HR Affective Computing

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13. HR affective computing

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INTRODUCTION

Affective computing, which is a noteworthy field within the sphere of artificial intelligence, interprets, analyzes, and reproduces human emotional expressions. More specifically, affective computing involves two separate computer technologies – emotion recognition and emotion expression – that may operate independently or in concert. Both of these applications are experiencing rapid growth and advances due to corresponding developments in the underlying hardware and software. The rise of wearable technology will almost certainly accelerate the expansion of affective computing systems in real-world applications. Some of these technologies are already creeping into use in consumer and organizational applications.

In this chapter, we will explore how affective computing can be applied in organizational settings, particularly in the field of human resource management, to improve and potentially revolutionize a few processes within the employee life cycle. To that end, we will first introduce the reader to the current state and likely future of affective computing. We then explore several areas within human resources where affective computing might be employed. More specifically, we discuss applications in personnel selection, human resource training, and performance management. These are not meant to be exhaustive, but rather a few of the most promising ways that affective computing technologies can be applied in the very near future.

REVIEW OF CURRENT STATE OF AFFECTIVE COMPUTING TECHNOLOGY

Affective computing refers broadly to the use of computers and other technologies to sense and/or produce authentic human emotional expressions (Picard, 2003). We begin by delineating each of the individual elements within the sphere of affective computing. For each, we define the scope, review the technological capabilities and research findings to date, and outline likely future advances in the near term. We begin with sensing emotion expressions by humans in organizational settings and then move to simulation of authentic emotion expressions by machines.

Sensing Emotions

The human brain has evolved with sophisticated automatic processing to read and interpret the emotional expressions of other human beings. While this has proven difficult to replicate with computer systems, significant progress has been made in dissecting and sensing the different modalities of emotion expression, such as speech and visual cues, with the ability to develop integrated emotion sensing systems on the horizon. For the purposes of this chapter, we will first explore audible-based measures and then visual measures.

Speech processing. Our spoken language is the most observable and readily analyzed mode of human emotion communication. A number of text analysis tools have been developed that assess the affective tone and meaning of words. These methods typically use a lexical approach at the word level using emotion word dictionaries or more complex rules-based linguistic approaches with or without dictionaries to infer emotion from patterns of words (Agrawal & An, 2012). For a more in-depth treatment of machine learning and text analysis, see Chapter 3 of this book. These programs are becoming increasing sophisticated and advances in speech to text software means real-time processing of human speech will continue to see improvements.

Of course, language is only one aspect of emotion expression, and likely the least informative for complex and low-intensity emotional expressions that characterize emotions in organizations. Computer interfaces that derive emotion in speech using prosody, pitch, intensity, speaking rate, vocal quality, and other characteristics have been developed (Vogt, André, & Wagner, 2008). Computer systems have been able to recognize a range of emotions in speech at a rate of 70 percent or better (Alu, Zoltan, & Stoica, 2017). The most promising of these employ deep learning convolutional neural networks. One useful tool that is currently available is OliverAPI (https://behavioralsignals.com/oliver/), a software developed by Behavioral Signals, which analyzes tone of voice, word choice, and engagement to formulate emotional reactions, such as empathy (Giannakopoulos et al., 2019). Of course, natural conversations with complex emotions poses a much more difficult problem. Still, this technology continues to advance and represents a much more nuanced window into human emotion speech than the words spoken. For more information about audio analysis methods, see Chapter 4, while Chapter 12 explores natural language processing in greater depth.

Facial expressions and body language. It is readily apparent that what we say conveys only a fraction of the emotions that we feel and express to others. The groundbreaking research by Ekman (Ekman & Oster, 1979) into universal human facial expressions is but one example of the richness of human body language. Once again, the human brain has specifically evolved to perform automatic and rapid facial monitoring and evaluation in the fusiform face gyrus. Automated facial analysis using computers is developing rapidly. In general, these systems extract vectors related to facial features and map these vectors onto specific emotions (Wang et al., 2018). Current facial expression recognition systems can sense emotions with over 90 percent accuracy in laboratory conditions, but struggle in real-world, dynamic situations where the accuracy drops below 50 percent (Samadiani et al., 2019). It currently performs best for well-lit frontal aspects with limited head movement, but continues to improve rapidly as technology and facial expression libraries mature.

