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Denver pain authenticity stimulus set (D-PASS)

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Abstract

We introduce the Denver Pain Authenticity Stimulus Set (D-PASS), a free resource containing 315 videos of 105 unique individuals expressing authentic and posed pain. All expressers were recorded displaying one authentic (105; pain was elicited via a pressure algometer) and two posed (210) expressions of pain (one posed expression recorded before [posed-unrehearsed] and one recorded after [posed-rehearsed] the authentic pain expression). In addition to authentic and posed pain videos, the database includes an accompanying codebook including metrics assessed at the expresser and video levels (e.g., Facial Action Coding System metrics for each video controlling for neutral images of the expresser), expressers' pain threshold and pain tolerance values, averaged pain detection performance by naïve perceivers who viewed the videos (e.g., accuracy, response bias), neutral images of each expresser, and face characteristic rating data for neutral images of each expresser (e.g., attractiveness, trustworthiness). The stimuli and accompanying codebook can be accessed for academic research purposes from https://digitalcommons.du.edu/lsdl_dpass/1/. The relatively large number of stimuli allow for consideration of expresser-level variability in analyses and enable more advanced statistical approaches (e.g., signal detection analyses). Furthermore, the large number of Black ($n=41$) and White ($n=56$) expressers permits investigations into the role of race in pain expression, perception, and authenticity detection. Finally, the accompanying codebook may provide pilot data for novel investigations in the intergroup or pain sciences.

Keywords Emotion · Intergroup relations · Pain · Interpersonal sensitivity

Denver Pain Authenticity Stimulus Set (D-PASS): A database of authentic and feigned facial pain expressions

Expressions of pain communicate distress to perceivers and thereby signal a need for help or cue dangerous situations or environments (for review, Williams, 2002). Pain expressions are characterized by a unique combination of verbal (e.g., vocal expressions, screaming) and nonverbal cues (e.g., body and facial movements) that differentiate pain from other emotional and physical communicative cues. Although the expression of pain is multifaceted, we focus here on one system of pain communication—facial expression.

Pain expressions involve multiple facial muscle movements classified as action units (AUs). These AUs include the lowering of the brow (corrugator supercilli muscle, AU4), raising of cheek and tightening of eyelids (both parts of the orbicularis oculi muscle–orbital and palpebral regions, AU6 and AU7), wrinkling of the nose, raising of the upper lip (both parts of levator labii muscle—superioris and alaeque nasi, AU9 and AU10), and closing of the eyes (orbicularis oculi muscle, AU43; e.g., Craig et al., 1992; LeResche & Dworkin, 1984; Prkachin, 1992; Prkachin & Solomon, 2008). Combinations of these AUs generate recognizable patterns of facial expressions that signal pain to perceivers, although it is important to note that pain expressions are dynamic, heterogeneous, and vary across types of pain or contexts (for review, Kunz et al., 2019). Nonetheless,

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facial expressions of pain are discernable from other facial expressions of emotion (Kappesser & de Williams, 2002; Simon et al., 2008).

Pain expression is theorized to serve the function of provoking sympathy or eliciting quick action from onlookers (Fordyce, 1976). Others' pain expressions quickly capture attention (Baum et al., 2013) and generate neural (for a review, Jackson et al., 2006; for a meta-analysis, Lamm et al., 2011) and behavioral (Vaughan & Lanzetta, 1980) responses consistent with actual experiences of pain. For example, viewing expressions of pain leads observers to engage in facial mimicry and to show activation in facial AUs consistent with actual pain expressions (Vaughan & Lanzetta, 1980). Further, experiencing pain and viewing others' pain both generate brain activation in the anterior cingulate cortex and the anterior insula (Lamm et al., 2011), areas associated with increased altruism and helping behavior (FeldmanHall et al., 2015; Hein et al., 2010). Thus, expressions of pain elicit automatic attentional, neural, and behavioral responses that can encourage supportive action from onlookers.

