methods applied (as in the case of artificial cognitive systems) but also human specific affective processes (as in the case of natural cognitive systems) are involved. This is crucial since contemporary interactions integrate both natural and artificial systems.

2. Potential for Affective Computing Application in Crisis Communication

The effects of emotion on crisis perception and development are still understudied. The environment in which crises emerge keeps changing, including media consumption patterns, increasing the importance of emotion-based communication in the digital era (Lu, 2017). As shown, the potential for further research on the various emotions a crisis can evoke has not been exhausted (Coombs, 2022). Furthermore, earlier scholarship on emotions in crises is of questionable value because of its methodological and theoretical limitations.

First, the theoretical limitations of earlier crisis communication theories, specifically the Situational Crisis Communication Theory and Integrated Crisis Mapping, are because they fail to consider that publics use emotional patterns of information processing rather than rational ones (Lu, 2017). Furthermore, earlier theories and research rely predominantly on the appraisal theory of emotion (Lazarus, 1991; Lazarus, 1999) the essence of which is that emotions are judgements grounded in (cognitive) appraisals of the personal significance of the surrounding environment (Ortony, 2022). Instead of an assumption that emotions are the result of a top-down process where evaluations and thoughts precede emotion and then emotions motivate behaviour, the theory of constructed emotion defines emotions as constructions of the world, not reactions to it (Barrett, 2017b). The constructivist approach explains the emergence of emotion as a bottom-up process where behaviour and bodily response precede and motivate emotion and cognition. It emphasizes the dynamic and context-dependent nature of emotions and views emotions as constructed by individuals based on their unique experiences and interpretations. Drawing on years of research in neuroscience, Barrett argues that an emotion is a brain's creation of what body sensations mean, a label a person assigns to the physiological state it senses (Barrett, 2017b). This, according to Barrett, (2017a) "makes classical appraisal theories highly doubtful, because they assume that a response derives from a stimulus that is evaluated for its meaning". The theory of constructed emotion provides insights for re-evaluation of crisis communication theories, as well as advantages for the development of an affective computing-supported crisis communication software.

The advantages of using the theory of constructed emotion in information technology are described in the context of the discipline of requirements engineering (Taveter and Iqbal, 2021), emphasizing that the theory of constructed emotion relates emotions to be constructed by software to the situations the software is meant for. The requirements that have been formulated by considering the theory of constructed emotion can be applied in designing interactive digital narratives and sociotechnical systems across a range of problem domains (Taveter and Iqbal, 2021).

Secondly, methodology, for example self-reporting surveys or media analysis, limits findings to the extent that survey participants can remember and articulate the emotions they experienced in response to a media outlet's decision to report and include emotions generated by crisis events in their agenda. Affective computing surpasses traditionally applied methods such as media content analysis, self-reported data, or even sentiment analysis that only determines the polarity of textual data. By analyzing actual behavior and expressions of emotions, affective computing allows for relatively objective and accurate assessment, modeling, and prediction of moods, emotions, and reactions in society and its various groups. Consequently, it successfully addresses the challenges of reliability and accuracy posed by experimental, quasi-experimental, and correlational research methods. Additionally, affective computing in multi-agent communication makes a vital contribution when compared to game or rational choice theories by accurately incorporating emotions and their impact into specific situations and their models (e.g. Saunier and Jones, 2014; Peng and Su, 2020).

Thirdly, even though the relevance of computational methods has been recognized for different areas of crisis communication: organizational crises, public health crises, natural disasters, and political crises (van der Meer et al., 2022), affective computing has not been explored as an avenue for crisis communication research. The few exceptions are studies that propose the application of affective computing in the design of realistic crisis management training, incorporating emotional and stress management aspects (MacKinnon and Bacon, 2012; Mackinnon et al., 2013; Daoudi et al., 2020).

The application of deductive and inductive computational techniques in the field of communication research has been accelerated by the significant amount of data and "digital traces" left around different digital sources such as online social media platforms like Twitter, Facebook, Instagram, and TikTok as they have become a dominant means for individuals to express their thoughts and emotions about current events. Thus, computational communication science is a quickly developing sub-field among communication researchers and is characterized by the involvement of large and complex data sets — e.g., communication artifacts such as tweets, posts, emails, reviews, and other digital traces or "naturally occurring" data, as well as algorithmic solutions developed to study human communication by applying and testing communication theories (van Atteveldt and Peng, 2018). Among the computational communication approaches applicable to crisis analysis, van der Meer et al. (2022) lists deductive approaches as *dictionary methods* and supervised machine learning, as well as inductive approaches such as unsupervised methods and different cluster techniques, network analysis, distributed word embeddings, deep learning or neural network models, and machine vision. Computational communication approaches are used both for confirmatory studies to verify researcher assumptions using predefined categories for the classification of text, for example, to detect sentiment or identify communication frames, and exploratory research such as texts might be automatically classified into (potentially) meaningful categories. (van der Meer et al., 2022).

Developing and integrating affective computing approaches into computational crisis communication research would significantly widen the potential outcomes of such research as it precisely focuses on emotions and adds research modalities other than text analysis, which dominates existing research. Affective computing presents a wide range of computational approaches, e.g., analysis of speech, facial expressions, gestures, audiovisual materials, physiological characteristics, etc., to deepen the understanding of how people actually feel when facing different types of crises. Hence, affective computing has a great potential to benefit both crisis communication researchers and practitioners by building a well-grounded understanding of the effects of emotion during crises.

3. Review of Emotion Representation in Crisis Communication Models

The growing focus on the role of emotions in crisis communication has resulted in several crisis communication models and adjustments to models that previously overlooked this phenomenon. This section introduces the two dominant crisis communication theories — SCCT and ICM — that both incorporate emotions into the reasoning about the crisis outcomes and best response strategies, the model that is developed based on the critique of the previously mentioned theories — Emotion-cognition dual-factor model of crisis communication, as well as the STREMII model that describes dealing with crisis communication in social media. Finally, the section summarizes the limitations of these crisis communication theories in relation to the presence and impact of emotions in crisis.

3.1. Situational Crisis Communication Theory

SCCT is the most dominant crisis communication model and was developed by W.T. Coombs (1995), later tested, evaluated, and clarified (e.g., Coombs 2005, 2007, 2022; Coombs and Holladay 1996, 2001, 2002, 2005; Choi and Lin, 2009; Frandsen and Johansen, 2017). Conceptually focusing on "rational" aspects of cognition, SCCT incorporates affect as one of a number of crisis outcomes along with the organization's reputation and behavioral intentions like purchase intentions and negative word-of-mouth (Coombs, 2022). SCCT is built on the idea that the most effective crisis response depends on situational influences. Its foundation lies in Attribution theory, which examines the cognitive process behind attributing responsibility for events. Based on this, SCCT suggests that the response to a crisis should align with the level of responsibility stakeholders will attribute to the organization.