Emotion expression is not limited to the face, however. Body gestures and movement also provide important and dynamic cues that convey emotion. Recognizing emotion in the body is significantly more difficult than facial expression due to more moving parts and the larger degrees of freedom. The most promising computer methodologies for analyzing body movement employ 3-D models of the human body and track its dynamic movement over time to infer emotion based on libraries of motion patterns (Arunnehru & Geetha, 2017). These systems are largely in their infancy, but promise to advance rapidly (Shen, Cheng, Hu, & Dong, 2019; Strathopoulou & Tsihirintzis, 2011).

Physiological emotion monitoring. The experience of emotion creates physiological reactions in the body. Thus far, we have focused on using technology to assess the emotional expressions observed in others. However, affective computing in organizational settings is also concerned with gauging the emotions being experienced and expressed by a focal employee who may be actively engaged in the process. Wearable technology with increasingly capable physiological measures could be used to provide an additional window into the emotion states of an individual. Smart watches and exercise bands can provide real-time measurements of heart rate, galvanic skin response, EKG, and blood oxygen saturation, to name just a few measurements that are currently available and could be used to assess emotional states in the wearer (Kutt et al., 2018). Using a variety of measures, physiology-based methods showed 70 to 80 percent accuracy for determining emotional arousal and valence (Jerritta, Murugappan, Nagarajan, & Wan, 2011) and off-the-shelf wearable devices showed similar capability to medical grade sensors (Ragot et al., 2017).

Multimodal emotion sensing systems. To date, most of these emotion sensing systems have been developed and tested separately. Much like the human brain, multimodal emotion recognition systems that combine all the measures discussed above would provide the capability to accurately detect even subtle and complex emotional expressions (He et al., 2020). Efforts to develop such systems have suggested that combining measures greatly increases the performance of automatic emotion recognition systems (Castellano, Kessous, & Caridakis, 2008). It would seem that the largest challenge in creating these systems lies in the development of software and algorithms to combine and model the multimodal data.

Despite this and other challenges, efforts to develop these multimodal corpus systems are emerging. One current system that employs multimodal sensing to assess emotions is Affectiva (https://www.affectiva.com/), a software developed by the MIT Media Lab. Affectiva uses a standard webcam to identify emotions such as anger, contempt, disgust, fear, joy, sadness, and surprise (McDuff et al., 2013). Speech detection is also integrated in Affectiva. Affectiva is also able to detect how something is said and the frequency at which it is said. These features make it a promising and powerful tool for reading the emotions of people in natural situations that could be employed in organizations right now.

Producing Emotions

While the technological problems facing automatic sensing of human emotions are relatively tractable, the realistic production of emotional expressions by computers faces more significant challenges that will take longer to overcome, particularly in practical applications. Much of this stems from the acuity of the human brain for attending to and interpreting natural human expressions and the difficulty of reproducing this in a natural way with computers. Despite this, some progress is being made, and at some point computers will be able to produce realistic emotion expression in a way that would be useful for a number of human resources applications.

Emotional speech synthesis. While synthetic speech has become more intelligible, it still lacks a naturalness that is capable of conveying emotional expressivity (Kuligowska, Kisielewicz, & Włodarz, 2018; Schröder, 2001). Thus far, efforts to accomplish this have relied on rules-based format synthesis which employs computer-generated speech or diphone concatenation that uses recordings of human voices to splice together synthetic speech. Neither of these methods is likely to be capable of generating the types of dynamic and natural conversations that would be needed for most of the affective computing applications that we discuss in this chapter. Nonetheless, newer methods of speech synthesis that employ deep learning and training show some promise (Ning et al., 2019). Undoubtedly, these problems will be overcome at some point, yielding systems capable of producing emotional voices that can be applied to situations that occur in organizations.

Facial emotion expression synthesis and body language. The dynamic generation of realistic 3-D facial expressions is in its relative infancy. Current systems are limited to talking avatars with a limited number of basic emotion expressions that can be produced through rule-based systems (Raouzaiou, Tsapatsoulis, Karpouzis, & Kollias, 2002). More recent efforts that render photorealistic facial expressions of target emotions from a single photograph show more promise for the level of naturalness that would be most conducive to the human applications we anticipate (Zhou & Shi, 2017). The synthesis of lifelike emotional body language is not likely to be realizable in the foreseeable future. However, there has been some work in this regard in the field of robotics (Marmpena, Lim, & Dahl, 2018). Nonetheless, we limit our discussion here to capabilities that are likely to be available for organizational applications in the next ten years.