Authenticity of facial pain expressions

Because facial pain expressions quickly attract attention and stimulate action, there are many motives for simulating pain expressions, including financial incentives, avoiding responsibilities, or gaining access to prescription pain medications for nonmedical use (e.g., profit; Fordyce, 1976; Rigg et al., 2010). Because pain is a common experience and numerous motivations for faking pain exist, researchers have become increasingly interested in investigating the process by which people differentiate genuine pain expressions from simulated (i.e., faked, posed) pain expressions. To investigate this phenomenon, many research teams have created stimulus sets depicting either authentic pain expressions (e.g., De Ruddere et al., 2013; Drwecki et al., 2011; Gruss et al., 2019; Lucey et al., 2011; Prkachin & Mercer, 1989; Velana et al., 2017; Yan et al., 2020; Zhang et al., 2014; Zhang et al., 2016) or posed pain expressions (e.g., Matuszewski et al., 2011; Mende-Siedlecki et al., 2020; Roy et al., 2007; Sheng & Han, 2012; Simon et al., 2008). Fewer teams have created stimulus sets containing *both authentic and posed* expressions of pain (e.g., Craig et al., 1991; Larochette et al., 2006; Littlewort et al., 2007; Prkachin, 1992; Walter et al., 2013). Importantly, databases incorporating both authentic and posed pain facilitate examining differences between genuine and posed pain expressions as well as exploring perceivers' capacity for differentiating authenticity, which may be central to appropriate responses to (e.g., helping behavior) and treatment of (e.g., opioid administration) pain. We define authentic pain databases as those featuring images of individuals' genuine facial expressions in response to painful stimuli (e.g., cold pressor task, electrical muscle stimulation). In contrast, we define posed pain databases as those featuring images of individuals who are feigning facial expressions of pain in the absence of a painful stimulus.

Current work

This work advances two goals. First, we briefly summarize extant pain stimulus sets. Compiling a (non-exhaustive) list of *accessible* pain expression databases will enable future researchers to more effectively identify and employ stimulus sets that meet their scholarly needs. Because stimulus creation is labor-intensive, identifying and encouraging the use of existing resources both increases research efficiency and acknowledges the researchers who created these stimulus sets. Second, we introduce a new database: the Denver Pain Authenticity Stimulus Set (D-PASS), including both authentic and posed expressions of pain. Despite the strengths of existing databases, there are shared limitations: (1) few sets include both authentic and posed expressions, (2) stimulus counts are often low, (3) databases can be difficult, if not impossible, to access, and (4) racial representation is limited. This new D-PASS database is uniquely beneficial to the field of pain expression and perception research because it provides a sample of primarily Black and White men and women expressing authentic and posed pain. The combination of racial and gender diversity, norming data, relatively high stimulus counts, and both authentic and posed expressions of pain represent notable strengths of the D-PASS. In combination, these features enable more advanced statistical approaches (e.g., signal detection theory) and more inclusivity in the science of pain expression and perception.

Existing pain databases

In Table 1, we identify a non-exhaustive list of eight databases featuring adults' facial expressions of pain[1] that are available to researchers. Although not summarized here, Hassan et al. (2021) also provide a more comprehensive review of data sets featuring facial expressions of pain that are not openly available. Databases included below are largely divided into two subgroups: posed pain databases and authentic pain databases. A major advantage of authentic pain databases is that they include genuine expressions of pain, in part because there are meaningful differences between authentic and posed expressions of pain (e.g., Bartlett et al., 2014; Craig et al., 1991; Hill

[1] There are also several pain databases not included here that feature pain through bodily movements (e.g., Walsh et al., 2014) or vocalizations (e.g., Belin et al., 2008).

Table 1 Existing pain expression databases featuring posed and/or authentic pain expressions

Authors	Database name	Number of expressers	Expressor demographics: race	Dynamic/static[a]	Authentic pain paradigm	Posed pain paradigm	Accessibility
DeRuddere et al., 2013	G-PAVIDA	34	Not reported	Dynamic	Physiotherapy for chronic patients with back pain	N/A	Contact Lies De Ruddere at Lies.DeRuddere@UGent.be or Liesbet Goubert at Liesbet.Goubert@UGent.be
Haque et al., 2018	MIntPAIN	20	Not reported	Dynamic	Electrical muscle pain stimulation	N/A	Sign agreement form http://www.vap.aau.dk/wp-content/uploads/2018/05/MIntPAIN_EULA.pdf and send to mah@create.aau.dk https://vap.aau.dk/mintpain-database/
Lucey et al., 2011	UNBC-McMaster Shoulder Pain Expression Archive	129	Not reported	Dynamic	Physiotherapy for chronic patients with shoulder pain	N/A	Sign and return an agreement form available from http://www.pitt.edu/~jeffcohn/PainArchive/
Zhang et al., 2014	BP4D	41	11 Asian 6 African American 4 Hispanic 20 Euro-American	Dynamic	Cold pressor task	N/A	Contact Dr. Lijun Yin at lijun@cs.binghamton.edu http://www.cs.binghamton.edu/~lijun/Research/3DFE/3DFE_Analysis.html
Zhang et al., 2016	BP4D+	140	46 Asian 15 African American 14 Latino/Hispanic 65 White 1 Other	Dynamic	Cold pressor task	N/A	Contact Dr. Lijun Yin at lijun@cs.binghamton.edu http://www.cs.binghamton.edu/~lijun/Research/3DFE/3DFE_Analysis.html
Matuszewski et al., 2011	Hi4D-ADSIP	80	Not reported	Dynamic	N/A	Asked to perform a facial articulation of mild, normal, and extreme pain	Upon requesting the database from the authors and sending authors an appropriate storage devices (3.0 Tbytes for pain expressions), database will be mailed.