At the core of SCCT are the crisis types or frames that are used to interpret the crisis and crisis interventions — words and actions used in response to the crisis. Depending on responsibility attribution, crisis types include victim, accidental, and preventable crises. While victim crises are those, where the organization is perceived as a victim, accidental crises are seen as unfortunate events where the organization's responsibility is limited; preventable crises evoke strong perceptions of crisis responsibility as it is assumed that the crisis could have been prevented if the organization had taken the proper steps (Coombs and Holladay, 2002). SCCT categorizes crisis response strategies into three clusters: deny, diminish, and deal. The "deny" crisis aims to dissociate the organization from the crisis. The "diminish" group strives to minimize the organization's responsibility and the impact of the crisis. The "deal" group takes steps to assist those affected by the crisis and is seen as accepting responsibility (Coombs and Holladay, 2010).

Additionally, SCCT describes factors that alter attributions of crisis responsibility and intensify the threat from the crisis. These factors are the organization's crisis history and prior reputation (Coombs 2004; Coombs and Holladay 2001). Later developments of SCCT also add cultural aspects (Huang et al. 2016), rhetorical arena, and the "multivocal approach" to crisis communication (Frandsen and Johansen, 2017)) as contextual modifiers to crisis responsibility attribution that can increase or decrease attributions of crisis responsibility associated with the crisis type. The rhetorical arena refers to the various voices speaking in the crisis, thus shaping attributions of crisis responsibility (Coombs, 2022).

As a result, depending on responsibility attributions, crises lead to different affective states. According to the research (Coombs and Holladay, 2005), crises from the victim-crisis cluster produced the strongest feelings of sympathy, while organizational misdeed crises produced the strongest feelings of anger and schadenfreude (the pleasure felt at someone else's misfortune (Smith, 2018)). Accident-cluster crises tended to produce muted emotional responses, whilst intentional-cluster crises generated the strongest anger. Anger, according to the research of Coombs and Halladay (2007) fuels the potentially damaging negative communication dynamic and is shown to be a mediator between crisis responsibility and negative word-of-mouth helping to convert attributions of crisis responsibility into negative word-of-mouth. Management misconduct and scansis crises (a combination of crisis and scandal) produce another emotional state caused by perceptions of unfairness and exploitation — moral outrage (Tachkova and Coombs, 2022). Based on appraisals, not attribution, moral outrage serves as a boundary condition for SCCT, where the theory's recommended crisis intervention has no effect on the common crisis outcomes of reputation.

3.2. Integrated Crisis Mapping Model (ICM)

By analyzing an audience's preferred coping strategies (problem-focused or cognitive-focused) and the level of involvement of the responsible organization, researchers predict the audience's expected emotional response — anger, sadness, anxiety, or fright (Jin et al., 2012).

ICM is derived from Lazarus's (1991, as seen in Jin et al., 2007) theory of cognitive appraisal in the field of emotion research. The authors of ICM propose the existence of two forms of coping: (a) problem-focused coping, which involves modifying the connection between the public and the organization through practical actions and steps taken; and (b) cognitive-focused coping, which involves altering only the perception of the relationship held by the public. The second aspect of the ICM model is the degree of involvement by the organization, which can range from high to low. The level of organizational involvement is determined by the relationship between the crisis events and the organization's objectives for operational and reputation success. This is based on Lazarus's primary appraisal concepts, as well as the organization's accountability for the crisis, as defined by Coombs's SCCT (Coombs, 2007). Each model's quadrant categorizations of crisis types are conceptualized based on three criteria: 1) Internal-external, 2) Personal-public, and 3) Unnatural-natural.

According to the initial ICM (Jin at el., 2007), four negative emotions - anger, fear, anxiety, and sadness - dominate public crisis situations in society. Additionally, multistage testing of the model found evidence that anxiety was the default emotion that publics felt in crises. ICM suggest that the primary audience is likely to experience two levels of emotions. The primary level of emotion represents the public's immediate reaction, while the secondary level of emotion emerges in subsequent encounters, contingent upon the organization's crisis responses. This secondary emotion might be transferred from the dominant emotion or exist alongside the primary emotional response (Jin et al., 2012).

Researchers have tested and confirmed the validity of this model by analyzing mass media publications, which are rather limited in their ability to draw full and comprehensive conclusions about the emotional reactions of the affected audiences. The need to further develop this model is demonstrated by studies analyzing people's reactions on social networks to crisis situations (Yeo et al., 2019; Varma and Perkins, 2020) It has been concluded that the list of crisis emotions defined by the ICM is not exclusive and can be refined or extended depending on the specific crisis event. This includes that the range of emotions can vary from one crisis phase to another, and that negative emotions can be accompanied by neutral or even positive ones, for instance, joy as a reaction to the important developments in a crisis (Yeo et al., 2019).

3.3. Emotion-Cognition Dual-Factor Model of Crisis Communication

Authors of the Emotion-Cognition Dual-Factor Model of Crisis Communication (EDMCC) (Lu and Huang, 2018) point out the theoretical limitations, oversimplified and unitary accounts of the cognitive process in SCCT and ICM that diminish the possibility of fully accounting for the interaction between emotion and cognition. They base their work on the assumption that the public processes crisis information in multiple stages rather than in a straightforward, unitary way. Second, depending on the intensity of the initial emotions from the crisis – defined as“the publics’ cognitive appraisal of initial crisis information that gives rise to discrete crisis emotions – the model proposes that perception, evaluation, and verdicts regarding organizations during a crisis can be driven not only by cognitive but also emotional factors. According to the model, the publics' initial emotional response is shaped not only by cognitive appraisal but also by the framing effects of crisis information and the mechanism of emotional contagion. Lu and Huang explain that emotional or rational framing of the crisis event may influence perception as, initially, publics' knowledge of the crisis event is based on information released by the organization involved or the media, rather than information about what has happened. Similarly, following the actual crisis event, publics' emotions are triggered or intensified by online emotional contagion during which the publics experiences the negative emotions communicated by online forums and comments.