AFFECTIVE COMPUTING AND HUMAN RESOURCE MANAGEMENT

While affective computing remains largely a laboratory research activity, workplace applications have been envisioned (Richardson, 2020). The technology is advancing at such a rapid rate that practical applications in the workplace will emerge sooner rather than later. Human resource management is one area where affective computing offers a myriad of promising potential applications. In this section of this chapter, we will discuss a number of these potential applications in greater detail as they pertain to selection, training and development, and talent management.

Selection

Despite vast empirical literature on selection practice, there are a number of ways that affective computing might be employed to improve the validity and reliability of current selection methods, address outstanding issues in selection research, and provide new capabilities that do not currently exist. Here we examine some of the most widely used personnel selection instruments: interviews, assessment exercises, and situational judgment tests.

Interviews. One obvious area where affective computing could be brought to bear would be in selection interviews. An interviews is a selection procedure that relies on both the verbal responses and nonverbal behaviors of potential job candidates to predict future job performance (McDaniel, Whetzel, Schmidt, & Maurer, 1994). Nonverbal behavior, particularly, lends itself to affective computing, as it is perceived both visually and aurally. While interviews are among the most commonly employed selection tools in practice, low predictive validity and questionable reliability of interviewers plague this selection practice (Judge, Cable, & Higgins, 2000; Ryan & Ployhart, 2014). The areas that primarily effect the validity and reliability of interviews include interviewee impression management and faking, as well as interviewer bias and capability. These, along with the ways in which affective computing technology can be utilized to mitigate these concerns, are discussed in more depth below.

Affective computing methods could use multiple analyses to observe and sense candidate emotional expression during the interview. One way this might be useful would be to identify employees who might suffer from interview anxiety and perform poorly in interviews despite possessing the requisite skills that the organization is looking for. Affective computing may soon have the ability to provide real-time information on candidate emotions to the interviewer. In this case, the interviewer could be made aware of the candidate's anxiety and attempt to put them at ease before proceeding with the interview.

Observing candidate emotions, particularly subtle emotional expressions, would help to identify candidates who are engaging in excessive impression management. Impression management is the attempt to manage or control the projected images during a social interaction (McFarland et al., 2005). This would be helpful because first impressions often are a disproportionate factor in interview scores (Stewart, Darnold, Barrick, & Dustin, 2008). As these technologies improve, they may also prove capable of detecting candidate deception during interviews. Again, if this information were provided in real time, the interviewer could avoid certain types of bias and even follow up with additional questions when potential deception is suspected.

Affective computing methods also have great potential in identifying interviewee faking behaviors. Faking behavior is "an intentional distortion or a falsification of responses on measures in order to create a specific impression or provide the best answer" (Levashina & Campion, 2006, p. 300). This includes a number of behaviors, such as overstating or fabricating skills, abilities, or experiences; not mentioning or attempting to hide deficiencies in skills, abilities, or experiences; and, finally, deceptive or insincere ingratiation towards the interviewer or the organization (Levashina & Campion, 2007; Buehl & Melchers, 2017). Matching the timeline of candidate emotions with structured interviews could also provide valuable insight into the values, attitudes, and interests of the candidate and how these align with the requirements of the positions and the needs of the organization. Whereas job seekers might attempt to engage in faking behaviors, their emotional reactions when the job is described to them might tell a different story. For example, when team processes are discussed, one candidate might show positive reactions while another might show uncertainty or negative emotions. Overall, these methods would provide a roadmap of the candidate's emotional responses that would provide a useful window into their emotional stability and self-regulation abilities.

Affective computing in interviews need not be limited to candidates. Interviewers contribute as much if not more to the poor predictive validity of selection interviews (Ryan & Ployhart, 2014). These technologies could just as easily be used to observe and track interviewer emotional expressions and responses during the interview. For instance, in their multimodal interview judgment system research, Nguyen, Frauendorfer, Mast, and Gatica-Perez (2014) found that while applicant audio cues were predictive of hirability, interviewer visual cues were also predictive. In the aggregate, organizations could use this to objectively quantify the performance of interviewers across multiple interviews. The training of interviewers has been demonstrated to result in more reliable ratings (Dipboye & Gaugler, 1993), ultimately improving their capability and creating awareness of bias. Individuals who struggle with their own emotions could be provided with additional training, or be removed from interviewing. Real-time feedback to interviewers has even more potential to improve interviews. With guidance and practice, interviewers could respond to prompts that their emotional expressions are moving in an unhelpful direction and take corrective action to move the interview in a more constructive direction. As the technology matures, it might even be possible that an interview tool could use the emotions of both parties to provide verbal prompts to the interviewer that would direct the conversation in effective ways.