Table 1 (continued)

Authors	Database name	Number of expressers	Expressor demographics: race	Dynamic/static[a]	Authentic pain paradigm	Posed pain paradigm	Accessibility
Mende-Siedlecki et al., 2019	Delaware Pain Database	229	48 Asian 59 Black 30 Latinx/Hispanic 84 White 8 Other	Static	N/A	Asked to express pain they would feel in response to imagined painful prompts	https://osf.io/2x8r5/
	Delaware Pain Database	16	4 Asian 4 Black 4 Latinx 4 White	Static	N/A	Digitally rendered pain expressions	https://osf.io/2x8r5/
Roy et al., 2007	STOIC	34	Not reported	Dynamic and static	N/A	Asked to facially express pain	frederic.gosselin@umontreal.ca (mapageweb.umontreal.ca/gosselif/STOIC.rar)
Walter et al., 2013	BioVid Heat Pain Database	90 (all participants provided authentic and posed pain expressions)	Not reported	Dynamic	Thermal pain administration (four intensities)	Posed pain with a case vignette	Fill and sign agreement form http://www.nit.ovgu.de/iesk_media/_users/pwerner/Agreement.pdf and send to biovid-db@ovgu.de http://www.nit.ovgu.de/BioVid.html

[a]Dynamic refers to videos, while static refers to still images

& Craig, 2002; Littlewort et al., 2007, 2009), raising important concerns about whether posed stimuli can serve as reasonable alternatives to authentic pain stimuli in pain perception and expression research. Posed databases likely capture caricatures of the pain expression as participants are recorded in response to single labels of emotions (i.e., pain) or brief descriptions of the emotion (Mende-Siedlecki et al., 2020; Roy et al., 2007). These designs may limit natural expression variability, and researchers have questioned the prominence and frequency of these posed (and often exaggerated) facial displays in daily life (Zhang et al., 2014).

We identified only one openly available adult pain database that includes both authentic and posed pain expressions: BioVid Heat Pain Database (Walter et al., 2013). In this database, 90 expressers underwent a thermal pain administration with four different pain intensities while being videotaped. This procedure was repeated with and without facial electromyography (EMG). Participants were also videotaped while posing pain. Thus, the BioVid Heat Pain Database provides useful stimuli for researchers interested in pain authenticity questions. Although other researchers have produced stimuli that include expressers displaying both authentic and posed pain, these stimuli have not been aggregated into a resource that is readily accessible via download or upon request. For example, among the most impressive data sets of this type is Craig et al.' (1991) stimulus set in which 120 patients with chronic lower back pain were asked to express genuine pain during painful physiotherapy exercises, to suppress pain during the same exercises, and then fake pain by attempting to mimic their previous genuine pain expression (Craig et al., 1991). Unfortunately, this data set is not able to be shared with outside researchers. Restrictions on shared materials are fairly commonplace in pain expression research due to human subjects constraints (e.g., IRB approval was not sought before stimulus collection for shared use) or protections (e.g., participants are patients whose privacy and health status must be protected) that often accompany pain expression stimuli. To advance the field of pain perception and expression, researchers must have access to reputable, high-quality stimuli that can fit their specific research needs.