In contrast to SCCT and ICM, EDMCC incorporates an emotion-to-cognition approach as possible and critical for understanding the publics' evaluation of organizational crises. Lu and Huang (2018) further explain that there are four ways that initial high-intensity crisis emotions may influence how publics process crisis information: information processing routine, selective processing, information recall, and responsibility attribution.

Referring to scholars working on the relationship between cognition and emotion (Lazarus, 1999; Gordon and Arian, 2001, as seen in Lu and Huang, 2018), the authors of EDMCC explain the two-way relationship between cognition and emotion. They emphasize the significance of emotions occurring prior to succeeding thoughts while recognizing that emotions might also be responses to prior meaning and demonstrate that both emotional and logical pathways can influence decision-making.

According to the model, a significant factor that impacts whether publics will lean towards cognitive-oriented or emotion-oriented patterns is the intensity of the initial crisis emotion. If publics experience initial crisis emotions with low intensity, they will follow a cognitive-oriented pattern and may not be influenced by crisis emotions. If publics experience the initial crisis with strong emotion, it will follow an emotion-oriented pattern, in which the effects of the initial emotion are evident in both their behavioral intentions and their cognitive processes. According to the model, individuals who have experienced initial crisis emotions with high intensity may exhibit behaviors intended to deal with the organizational crisis prior to processing subsequent crisis information, perform systematic or heuristic processing of subsequent crisis information, as well as selective processing of emotion-congruent crisis information. The intense initial crisis emotions may also promote emotion-congruent recall of crisis memories concerning the crisis-bearing organization and influence the publics' attributions of crisis responsibility and attribution approach (situational or dispositional) (Lu and Huang, 2018).

3.4. Dealing with a Crisis in the Digital Era: STREMII Model

When facing a crisis, people use social media platforms to share information — text, images, videos, or social media posts made by other users. Social media significantly changed the communication landscape by enabling dynamic, often real-time interaction and gives voice to consumers as pivotal authors of brand stories (Gensler et al., 2013). Referring to the prior research on emotions, Lu and Huang (2018) noted that intense emotions are increasingly likely to trigger behaviors in digital environments directly. This might include the desire to share online content, "share" or "like" videos, thus dramatically expanding the negative influence of organizational crises through viral forwards and negative online comments. Consequently, such activity triggers high levels of emotional intensity. By not considering emotions, organizations may fail to properly evaluate the crisis and fail in attempts at crisis communication.

On the other hand, social media platforms aid crisis managers in spreading their information in real-time and directly to the target audiences, thus providing an alternative to media framing and the agenda-setting effects on information that reaches crisis stakeholders. As SCCT and other dominant crisis communication models emerged from a mass communication model that was qualified as supporting a one-to-many communication flow and social media has changed the communication landscape significantly, the STREMII model of social media crisis communication has been proposed to fill the gap on social media effects on crisis communication (Stewart and Wilson, 2016).

The STREMII model builds on the SCCT and explains social media crisis communication as a cyclical process consisting of six elements: (1) surveillance and social listening, (2) targeting the appropriate audience, (3) responding to the crisis and conversation, (4) monitoring the landscape and evaluating outcomes, (5) interacting with consumers and publics, and (6) implementing necessary changes. Unlike SCCT, ICM and EDMCC, the STREMII model does not explain the crisis communication process and effects from the public's perspective, it rather is an actionable step by step explanation of the activities required from crisis communicators to control crisis information flow and comprehending the communication specifics in the social media environment. It does not incorporate or explain the role of emotions in crisis situations, however as the most prominent model that explains crisis communication in the context of the latest developments in the media environment (Bukar et al., 2020), it is still important in the context of this article's ambition to propose a framework for emotional AI in crisis.

The STREMII model is consistent with the Coombs view of the crisis lifecycle as divided into three stages: pre-crisis, crisis, and post-crisis (Stewart and Wilson, 2016). The first two STREMII elements — surveillance and social listening and precise targeting are both related to the pre-crisis phase. Responding and monitoring the social media landscape (the third and fourth element of the STREMII model) are part of the active crisis phase. The post-crisis phase is associated with the fifth and sixth elements — interacting with consumers and other stakeholders and implementing necessary changes.

Revisiting the model, Stewart and Young expanded the role of the first element of the model — surveillance and social listening, which is widely known as the process of identifying and assessing what is being said about a person, brand, or business online (Jaume, 2013, as seen in Stewart and Young 2018)).

The phrase "social listening" is commonly used to describe the practice of using specific software for monitoring discussions, complaints, and trends related to specific topics or brands of significance across different social media platforms. It is done to better engage with their customers, research competitors, be able to address user complaints immediately, or even replace focus groups and surveys to determine user needs (Pomputius, 2019). Westermann and Forthmann (2021) have demonstrated how explicit and implicit experiences, which are the drivers of reputation, can be systematically recorded and analysed using social listening, thus replacing traditional reputation surveys, and expanding the possibilities to investigate reputation on a large scale.

In the revised STREMII model, social listening is not limited to detecting early signs of the potential crisis, done to prevent the crisis from erupting, or the fourth step – monitoring the social media landscape and evaluating outcomes. According to the revised model, social listening should be used in each of the practices presented by the model to ensure ongoing responsive engagement — another element that has been added to the STREMII. Responsive engagement, similar to social listening, is an activity that accompanies all six elements of the initial version of the model. Social listening involves observing stakeholders' opinions and concerns, while responsive engagement involves promoting dialogue and actively engaging with stakeholders (Stewart and Young 2018).

3.5. Research gap – from discrepancies to overlooked aspects of emotions in crisis communication theories

Different crisis communication theories have different conclusions and sometimes even contradictory views on the effects of emotion in crisis and their influence on the most effective crisis intervention, as described in previous sections. Discrepancies are the result of the underlying theories like attribution theory or appraisal theory of emotions these different models are based on, and focus these theories are willing to contribute to. All the described models overlook the most current theory of emotions – the theory of constructed emotions that is increasingly gaining support in academia.

Attribution theory, on which Coombs bases his SCCT, looks at crises primarily from the perspective of the organization's reputation in the traditional media landscape. This approach does not explore phenomena including flashbulb memories ("durable memories formed in response to strong emotional experiences" (Diamond et al, 2007)) that were first defined by Brown and Kulik (1977), initial crisis reactions, and online emotional contagion described by EDMCC. Initial crisis reactions are not necessarily related to how the public sees the company's involvement, or responsibility. For example, it might be assumed that in the case of people dying in an airplane accident, the initial emotions would be sadness and sympathy towards victims – emotions that do not depend on the airline's responsibility.