The shortcomings of interviewers could actually be overcome with affective computing systems capable of producing emotionally appropriate and consistent interactions across all interviewees. With the growing prevalence of online interviews, particularly for screening, currently available technology has the potential to be adapted to produce an online interviewer whose emotional expressions could be carefully scripted and controlled. Eventually, it might even be possible to develop animatronic interviewers who could monitor and interact with candidates in lifelike and adaptable ways that could eliminate interviewer bias while also providing adaptable assessments of candidates.

Assessment center exercises and situational judgment tests. Both assessment center exercises and situational judgment tests (SJTs) have shown relatively strong predictive validity in more complex jobs (Ryan & Ployhart, 2014). Advances in technology have made it easier to incorporate these methods without resorting to off-site centers or third-party providers, because relatively robust exercises and simulations can be conducted in-house or even online. Adding affective computing to these methods offers several advantages. An assessment center consists of a "… standardized evaluation of behavior based on multiple inputs" (Rupp et al., 2015, p. 1250). Assessment centers consist of both behavioral and simulation exercises, including managerial simulation exercises, leaderless group discussion, role-play, case analysis, and oral presentations (Hoffman et al., 2015). Assessment exercises are generally designed to evaluate specific knowledge, skills, and abilities. By adding emotion, these methods could not only measure how skilled a candidate is at a task, but also how much they enjoy or dislike the task. This would seem to be a much better predictor of their long-term engagement and performance on such a task. This has the potential to greatly expand our ability to assess "other characteristics" which have often been ill-defined but seem to be most strongly associated with in-role performance.

Along these lines, affective computing and observing candidate emotions during these exercises provides a window into several abilities and other characteristics that have proved difficult to quantify with traditional methods. Emotional intelligence and interpersonal skills stand out and are frequently sought after by organizations. By observing candidate emotions during task-oriented exercises and interactive simulations (more on these in the training section), these methods could provide object measures of each of the emotional intelligence domains as well as interpersonal skills that are not really possible through any other available selection method.

Similarly, SJTs where candidates are presented with work-related situations and behavior or knowledge response is assessed, have proven to be some of the most valid selection methods for assessing social skills and ethical decision making (Christian, Edwards, & Bradley, 2010; McDaniel, Hartman, Whetzel, & Grubb, 2007). Adding candidate emotional responses to these methods would have similar benefits to those described above. In additional, adding emotions to SJTs would provide a means for detecting social desirability and deception in candidate responses. Candidate emotions might also be used to detect and account for racial and gender subgroup differences (Ryan & Ployhart, 2014) and thereby reduce any bias that may be inherent in some SJTs.

Training and Development

Affective computing has already been applied to improving electronic learning (Lin et al., 2010). Because affective computing can combine multiple modes of emotion analysis, such as speech, facial expressions, and body language, its application can be extended to new avenues of human resources management training. As discussed previously, affective computing can produce systems that can detect emotions in humans and also express authentic human emotions using video or robotic simulations. These machines are useful in helping to enhance skills that require the combination of emotional states and cognitions. Indeed, adding computer vision for affect recognition leads to the adaptation of behavior that could improve the quality of learning (Ivanova, 2013). Hence, affective computing could lead to training in human resources management in at least three areas: 1) leadership development, 2) emotional intelligence, and 3) diversity and inclusion.

Affective computing and leadership training and development. In the domain of leadership development, organizational scholars contend that emotional intelligence is a critical component of effective leadership (Mayer & Salovey, 1990; Goleman, 1995). Hence, affective computing could become a useful training tool. Training programs using artificial emotional intelligence could involve machines mimicking real-life scenarios where employee or managers would react while their emotions are recorded and analyzed. Participants could interact with computers or directly with fellow humans while their emotional reactions are being recorded.

Leadership training using affective computing would be extremely beneficial for developing leadership skills that are extremely difficult to learn by instruction or self-reflection. One such shortcoming in many leaders is false consensus, the belief that others perceive and respond to the world in the same way that we do (Martinko & Gardner, 1987). Leader simulations could be done in an iterative fashion using affective computing emotion expression systems to simulate a subordinate who is programmed to respond consistent with systematic variance of different individual difference variables such as personality traits and social and work identities. Over time, leaders could learn to appreciate and recognize clues in how employees respond and adapt their communication, feedback, and influence strategies in more dynamic and effective ways.