Additionally, most existing and accessible pain expression databases do not purposefully recruit for racial diversity, limiting generalizability of findings beyond White expressers. Indeed, Dildine and Atlas (2019) highlight the homogeneity of pain expression stimuli particularly with respect to race and ethnicity, calling for pain researchers to (1) collect diverse samples, (2) more conscientiously report demographics, and (3) systematically consider ethnic and cultural factors in the study of pain. Further amplifying this call, previous emotion research supports the existence of cross-cultural and sub-cultural (e.g., racial, ethnic, gender) differences in display rules (prescribed rules about emotional expression learned through socialization) and expression dialects (i.e., patterns of expression akin to dialects in language; Elfenbein, 2013; Elfenbein et al., 2007; Matsumoto, 1990, 1993). Thus, it remains an open question whether pain expressions (intensity, frequency, or patterns of action unit activation) and expression decoding might differ by expresser race. Greater representation in stimuli would also allow researchers to examine contributions of pain expression or pain perception biases to race disparities in pain care. Indeed, people of color and especially Black individuals in the United States receive less intensive (Anderson et al., 2009; Pletcher et al., 2008; Singhal et al., 2016), less guideline-directed (Schpero et al., 2017), and less satisfactory (Goldstein et al., 2010) pain care than comparable White individuals. These disparities make the lack of racial diversity in pain expression databases a substantive concern.

Despite the overall lack of expresser diversity, there are research teams attending to issues of representation (Mende-Siedlecki et al., 2020; Zhang et al., 2014; Zhang et al., 2016). For example, Mende-Siedlecki et al.' (2020) Delaware Pain Database has 229 posed pain expressions from Asian, Black, Hispanic/Latinx, and White male and female models. The available stimuli consist of models exhibiting posed painful expressions in response to several different pain related prompts (e.g., "receiving an electric shock via electrode") and were asked to create expressions varied in intensity (e.g., 2, 5, or 8 out of 10 in intensity). In this way, the authors sought to elicit variable pain expressions from models. Importantly, this database enables integration of previously unconnected subfields (e.g., intergroup relations and pain expression) and allows for exploration into the role of perceivers' perceptual and judgment biases in pain recognition. For example, Mende-Siedlecki et al. (2019) used this database to provide evidence for racial bias in pain perception, such that White participants had a higher threshold for identifying pain on Black (relative to White) faces. That is, White participants required more intense pain displays to label a face as in pain for Black faces relative to White faces. However, the Delaware Pain Database features only posed and computer-generated pain expressions. Although this work thoughtfully and creatively examines racial biases in pain perception, it is unclear whether such biases exist in response to authentic or spontaneous expressions of pain (the types of pain expressions that medical providers are pressed to identify and treat) or whether expression dialect or display norms may vary across race in authentic pain expression. Further, without authentic pain expression stimuli, questions concerning pain authenticity detection cannot be directly tested.

The Denver pain authenticity stimulus set (D-PASS)

We introduce the Denver Pain Authenticity Stimulus Set (D-PASS), which includes 315 videos of 105 unique individuals. Individuals featured in the database (referred to as "expressers") self-reported their race (41 Black, one Latino/a, six Multiracial, 56 White, one who did not wish to disclose) and gender (52 men, 53 women). All expressers were recorded displaying one authentic (105) and two posed (210) expressions of pain (one posed expression recorded before [posed-unrehearsed] and one recorded after [posed-rehearsed] the authentic pain expression). The total set of 315 videos constitutes a relatively large set of authentic and posed pain stimuli. In addition to making the videos available for academic research purposes, we provide an accompanying codebook including metrics assessed at the expresser (e.g., demographics, pain tolerance, naïve rater evaluations) and video level (e.g., average accuracy, action unit analyses; see below for additional details). We believe the D-PASS provides at least four advantages to the research community.

First, the D-PASS purposefully recruited Black and White men and women. By considering expresser race and gender, researchers can begin to investigate expresser features that may impact pain expression and pain perception, or at the very least can better control for expresser-level variance. The inclusion of largely Black and White expressers may also attract interest from researchers outside the pain literature. For example, intergroup and person perception researchers might find a database of Black and White expressers useful for examinations of own-race advantages in emotion recognition or for documenting race-based biases in pain perception or empathetic responding.

Second, the D-PASS includes both authentic and posed pain expressions, enabling continued investigation into the unique characteristics of authentic and posed pain expressions. Further, by ensuring the same expressers displayed both authentic and posed pain, researchers can de-confound identity and expression, or at least separate expression variance from expresser variance. Illustrating the importance of a database that offers authentic and posed stimuli alongside racial diversity, the intergroup relations literature suggests perceivers struggle to discern expression authenticity when attempting to read the emotions of racial outgroup and minority group members relative to racial ingroup and majority group members (Friesen et al., 2019; Gray et al., 2008; Lloyd et al., 2017; Lloyd & Hugenberg, 2021; Weathers et al., 2002). Recent work using a subset of the D-PASS stimuli found that race deficits in emotion authenticity detection extended to pain expressions (Lloyd et al., 2022). Across six studies (three of which feature D-PASS stimuli), the authors provided evidence that perceivers, regardless of race (Black and White) and medical expertise (laypeople and medical providers), struggled to discern real from fake expressions of pain on the faces of Black relative to White D-PASS expressers.