Furthermore, the STREMII model posits that communication is an ongoing, cyclical process where the situation, including the public's perception of the crisis event and involved organizations, is subject to change. Emotions, including emotions towards the responsibility-bearing organization, might evolve and transform over the course of the crisis event. An organization's response might trigger a change in primary emotions; for instance, if the response is not appropriate or does not match the public's expectations, it can trigger a negative wave of emotions. Even though the STREMII model emphasizes the evolving nature of cases of crisis, it does not explicitly incorporate or analyze emotions.

ICM overlooks that emotions might be contrasting and multi-dimensional – sadness and empathy towards victims, anger towards the responsible organization, and respect for institutions that solve the issue, e.g., firefighters. Finally, EDMCC, a framework that integrates emotional factors into the processing and analysis of crisis information, includes some questionable assertions. For instance, it emphasizes a clear distinction between cognition-oriented and emotion-oriented patterns in crisis communication, which contradicts the theory of constructed emotion and its supporting evidence that emotions and cognition mutually support each other, operating in tandem. Similarly, the assertion that individuals initially experiencing crisis emotions with low intensity will adopt a cognitive-oriented pattern, thereby remaining unaffected by crisis emotions, and vice versa, is equally dubious.

4. Conceptual Framework for Affective Computing Supported Crisis Communication

The affective computing methods and techniques described above have the potential to deepen the understanding of the effects of emotion on crisis perception and development, as well as contribute to crisis communication practice (see Figure 1). Affective computing applications in lab settings, used to evaluate the emotional reactions of participants exposed to crisis-related stimulus could contribute to the debate on emotions in crisis. For instance, such experiments might provide further insights into assumptions presented by EDMCC, explaining how the intensity of the initial crisis emotions, framing effects and influences of emotional contagion have an impact on how the public perceives, evaluates, and makes verdicts about organizations during a crisis. Affective computing methods would be beneficial in testing different emotion-based crisis intervention and messaging strategies (such as emotion mirroring or empathy) and evaluating how their effectiveness is affected by the type of specific crisis case based on attribution theory – the victim, accidental or intentional crisis as defined by Coombs.

Moreover, as crisis communication models are mainly based on the appraisal theory and that is challenged by the theory of constructed emotions, the relevance of these theories for analyzing the emotion aspects in crisis situations can be tested by applying research methods rooted in affective computing. As the theory of constructed emotion acknowledges that the body's response is the driver and motivator of emotions and cognition, affective computing methods that assess physical measures such as skin conductance, blood volume pulse, skin temperature, as well as physiological modalities like electroencephalogram (EEG) and electrocardiogram (ECG) in combination with self–defined emotional states might provide novel knowledge about crisis emotions development and effects. Constructivists emphasise the highly individualised, subjective and context–dependent nature of emotional experience, so affective computing experiments have the potential to deepen understanding of the contextual background of crisis situations and explain how this affects the formation of emotional responses.

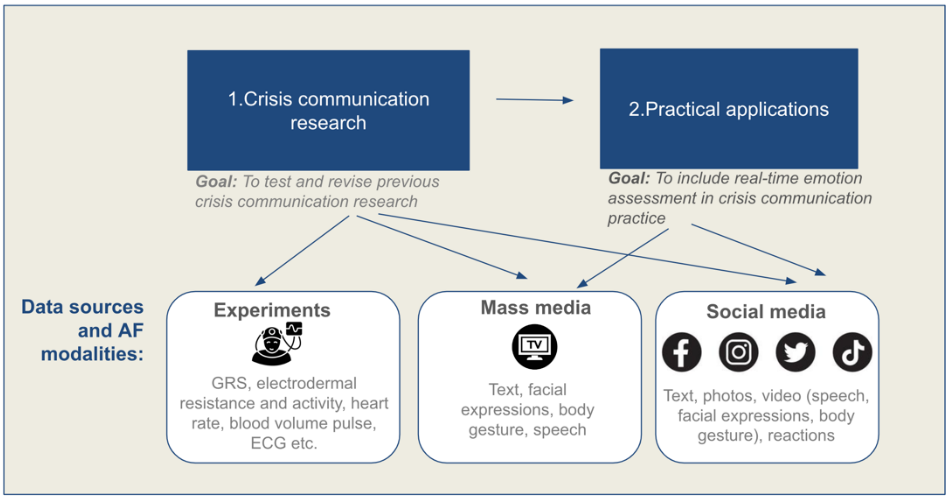

Figure 1. Applications of Affective Computing Methods for Crisis Communication research and practice

While crisis communication research could benefit from affective computing experiments in laboratory settings and conventional and social media analysis, for practical application, only less intrusive approaches would be successful. With the goal to include real-time emotion assessment to ensure more effective and precise crisis communication, affective computing methods can be applied to social networks and mass media analysis. Social media posts provide rich material for emotion analysis. That material includes texts, photos and videos of facial expressions, body gestures, speech patterns of affected people, and social media reactions that are used to signal the attitudes towards social media posts. Such information contributes to the deeper understanding of emotions related to crisis events and might be used in the calculations involved in the decision-making process in choosing the most appropriate crisis response.

To describe the potential of the application of affective computing methods in crisis communication, the Conceptual Framework for Affective Computing-Supported Crisis

Communication (ACSCC) is proposed (see Figure 2). It combines and builds on the cyclical, process-oriented approach of STREMMI and crisis phases (pre-crisis, crisis, and post-crisis) defined by Coombs. However, it redefines the activities in each crisis phase, incorporating a new concept – affective social listening – as an ongoing process that supports each crisis communication step. By incorporating emotion analysis, affective social listening evolves the concept of social listening, which is an integral part of STREMII. Affective social listening, thus, is defined as using affective computing methods for monitoring information, discussions, and trends related to topics across social media platforms to detect and interpret the public's emotions.

The proposed ACSCC defines two phases (development and application phases) and three steps of crisis communication (pre-crisis, crisis, and post crisis). The first phase corresponds to the development phase where computing research is applied to gather information necessary for the development of an affective social listening tool dedicated to crisis communication. The second phase explains the practical application of the affective social listening tool and its focus on each step in crisis communication.

To support the first step of the proposed framework (apply affective social listening to crisis risk detection), it would be necessary to analyze which emotions are associated with an emerging crisis and what social media activities, for instance, emotion words used in social media posts signal this emerging condition. The importance of emotion words has been emphasized by the theory of constructed emotions that suggests that emotion words provide an important context in emotion perception (Gendron, et al, 2012). According to this theory, conceptual knowledge about emotion, anchored with emotion words plays a key role in generating the perception of emotion.