Real-life applications could also include hiring interviews, counseling situations, performance reviews, or situations involving promotion decisions. For example, computer-assisted performance appraisal could record both the leader's and employee's emotional expressions and reactions. Trainers could then review these interactions to highlight effective and counterproductive elements. These kinds of objective coaching experiences have been shown to be more effective at developing leadership skills (Ladegard & Gjerde, 2014).

Affective computing and training in emotional intelligence. Emotional intelligence is widely regarded to be extremely important for organizational success and yet is widely lacking at all levels of organizations (Kotsou et al., 2019; Goleman, 1995). Affective computing can serve as a tool for organizations to provide practical, skill-based training in emotional intelligence. To this end, emotional self-awareness is a cornerstone of emotional intelligence and a skill that many individuals in organizations lack (Jordan & Ashkanasy, 2006). As mentioned previously, emotion recognition tools could allow organizations to collect an array of emotional reactions from their employees and use them for training purposes to help employees increase their awareness of how their emotions impact their effectiveness. Managers and employees could engage in self-training by using emotion-enhanced computer devices. Automatic face analysis (AFA) software could provide real-time indicators of employee emotions, such as frustration, so that they could be aware of their emotions and respond in adaptive ways. The benefit of such an approach is particularly relevant in the age of COVID-19, where remote working is becoming the norm.

Of course, emotional intelligence also requires that employees not only recognize their emotions but are able to also regulate them appropriately (Grandey, 2000). As discussed previously, affective computing systems could be used to actively monitor a number of everyday interactions and provide real-time indicators to employees of when their emotions are inconsistent with display rules and recommended deep acting tactics for regulating their emotions. A wealth of research has shown that individuals are often able to successfully employ emotion regulation strategies when prompted (Grandey & Melloy, 2017).

In a more training-oriented perspective, affective computing could be used to provide interactive emotional intelligence training. Employees at all levels in the organization could engage in dynamic computer simulations where they are presented with unpredictable emotionally charged interactions. These sessions could be interrupted at any point to provide immediate and detailed feedback as well as allowing participants to rewind and modify their approach to the situation. While emotional intelligence training efforts to date have shown modest improvements, they suggest that practice and feedback are key to developing these skills (Mattingly & Kraiger, 2019). As such, it seems that a training program based on affective computing technology offers a means of improving the relationship management skills which are the most challenging aspect of emotional intelligence to develop.

Affective computing and diversity training. Diversity training is more than important in today's environment where concerns for social justice and inequality are becoming important issues that organizations must address. Years of diversity training has proven only marginally successful (Bezrukova, Spell, Perry, & Jehn, 2016). To successfully train employees in diversity, organizations must ensure that they understand the emotions that employees experience as they interact with individuals from various and different backgrounds. Research in neuroscience has highlighted the neural foundations of in-group and out-group bias (Van Bavel, Packer, & Cunningham, 2008; Moreira, Van Bavel, & Tezler, 2017). It has also demonstrated that perceiving someone to be a member of an out-group elicits some emotional reactions, such as fear and anxiety (Van Bavel, Packer, & Cunningham, 2008). Hence, affective computing could help to record the emotional reactions that individuals experience as they interact with dissimilar others.

Training using emotional artificial intelligence tools could be situational, scripted, or more interactive. Trainees may be engaged in situations where they directly interact with dissimilar others while their emotional reactions are being recorded by a computer. Using AFA software could allow the detection of specific emotions that participants are experiencing. For example, scenarios involving "inappropriate" comments about one's in-group could be expressed by a computer to test participants' emotional reactions. Similarly, participants could be engaged in conversation with in-group and out-group members while their emotional reactions are being recorded. Computers may record emotional reactions to the words and tones of similar and dissimilar others and analyze them. Results could help to determine whether people react differently to words or speech patterns from similar compared to dissimilar others. As these examples illustrate, affective computing offers several applications in human resource management. Hence, it could be a useful tool in the toolkit of managers.