Third, the D-PASS is a large database of videos ($N = 315$) matching or exceeding the size of comparable databases. This size provides multiple advantages, perhaps foremost that it permits conducting signal detection analyses (Green & Swets, 1966; Macmillan & Creelman, 2005), affording greater insights into the mechanisms underlying pain detection. Historically, researchers have focused on accuracy as the key metric of pain detection. In contrast, signal detection approaches allow researchers to avoid confounding the ability to discriminate between authentic and posed pain (i.e., sensitivity) with the tendency to favor one response over another (i.e., response bias). Few studies in the pain detection literature have used signal detection analyses, a shortcoming that is due, at least in part, to small stimulus sets prohibiting signal detection analyses. Notably, the Lloyd et al.' (2022) work cited above conducted signal detection analyses in all studies employing D-PASS stimuli. This approach allowed for a test whether race *biased* pain authenticity judgments (e.g., do perceivers use the fake response more frequently for Black than White expressers) or whether race impacted *sensitivity* in discerning pain authenticity (i.e., were perceivers less able to discern authentic from posed expressions for Black than White expressers). Lloyd and colleagues observed robust evidence for sensitivity deficits; however, there was not compelling evidence for response bias effects across expresser race. In sum, having a database with a larger number of stimuli will provide researchers with more sophisticated inferential tools, and accordingly, with better insights into the psychological processes underlying pain judgments. To our knowledge, the D-PASS constitutes the only database that includes a large stimulus set of Black and White men and women expressing both authentic and posed pain. Thus, this database will serve the needs of many pain and intergroup researchers and support scholarly advances.

Finally, the D-PASS not only provides access to authentic and posed pain videos, but it provides supporting data and materials. The D-PASS includes Facial Action Coding System (FACS) data for each video (controlling for neutral images of the expresser), expressers' pain threshold and pain tolerance values as assessed by a pressure algometer (described in detail below), averaged pain detection performance by perceivers who viewed the videos (e.g., accuracy), neutral images of each expresser, and face characteristic rating data for neutral images of each expresser (e.g., attractiveness, trustworthiness). These additional elements of the D-PASS may provide pilot data for new lines of inquiry.

In sum, we believe the D-PASS can offer insights into numerous pain expression (e.g., "Are people better at faking pain after experiencing it?"), pain perception (e.g., "How do real expressions of pain differ from feigned expressions of pain?"), and intergroup relations (e.g., "Are Black individuals evaluated as less trustworthy or attractive than White individuals?") questions, as well as questions at the intersection of these fields (e.g., "Do Black and White individuals differentially suppress pain?"). Indeed, researchers have already begun to use this resource to answer theoretically and practically valuable questions (Lloyd et al., 2022).

Our primary goal in generating the D-PASS was to create a resource (stimuli and accompanying data) to facilitate new investigations, inquiries, and advances. Thus, we aimed to address previous stimuli limitation, collect auxiliary measures and relevant constructs, share norming data, and make this resource easily accessible. Although we suggest research questions and ideas throughout this manuscript that can be tested with the D-PASS, *the goal of the current work is to describe and disseminate the resource* rather than to test specific theory-driven hypotheses. Accordingly, we describe the creation and composition of the D-PASS database, and we provide instructions for accessing the database. Creation of this database was not preregistered.

Database access

This database has been made accessible to academic researchers who agree to the usage terms at https://digitalcommons.du.edu/lsdl_dpass/1/. Before downloading, researchers are required to agree to the terms of use indicated on the website and return the signed usage agreement as directed. Upon agreement, the entire database and associated codebook can be downloaded for free. Of note, the openly accessible D-PASS and codebook do not include either expresser responses to questionnaires (described in more detail below) or the full video recording from each expresser lab session (from which video clips and still images were extracted). These components include personal (e.g., name) and health (e.g., history of painful injury) information from expressers as well as experimenter identifying information (i.e., name, video). Access to these components are therefore restricted in accordance with human subjects' protections (IRB#01365r).

Database creation

Creation of the D-PASS involves five phases. Phase 1 describes the generation of neutral expression and pain expression stimuli from expressers. Phase 2 outlines editing and preparation of these stimuli for inclusion in the database. Phase 3 explains FACS coding of the videos. Phase 4 describes the collection of trait norming data of the neutrally expressed images. Finally, Phase 5 reports average performance data (i.e., average video-level accuracy) from participants who viewed the D-PASS pain videos. This research program was approved by the institutional review boards at Miami University (IRB#01365r; Phases 1–5) and the University of Denver (IRB#1329885; Phases 4–5).