Applying affective social listening to stakeholder segmentation as part of preparing an organization for potential crises would require empirical analysis of the connection between individual personality traits, emotional states expressed in social media, and their reactions and behaviors in crises. Affective intelligence theory analyzes such connections in the context of political communication (Marcus et al., 2011) and would be a feasible guide for similar analysis as connected to crisis communication.

To put the second step – identifying crisis emotions – into practice, crisis case studies applying affective computing methods are necessary to analyze conventional media and social media content to detect and define interconnections between specific crisis types and scenarios and the public's expressions of emotion. Such studies would also provide insights into whether and how the intensity of the initial crisis emotions, framing effects, and influences of emotional contagion have an impact on society's perception, evaluation, and verdict on organizations during a crisis. Appropriate crisis intervention requires testing different emotion-based crisis intervention and messaging strategies (such as, for instance, emotional versus rational framing of crisis response (Claeys and Cauberghe, 2014), demonstration of shame and regret (van der Meer and Verhoeven 2014 etc.) and evaluating how their effectiveness is affected by the type of specific crisis. Gathering and analyzing such information sets the ground for building an emotion-aware information technology tool that supports crisis managers in decision making regarding crisis communication.

The third step – post-crisis reputation evaluation and learning from crises resulting in implementing necessary changes – need to be detailed by applying computational reputation measurement and stakeholder analysis solutions similar to that presented by Westermann and Forthmann (2021).

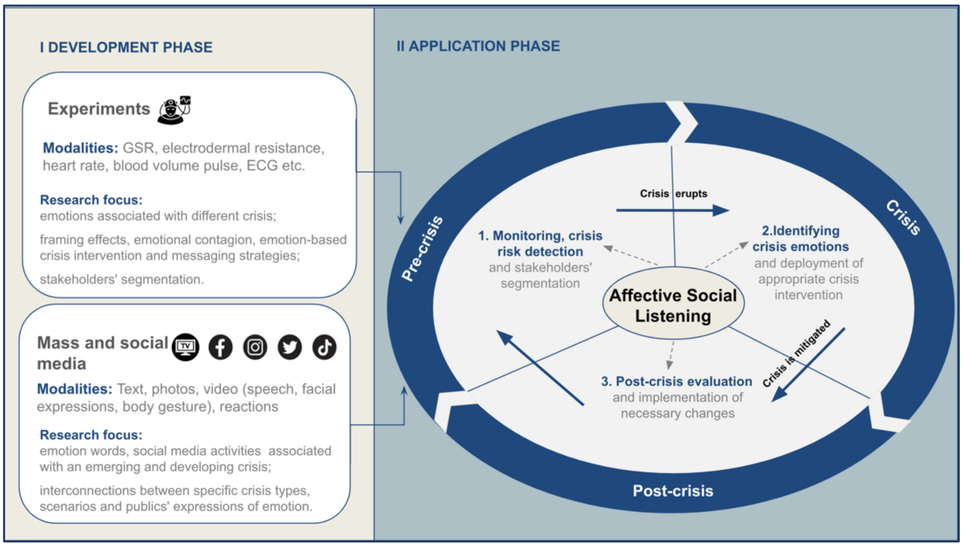

Figure 2. Conceptual Framework for Affective Computing Supported Crisis Communication (ACSCC)

All three ACSCC crisis communication steps in the application phase are supported by affective social listening that informs crisis communication decision-making. The first – monitoring and crisis risk detection – is related to the pre-crisis phase where affective social listening would contribute to an organization's ability to identify issues early and provide timely response to the potential crisis. In the pre-crisis phase, social affective computing can also be applied to stakeholder segmentation, thus preparing an organization for effective communication in case a crisis erupts. Identifying crisis emotion is part of the active crisis phase where affective social listening informs about initial crisis emotions and allows an organization to detect and address stakeholder concerns and adjust responses according to the development of their emotional reactions. Affective social listening provides the opportunity to evaluate the effectiveness of crisis intervention and adjust it accordingly. The final stage – the post-crisis phase – is focused on the post-crisis reputation evaluation and learning from crises that results in implementing changes that are necessary.

ACSCC may increase the efficiency of crisis communication by acknowledging the importance of emotions in crisis communication. ACSCC supports emotions as a factor driving attitudes and behaviors and influencing crisis communication strategies. It assumes that the ability to monitor and address society's emotional states in real-time, combined with machine learning solutions that support crisis communicators with predicting potential outcomes in different crisis scenarios, would make crisis communication more efficient, resulting in achieving intended emotional states, behaviors and mitigating reputation risks. As previously demonstrated (Iqbal, et al, 2023), the discipline of requirements-engineering combined with the theory of constructed emotion would be applied to the development of such emotion-aware technology that has the ability to influence the emotional states of the public.

5. Conclusions

The article reviews emotion representation in different crisis communication models, leading to the identification of the research gap in these models and proposing an initial version of the Conceptual Framework for Affective Computing Supported Crisis Communication. Affective computing methods and techniques have the potential to contribute to crisis communication theory and practice by deepening the understanding the effects of emotion during crises and providing options for operationalizing research tools and methods in the field of affective computing in crisis communication. Experiments involving affective computing methods would add valuable empirical material to the theoretical debate on emotions in crisis, particularly in understanding the evolving nature of emotions over the course of a crisis event. Furthermore, in real-life crises, the ability to monitor and address the public's emotional states in real-time, combined with machine learning solutions that support crisis communicators with prognoses of potential outcomes in different crisis scenarios, provides opportunities to increase the efficiency of crisis communication. This could mitigate reputation risks and assure that the intended behaviors are achieved.

The conceptual framework for affective computing-supported crisis communication (ACSCC) considers crisis communication theories and previous research on affective computing. It incorporates emotion analysis into the cyclical, process-oriented approach of crisis communication, acknowledging emotions as a factor driving attitudes and behaviors and influencing crisis communication strategies. The three steps of the ACSCC crisis communication process are supported by affective social listening – the author's proposed concept that evolves from social listening and is defined as an ongoing process that supports communication management by using affective computing methods for monitoring the information, discussions, and trends related to specific subjects across social media platforms to detect and interpret the public's emotions. The role of affective social listening is to inform crisis communication decision-making by monitoring and interpreting the public's emotions in real time.

As the proposed framework currently provides a conceptual architecture of a combined collection of methodological approaches, it requires empirical tests for its validation and further practical application.