Talent Management

Employee well-being. Poor health and well-being results in reduced availability and productivity among even typically high-performing employees. A number of recent studies have begun to explore the use of affective computing to actively monitor the emotions and well-being of employees in the workplace (Lee, 2019). Other researchers have tested a system to monitor employees for stress and depression (Lee, Lam, & Chiu, 2019). These efforts show that this is an area of great promise for the use of affective computing technology, which can be used to identify employees who are at risk of poor well-being and burnout early on, and at a stage when the situation can be addressed before it results in reduced productivity or absenteeism.

Performance management. Affective computing also has a variety of applications within the sphere of performance monitoring and improvement. Performance appraisal systems have long struggled to objectively measure employee performance in a way that connects performance to organizational outcomes while also improving the performance of individual employees (Schleicher et al., 2018). The ability to perceive emotions in employees, customers, clients, and leaders in real-world organizational situations would allow human resource professionals to develop systems to record and catalog emotional expressions to track performance metrics for individuals and relate them to organizational outcomes.

Researchers have already tested an affective computing system for detecting flow states in employees (Lee, 2020). Flow at work results in periods of ultra-high performance and efficiency and is associated with concentration in the work activity, work enjoyment, and intrinsic work motivation (Bakker, 2005). In another study, researchers used affective computing to monitor employee productivity (Verma, Verma, & Dixit, 2020). While collecting this type of information may present some concerns, the assumption here is that this technology would be utilized in a transparent way to help individuals understand and improve their performance. To that end, we will discuss some specific ways that affective computing might be used in customer service contexts and then how it might be used to improve interpersonal interactions within organizations.

Customer service. Managing the emotions of customer service employees has been a topic of a wealth of human resources research that includes subjects such as emotional labor, emotional intelligence, and display rules, to name just a few. While this research has yielded a number of interesting insights, it has relied almost entirely on survey research. Affective computing technology provides the ability to extend both research and practice in this area by providing real-time measures of emotions in customer service employees. One recent study used artificial intelligence to monitor stress in customer service agents (Bromuri, Henkel, Iren, & Urovi, 2021).

Initially, this would provide HR professionals access to how employees express emotions to customers over the course of daily interactions. Unlike previous methods, affective computing technology would not be limited to traditional customer service settings such as call centers. With a few well-placed cameras and microphones, it could be employed in settings such as retail stores, restaurants, and hospitals, to name just a few. This would greatly expand our knowledge of how emotional intelligence and emotional labor play out in dynamic real-world service interactions. The objective nature of affective computing technology could provide reliable time-averaged measures of service employee performance in a variety of situations and circumstances. In situations where display rules exist or are developed, employee compliance with these rules could also be quantified and included in performance assessments.

This discrete data could be analyzed against the wealth of customer satisfaction survey data to identify emotional expressions and patterns of expressions that are particularly effective or ineffective in the eyes of customers. More interestingly, affective computing could also be used to monitor real-time customer emotions. This could provide a more accurate view of customer service employee performance by placing equal or greater emphasis on customer reactions over employee displays. This richer data could also help to develop more nuanced and advantageous emotion display rules and guidance for employees. The customer emotion data could also be used to provide a more balanced picture of employee emotional performance in discrete customer interactions. For example, a wait staff member who displayed a negative emotion to a particularly belligerent diner would be rated differently to one who displayed the same emotion to a happy diner. This would allow supervisors to provide timely and specific feedback on service encounters that went well and poorly, which is key for performance improvement (DeNisi & Murphy, 2017).

In the not so distant future, affective computing devices could provide real-time, in-situ information feedback to service employees regarding their own emotional displays and the emotional responses of their customers. This information could be discreetly provided via wearable technology so that it would be invisible to the customer even during face-to-face interactions. Self and other emotional awareness are key components of emotional intelligence that are extremely important for the management of emotions at work (Ashkanasy & Daus, 2002). Simply providing this information has significant potential to improve employee performance. However, affective computing technology could go even further by incorporating improved display rule algorithms. It could also provide coaching and prompts to help employees manage their emotions and those of their customers. Such a system could drastically reduce the cognitive and emotional load on customer service employees while improving their performance and customer satisfaction.

In a more revolutionary vein, affective computing sensing and expression technology could be employed to develop automated service agent chatbots. Prototypes of these systems have already been proposed and examined in academic settings for text-based interactions (Ghandeharioun, McDuff, Czerwinski, & Rowan, 2019). Customer service call centers have high emotional demands but only pay low wages, and the result is often reduced well-being, high turnover, and low customer satisfaction (Grandey & Sayre, 2019). Emotionally intelligent chatbot service agents could be programed to respond appropriately and empathetically to customers, no matter how irate or disrespectful, with natural voice responses that could even be tailored to the specific local dialect of the customer. This technology could eliminate the need for human agents in all but the most unusual or demanding circumstance, in which case the call could be turned over to a more senior agent to resolve after the customer had vented and their concerns had been recorded and analyzed.