The full-scale application of affective computing methods to support real-time decision-making amid crisis situations is limited by its intrusive nature and ethical considerations. First, intrusive affective computing methods that measure physical modalities such as skin conductance, blood volume pulse, and skin temperature, as well as physiological modalities such as electroencephalogram or electrocardiogram, are only applicable in laboratory settings and only indirectly contribute to real-life applications. Second, all the data that might provide insights into emotions generated by crisis events must be gathered ethically with the consent of analyzed individuals. Parameters such as facial expressions captured by phone or computer camera, data provided by smartwatches, mouse and keyboard inputs, and text input patterns on a smartphone may all be valuable data sources; however, their use is in question as users might not want to share such data freely and willingly. Thus, the affective computing methods applied for real-time crisis emotion analysis might be limited to publicly available data sources such as conventional and social media content. However, the current approach assumes that complementary micro-level (experimental) and macro-level (large-scale digital social network) resources might provide a necessary insight for an accurate affective computing-based crisis management tool.

References

Alarcao, S.M., Fonseca, M.J. (2019). Emotions recognition using EEG signals: a survey, *IEEE Trans. Affect. Comput*., **10**, 374–393, https://ieeexplore.ieee.org/document/7946165.

Balaji, T.K., Annavarapu, C. S. R., Bablani, A. (2021). Machine learning algorithms for social media analysis: A survey. *Computer Science Review*, **40**, 100395.

Barrett, L.F. (2017a). The theory of constructed emotion: an active inference account of interoception and categorization, *Social Cognitive and Affective Neuroscience*, **12** (1), 1–23, https://doi.org/10.1093/scan/nsw154

Barrett, L. F. (2017b). *How emotions are made: The secret life of the brain*. Houghton Mifflin Harcourt, Boston, Massachusetts, 425 pp.

Batliner, A., Schuller, B., Seppi, D., Steidl, S., Devillers, L., Vidrascu, L., Vogt, T., Aharonson, V., Amir, N. (2011). The automatic recognition of emotions in speech, *Emotion-Oriented Systems*, **2**, 71-99.

Blocher, K., Picard, R.W. (2002). Affective social quest: emotion recognition therapy for autistic children. In: Dautenhahn, K., Bond, A.H., Canamero, L., Edmonds, B. (Eds.), *Socially Intelligent Agents: Creating Relationships with Computers and Robots*. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Brown, R., Kulik, J. (1977). Flashbulb memories. *Cognition.* **5** (1): 73–99. doi:10.1016/0010-0277(77)90018-X. S2CID 53195074.

Bukar, U. A., Jabar, M. A., Sidi F., Nor, R. N. H. B., Abdullah S., Othman M. (2020). Crisis Informatics in the Context of Social Media Crisis Communication: Theoretical Models, Taxonomy, and Open Issues, *IEEE Access*, vol. **8**, pp. 185842-185869, doi: 10.1109/ACCESS.2020.3030184.

Claeys A.S., CaubergheV. (2014), What makes crisis response strategies work? The impact of crisis involvement and message framing, *Journal of Business Research*, **67**(2), 182-189.

Coombs, W. T. (1995). Choosing the Right Words: The Development of Guidelines for the Selection of the “Appropriate” Crisis-Response Strategies. *Management Communication Quarterly*, **8**(4), 447–476. https://doi.org/10.1177/0893318995008004003

Coombs, W. T., Holladay, S. J. (2005). Exploratory study of stakeholder emotions: Affect and crisis. In N. M. Ashkanasy, W. J. Zerbe, C. E. J. Hartel (Eds.). *Research on emotion in organizations: Volume 1: The effect of affect in organizational settings* (pp. 271–288). New York: Elsevier.

Coombs, W.T. (2007). Protecting Organization Reputations During a Crisis: The Development and Application of Situational Crisis Communication Theory. *Corp Reputation Rev* **10**, 163–176. https://doi.org/10.1057/palgrave.crr.1550049

Coombs, W. T. (2010). Parameters for Crisis Communication. *The Handbook of Crisis Communication*, 17–53. https://doi.org/10.1002/9781444314885.CH1

Coombs, W.T. (2022). Situational Crisis Communication Theory (SCCT). In *The Handbook of Crisis Communication* (eds W.T. Coombs and S.J. Holladay). https://doi.org/10.1002/9781119678953.ch14

Coombs W. T., Holladay S.J. (1996). Communication and Attributions in a Crisis: An Experimental Study in Crisis Communication, *Journal of Public Relations Research*, **8**:4, 279-295, DOI: 10.1207/s1532754xjprr0804_04

Coombs W. T., Holladay S.J. (2001). An Extended Examination of the Crisis Situations: A Fusion of the Relational Management and Symbolic Approaches, *Journal of Public Relations Research*, **13**:4, 321-340, DOI: 10.1207/S1532754XJPRR1304_03

Coombs, W. T., Holladay, S. J. (2002). Helping Crisis Managers Protect Reputational Assets: Initial Tests of the Situational Crisis Communication Theory. *Management Communication Quarterly*, **16**(2), 165–186. https://doi.org/10.1177/089331802237233

Coombs W. T., Holladay S.J. (2005). An Exploratory Study of Stakeholder Emotions: Affect and Crises, Ashkanasy, N.M., Zerbe, W.J. and Härtel, C.E.J. (Ed.) *The Effect of Affect in Organizational Settings (Research on Emotion in Organizations,* Vol. 1, Emerald Group Publishing Limited, Bingley, pp. 263-280. https://doi.org/10.1016/S1746-9791(05)01111-92005

Coombs, W. T., Holladay, S. J. (2010). *PR strategy and application: Managing influence*. Wiley-Blackwell.

Choi, Y., Lin, Y.-H. (2009). Consumer Responses to Mattel Product Recalls Posted on Online Bulletin Boards: Exploring Two Types of Emotion. *Journal of Public Relations Research*, **21**(2), 198–207. doi:10.1080/10627260802557506

Daoudi, I., Tranvouez, E., Chebil, R., Espinasse, B., Chaari, W.L. (2020). An EDM-based Multimodal Method for Assessing Learners' Affective States in Collaborative Crisis Management Serious Games, 13th International Conference on Educational Data Mining, online, France. ⟨hal-02961310⟩

Deshpande, M., Rao, V., (2017). Depression detection using emotion artificial intelligence, International Conference on Intelligent Sustainable Systems (ICISS), Palladam, India, 2017, pp. 858-862, doi: 10.1109/ISS1.2017.8389299.