Intra-organizational interpersonal interactions and leadership. These improvements of performance appraisal and management should not be limited to service jobs because emotions and interpersonal skills play a key role in most modern organizations (Ashkanasy & Daus, 2002). The technologies described above could be employed in a myriad of situations within organizations, such as team interactions and meetings, mentoring sessions, annual reviews, counseling sessions, exit interviews, and numerous other interactions between employees and coworkers or supervisors. By improving emotional awareness and regulation, this technology could improve working relationships and effectiveness throughout an organization and increase employee engagement, motivation, and both in-role and extra-role performance.

One of the most interesting, yet difficult to investigate phenomena in organizations is emotional contagion, whereby the emotions of a few employees can spread rapidly and unconsciously throughout a workgroup or organization (Barsade, Coutifaris, & Pillemer, 2018). Affective computing provides an unprecedented means to observe and track the transmission of emotions between individuals through discrete interpersonal interactions. Finally, we could better understand what factors can predict how and why different emotions spread within organizations. This is important because different emotions have unique effects on organizational outcomes such as attitudes and decision making which directly affect performance. Human resource scholars and practitioners could then develop methods to encourage beneficial emotional contagion while limiting the spread of detrimental emotions.

Probably the most impactful application of affective computing would be to improve the emotional intelligence capabilities of leaders at all levels of organizations (Antonakis, Ashkanasy, & Dasborough, 2009). Emotion data could be used to evaluate leadership performance in ways that have not previously been possible. Good leaders could be identified early thus ending the unfortunate tendency to promote individuals to leadership positions who demonstrate excellent task performance but poor interpersonal skills. The data could also be used to provide specific feedback to individual employees on how to improve their leadership skills, and in particular situations where they need to adapt their leadership style and behaviors.

Affective computing emotion data could also be used to investigate and reduce the troubling phenomenon of abusive supervision that is all too prevalent in organizations (Tepper, 2007). Thus far, this research has relied almost entirely on employee perceptions of abusive leader behaviors (Mackey, Frieder, Brees, & Martinko, 2017). By assessing both leader and follower emotions, it would be possible to objectively assess the congruence of perceptions of abusive supervision and actual leader behaviors and emotion expressions. It may be that some of the mixed findings in the empirical literature might be due to inaccurate perceptions of leader emotion expressions (Tepper, Simon, & Park, 2017). In addition, to improving leader performance through the methods discussed in the previous paragraph, inaccurate perceptions by employees could be addressed by identifying the conditions that lead to these misperceptions. Misperception could be reduced by improving the situational awareness of leaders and followers.

CHALLENGES OF AFFECTIVE COMPUTING IN HUMAN RESOURCES

For all its promise, the use of affective computing technology in organizations is not without a number of potential challenges and ethical concerns. First, while most of these systems have performed quite well at emotion detection and expression in laboratory settings, there are concerns over their methodological reliability and validity in dynamic, real-world settings (Beringer et al., 2019). There is already growing concern over using these types of technologies in human resources situations where the rights and livelihood of employees may be negatively impacted by decision systems that haven't been rigorously tested and validated (Buolamwini & Gebru, 2018; Rhue, 2019). Amazon recently stopped using its AI recruitment system after it proved to be biased against female applicants (Dastin, 2018).

Artificial intelligence and affective computing also raise a number of privacy issues (Tucker, 2019). The use of cameras for video recording the workplace and public spaces is growing rapidly. The COVID pandemic has also drastically increased the reliance on videoconferencing technology. While employees might willingly become comfortable with the technology and waive their privacy concerns, some of the applications we have discussed would involve retail, medical, and educational settings where non-employees would potentially be monitored, evaluated, and recorded by these systems. Strict guidelines for these situations would be needed to protect individuals' rights to privacy, particularly where protected information might be involved.