Diamond, D. M., Campbell, A. M., Park, C. R., Halonen, J., Zoladz, P. R. (2007). The temporal dynamics model of emotional memory processing: a synthesis on the neurobiological basis of stress-induced amnesia, flashbulb and traumatic memories, and the Yerkes-Dodson law. *Neural plasticity*, 60803. https://doi.org/10.1155/2007/60803

Fortin-Cote, A., Beaudin-Gagnon, N., Campeau-Lecours, A., Tremblay, S., Jackson, P. L. (2019). Affective Computing Out-of-The-Lab: The Cost of Low Cost. 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC).

Frandsen, F., Johansen, W. (2017). *Organizational crisis communication: A multivocal approach*. London: Sage. 280 pp.

Gendron, M., Lindquist, K. A., Barsalou, L., Barrett, L. F. (2012). Emotion words shape emotion percepts. *Emotion*, **12**(2), 314.

Gensler, S.,Völckner, F., Liu-Thompkins, Y., Wiertz, C. (2013). Managing Brands in the Social Media Environment. *Journal of Interactive Marketing*, **27**, 242–256. 10.1016/j.intmar.2013.09.004.

Ghosh, S., Hiware, K., Ganguly, N., Mitra, B., De, P. (2019). Emotion Detection from Touch Interactions during Text Entry on Smartphones. *International Journal of Human-Computer Studies*, Vol. **130**, 47-57

Gordon, C., Arian, A. (2001). Threat and decision making. *Journal of Conflict Resolution*, **45**(2), 196–215.

Hamborg, F.. (2022). Towards Automated Frame Analysis: Natural Language Processing Techniques to Reveal Media Bias in News Articles. http://nbn-resolving.de/urn:nbn:de:bsz:352-2-k1jb5j3vd9oq4

Ho, M., Mantello, P., Nguyen, H.K., Vuong, Q. (2021). Affective computing scholarship and the rise of China: a view from 25 years of bibliometric data. *Humanities and Social Sciences Communications*, **8**, 1-14.

Huang Y, Fei T, Kwan M-P, Kang Y, Li J, Li Y, Li X, Bian M. (2020) GIS-Based Emotional Computing: A Review of Quantitative Approaches to Measure the Emotion Layer of Human–Environment Relationships. *ISPRS International Journal of Geo-Information*, **9**(9):551. https://doi.org/10.3390/ijgi9090551

Huang, Y., Wu, F., Cheng, Y. (2015). Crisis communication in context: Cultural and political influences underpinning Chinese public relations practice. *Public Relations Review*, **42**(1): 201–213.

Iqbal, T., Marshall, J. G., Taveter, K., Schmidt, A. (2023). Theory of constructed emotion meets RE: An industrial case study. *Journal of Systems and Software*, ***197***, 111544.

Jin, Y., Pang, A., Cameron, G. T. (2007). Integrated crisis mapping: Towards a publics-based, emotion-driven conceptualization in crisis communication. *Sphera Publica*, **7**, 81–96. https://ink.library.smu.edu.sg/lkcsb_research/6034

Jin, Y., Pang, A., Cameron, G.T., (2012). Toward a Publics-Driven, Emotion-Based Conceptualization in Crisis Communication: Unearthing Dominant Emotions in Multi-Staged Testing of the Integrated Crisis Mapping (ICM) Model, *Journal of Public Relations Research*, **24**:3, 266-298, DOI: 10.1080/1062726X.2012.676747

Yin, Z., Zhao, M., Wang, Y., Yang, J., Zhang, J. (2017). Recognition of emotions using multimodal physiological signals and an ensemble deep learning model. *Computer methods and programs in biomedicine*, **140**, 93-110.

Kapur, A., Kapur, A., Virji-Babul, N., Tzanetakis, G., Driessen, P.F. (2005). Gesture-Based Affective Computing on Motion Capture Data. In: Tao, J., Tan, T., Picard, R.W. (eds) *Affective Computing and Intelligent Interaction*. ACII 2005. Lecture Notes in Computer Science, vol **3784**. Springer, Berlin, Heidelberg. https://doi.org/10.1007/11573548_1

Lazarus, R. S. (1991). *Emotion and adaption*. New York, NY: Oxford University Press.

Lazarus, R. S. (1999). The cognition-emotion debate: A bit of history. In T. Dalgleish, M. J. Power (Eds.). *Handbook of cognition and emotion* (pp. 3–19). Chichester, UK: Wiley.

Lee, H., Choi, Y. S., Lee, S., Park, I. P. (2012), Towards Unobtrusive Emotion Recognition for Affective Social Communication. In: 9th Annual IEEE Consumer Communications and Networking Conference, pp. 260- 264.

Lisetti, C., LeRouge, C. (2004). Affective computing in tele-home health. 37th Annual Hawaii International Conference on System Sciences. Proceedings of the Big Island, HI, USA, pp. 8 pp.-, doi: 10.1109/HICSS.2004.1265373.

Lu, Y., Huang, Y-H. C. (2018). Getting emotional: An emotion-cognition dual-factor model of crisis communication. *Public Relations Review*, **44**(1), 98-107. https://doi.org/10.1016/j.pubrev.2017.09.007

MacKinnon, L.M., Bacon, L. (2012) "Developing Realistic Crisis Management Training," in ISCRAM.

Mackinnon, L.M., Bacon, L., Cortellessa, G., Cesta, A. (2013). Using Emotional Intelligence in Training Crisis Managers: The Pandora Approach. *International Journal of Distance Education Technologies* (IJDET), 11(2), 66-95.

Marín-Morales, J., Llinares, C., Guixeres, J., Alcañiz, M. (2020). Emotion Recognition in Immersive Virtual Reality: From Statistics to Affective Computing. *Sensors*, **20**(18), 5163.

Marcus, G., MacKuen, M., Neuman, W. R. (2011). Parsimony and Complexity: Developing and Testing Theories of Affective Intelligence. *Political Psychology*. **32**. 323 - 336. 10.1111/j.1467-9221.2010.00806.x.

Oehl, M., Siebert, F.W., Tews, T.-K., Höger, R., Pfister, H.-R. (2007). Improving human-machine interaction—a noninvasive approach to detect emotions in car drivers. In: Jacko, J.A. (Ed.), *Human-Computer Interaction, Part III*, HCII 2011, LNCS 6763. Springer-Verlag, Berlin Heidelberg, pp. 577–585.

Ortony, A. (2022). Are All "Basic Emotions" Emotions? A Problem for the (Basic) Emotions Construct. *Perspectives on Psychological Science*, **17**(1), 41-61. https://doi.org/10.1177/1745691620985415

Peng, C., Su, C. (2020). A multi- agent affective interactive MAGDM approach and its applications. *Expert Systems*, *37*.

Picard, R.W. (1995). Affective Computing, MIT Media Laboratory Perceptual Computing Section Technical Report #321

Picard, R.W.(1997). *Affective Computing*, MIT Press, Cambridge, MA, USA.

Picard, R.W., Vyzas E., Healey J. (2001). Toward machine emotional intelligence: analysis of affective physiological state, *IEEE Trans. Pattern Anal. Mach. Intell*. **23**, 1175–1191 https://doi.org/10.1109/34.954607.

Politou, E., Alepis, E., Patsakis, C. (2017). A survey on mobile affective computing. *Computer Science Review*, **25**, 79–100. doi:10.1016/j.cosrev.2017.03.001

Pomputius, A. (2019) Can You Hear Me Now? Social Listening as a Strategy for Understanding User Needs, *Medical Reference Services Quarterly*, **38**:2, 181-186, DOI: 10.1080/02763869.2019.1588042

Rattanyu, K.; Ohkura, M.; Mizukawa, M. Emotion Monitoring from Physiological Signals for Service Robots in the Living Space. In Proceedings of the ICCAS 2010, Gyeonggi-do, Korea, 27–30 October 2010; pp. 580–583.

Sarkar, P., Etemad, A., (2020). Self-supervised ECG representation learning for emotion recognition, *IEEE Trans. Affect. Comput*., 1, DOI: 10.1109/ TAFFC.2020.3014842. –1.

Saunier, J., Jones, H. (2014, May). Mixed agent/social dynamics for emotion computation. In *AAMAS* (pp. 645-652).

Smith, T. W. (2018). *Schadenfreude: The joy of another's misfortune*. Little, Brown Spark.

Stockmyer, J. (1996). Brands in crisis: Consumer help for deserving victims. *Advances in Consumer Research*, **23**: 429–435.

Stewart, M. C., Wilson, B. G. (2016), The dynamic role of social media during hurricane #sandy: An introduction of the STREMII model to weather the storm of the crisis lifecycle, *Comput. Hum. Behav.*, vol. **54**, pp. 639-646

Stewart, M. C., Young, C. (2018). Revisiting STREMII: Social media crisis communication during Hurricane Matthew. *Journal of International Crisis and Risk Communication Research*, **1**(2), 279–301. https://search.informit.org/doi/10.3316/INFORMIT.096867150007700

Tachkova, E. R., Coombs, W. T. (2022). *Communicating in Extreme crises: Lessons from the Edge.* Routledge.

Tsao, D. Y., Livingstone, M. S. (2008). Mechanisms of Face Perception. *Annual Review of Neuroscience*, **31(**1), 411–437.

Tao, J., Tieniu, T., (2005). Affective Computing: A Review. Affective Computing and Intelligent Interaction. Vol. LNCS 3784. Springer

Taveter, K., Iqbal, T. (2021). Theory of constructed emotion meets RE. In *2021 IEEE 29th International Requirements Engineering Conference Workshops (REW)*, pp. 383-386. IEEE.

Tuncer, T., Dogan, S., Acharya, U. R. (2020). Automated accurate speech emotion recognition system using twine shuffle pattern and iterative neighborhood component analysis techniques. Knowledge-Based Systems, 106547.

Yeo, S. L., Pang, A., Cheong, M., Yeo, J. Q. (2019). Emotions in Social Media: An Analysis of Tweet Responses to MH370 Search Suspension Announcement. *International Journal of Business Communication*, 232948841988275.

Varma, T. M., Perkins, S. C. (2020). Nestle India in a soup: Mapping emotions to the use of coping strategies. *Journal of Marketing Development & Competitiveness*, **14**(4), 101-115.

Valle-Cruz, D., Lopez-Chau, A., Sandoval-Almazan, R. (2021). How much do Twitter posts affect voters? Analysis of the multi-emotional charge with affective computing in political campaigns. DG. O2021: The 22nd Annual International Conference on Digital Government Research.

van der Meer, T.G.L.A., Kroon, A.C. (2022). Crisis Communication and Computational Methods. In *The Handbook of Crisis Communication* (eds W.T. Coombs and S.J. Holladay). https://doi.org/10.1002/9781119678953.ch1

van der Meer T.G.L.A., Verhoeven Joost W. M. (2014), Emotional crisis communication, *Public Relations Review*, Volume **40,** Issue 3, Pages 526-536,

Wang, Y., Song, W., Tao, W., Liotta, A., Yang, D., Li, X., Gao, S., Sun, Y., Ge, W., Zhang, W., Zhang, W. (2022). A Systematic Review on Affective Computing: Emotion Models, Databases, and Recent Advances. *Inf. Fusion*, 83-84, 19-52.

van Atteveldt W., Peng T., (2018) When Communication Meets Computation: Opportunities, Challenges, and Pitfalls in Computational Communication Science, *Communication Methods and Measures*, 12:2-3, 81-92, DOI: 10.1080/19312458.2018.1458084

Westermann, A., Forthmann, J. (2021), "Social listening: a potential game changer in reputation management How big data analysis can contribute to understanding stakeholders' views on organisations', *Corporate Communications: An International Journal*, Vol. **26** No. 1, pp. 2-22. https://doi.org/10.1108/CCIJ-01-2020-0028

Ward, J., Richardson, D., Orgs, G., Hunter, K., Hamilton, A. (2018). Sensing interpersonal synchrony between actors and autistic children in theatre using wrist-worn accelerometers., ISWC '18. Proceedings of the 2018 ACM International Symposium on Wearable Computers, 148–155, https://doi.org/10.1145/3267242.3267263

Wu, C.H., Huang, Y.M , Hwang, J.P. (2015). Review of affective computing in education/learning: Trends and challenges. *British Journal of Educational Technology*. **47**. 10.1111/bjet.12324.

Zimmermann, P., Guttormsen, S., Danuser, B., Gomez, P., (2003). Affective computing—a rationale for measuring mood with mouse and keyboard. *Int. J. Occup. Saf. Ergo.* **9** (4), 539–551.

Zhang, J., Yin, Z., Cheng, P., Nichele, S. (2020). Emotion Recognition Using Multimodal Data and Machine Learning Techniques: A Tutorial and Review. *Information Fusion*. **59**. 10.1016/j.inffus.2020.01.011.

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