Another concern that would have to be addressed in the design and implementation of this technology is the adverse impact on any subgroups within the workforce or population in general. While much of human emotional experience and expression is universal, there can also be subtle cultural differences between subgroups based on factors such as culture, gender, and age (Keltner, Sauter, Tracy, & Cowen, 2019). Therefore, it might be possible for affective computing systems to evaluate some individuals inaccurately of "prefer" some forms of emotional expression over others. Care would need to be taken, particularly when these systems are initially deployed. Multimodal systems would be less susceptible to these differences. In addition, the artificial intelligence baked into affective computing technology can be designed to adaptively learn on the fly. Especially over time, these systems could assemble a personalized profile of emotional expression for each employee that would transcend any subgroup differences.

One group that would certainly be revealed and disadvantaged by affective computing systems would be psychopaths. There has been growing evidence regarding the prevalence and negative impacts of psychopaths in the workplace (Boddy & Taplin, 2016; Dutton, 2012). Psychopaths are masters of emotional deception and manipulation, but affective computing systems may have the potential to detect this deception and see through misbehavior, quickly and reliably. Some have argued that it is unethical to discriminate against psychopathy (Lindebaum & Zundel, 2013). It is our position that leveraging this technology to identify affective manipulation and misbehavior is not discriminatory. However, this further illustrates the importance of strict guidelines and close monitoring in utilizing this type of technology in organizational settings.

FUTURE RESEARCH ON AFFECTIVE COMPUTING IN HUMAN RESOURCES

Basic research into the technology and software underlying affective computing systems will certainly continue to advance at a rapid rate. In order for these systems to be applied effectively and ethically in human resources management applications, we believe that it will be essential for researchers in business and psychology to take notice and get involved in interdisciplinary research to properly test and validate these systems before they come into widespread use. One such area of promise is the use of qualitative, not just quantitative, research to better understand the potential for bias associated with affective computing and how to actively prevent it in the workplace. While developers of affective computing technology are increasingly looking to the social sciences in their experimentation of affective computing (Irving & Askell, 2019), leveraging qualitative social research approaches can unlock a better understanding of the impacts of this technology, but also serve as a foundation for future empirical research (Sloane & Moss, 2019).

Another evident area for future research is the use of this technology in the field. Given the recent emergence of this technology, much of the related research has occurred in laboratory settings. However, the importance of social context in measuring and displaying human emotional (and subsequently behavioral) responses cannot be understated. Take, for example, the expression of a smile. A smile can be used to express positive emotions, but there are a myriad of reasons why someone may smile. For instance, smiles can be a response to when we are feeling scared or uncomfortable, or even when a person is in pain (Ambadar, Cohn, & Reed, 2009). Distinguishing between these types of smiles relies heavily on the context in which they are displayed. In order to be employed responsibly, these laboratory systems must be vigorously validated in field settings.

Finally, while context is incredibly important, researchers must also consider the individual differences, such as culture or personality, associated with the display of emotion and not rely on a single mode for interpretation. In their review of more than a thousand studies, Barrett and her colleagues (2019) found that many expressions of emotion are not as universal as previously thought and that inferring emotion from only facial expressions is imprecise at best. Among their conclusions, they point to the many factors, including verbal and physical cues, humans rely on when making emotional assessments. Future research in affective computing should then move heavily to a multimodal approach, leveraging multiple technological sources (i.e. videos, biometrics, and if possible, electroencephalography (EEGs)) in advancing the efficacy of assessing and replicating human emotion in the workplace.

CONCLUSION

Technology that senses emotion expressions by humans, as well as the capability to simulate authentic human emotional expressions, has tremendous potential to influence, and have impacts within, organizational settings. The purpose of this chapter was to provide an overview of affective computing and some of the ways in which it will be incorporated into human resource practices that govern organizational life. From selection practices, to training and development, to performance management, affective computing has a myriad of promising applications. Given that concerns plague current selection practices, affective computing may be a resource that not only improves the validity and reliability of existing selection practices, but addresses outstanding issues in research, as well as brings in new capabilities that extend existing practices. Performance management systems with the ability to record and catalog the emotional expressions of employees and leaders in real-world organizational settings through affective computing have the potential to not only track performance metrics for individuals, but also make important connections to core organizational outcomes. Finally, through combining multiple modes of emotion analysis, affective computing can be extended to advance leadership development, emotional intelligence, and diversity and inclusion within human resources training. Despite this tremendous impact, the implications of this technology are not without ethical concerns. Privacy concerns, as well as the mitigation of adverse impacts to individuals based on cultural differences, highlight the importance of strict guidelines and monitoring in the use of affective computing in organizations.

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