Phase 1: Stimulus generation

Expressers

One hundred and eleven college student, staff, and community member participants were recruited to serve as pain expressers from a small college town in Ohio. Individuals with a current or history of permanent injury or nerve damage in the hand were not eligible to participate. Recruitment efforts targeted individuals who self-identified as Black or White. Expressers were recruited via Sona Systems, flyers, emails to campus organizations, and snowball recruitment strategies (e.g., participants were encouraged to invite their friends to participate). In exchange for participation, expressers received course credit, \$10, or \$20 (cash values differed dependent on time-point collected; payment increased over time). Incentives and recruitment strategies likely restricted age, socioeconomic, and cultural variability among expressers (a point to which we return in the discussion); however, we did not collect information on cultural background or experiences (e.g., place of birth, list of places lived). Five individuals were excluded from the data set (two did not engage in the pain administration task, two had video recording errors, and one withdrew their hand suddenly during the pain administration task). Finally, one individual participated twice, and we excluded all data and videos collected during this individual's second session. Thus, there are 105 unique expressers in the D-PASS database. The final sample of expressers ranged in age from 17–28 ($M_{age} = 19.47$; $SD_{age} = 1.91$); 52 identified as men, and 53 as women; 41 identified as Black, one Latinx, six Multiracial, 56 White, and one did not disclose race.

Materials and laboratory configuration

Pressure algometer Algometers are devices used by researchers and medical providers to elicit and measure pain via the precise application of increasing force. We used a Wagner Force FPX50 algometer, which is a hand-held device with a 1 cm rubber tip that is pressed into bone, muscle, joint, tendon, or ligament with increasing pressure to impose painful pressure and to gauge pain threshold (i.e., point at which pressure is first considered to be painful) and tolerance (i.e., point at which painful pressure stimulus is no longer tolerated). In this case, the algometer was placed on the fifth metacarpal of the expresser's left hand. The left hand was selected based on the configuration of the room and camera location (described in greater detail below). This placement and brand of algometer have been successfully used in previous pain research (Kinser et al., 2009; Schwartzman et al., 2009).

Camera Videos were recorded using a Sony DSCWX220/B 18.2 megapixel digital camera. The camera was attached to a tripod with a fixed location 48 inches from the expresser.

Laboratory configuration During video recording, expressers sat in a chair behind a table facing the camera. The chair's height was adjusted for each expresser to ensure they were in frame without moving the stationary camera. Behind expressers, a white wall and white screen obstructed all other visual information in the environment. Expressers placed their right hands on a push-button bell affixed to the table. This bell enabled expressers to signal pain threshold (the point at which they first felt pain) and tolerance (the point at which they could no longer endure the pain) during video recordings without speaking or vocalization. Expressers placed their left hands through a small slot in a divider screen attached to the table. This configuration allowed the experimenter to administer painful pressure while preventing expressers from viewing the experimenter or the pressure administration and thereby encouraged expressers to face the camera during the procedure.

Questionnaires Expressers completed several questionnaires assessing self-reported previous experiences with pain (adapted from Ruben & Hall, 2013), pain sensitivity (Hoffman et al., 2016), life hardship (Hoffman & Trawalter, 2016), and experiences of discrimination (Major et al., 2013). These questionnaires are not included as part of the openly accessible D-PASS database. Although expressers consented to their videos and demographic information (age, race, gender) being shared as part of the D-PASS database, they did not consent to include these questionnaire responses (which include personal life and health history). If researchers wish to examine research questions using data from these questionnaires, they may contact the corresponding author to discuss access to aggregate data analyses or de-identified questionnaire responses.

Procedure Participants (i.e., expressers) arrived at the laboratory one at a time. Upon entering the laboratory, expressers were greeted by two experimenters. The primary experimenter directed the session, while the secondary experimenter administered the pressure algometer. The same person served as secondary experimenter for all sessions to ensure consistency in the use of the apparatus. The primary experimenter greeted expressers at the beginning of each session and explained that expressers would be creating stimuli for use in future research. Before beginning recording, expressers were instructed how the pain administration task would proceed. The primary experimenter explained that the secondary experimenter would place the pressure algometer on the expresser's left hand[2] and slowly increase pressure. Expressers were instructed to ring the bell with their right hand when their pain threshold was met and a second time when their pain tolerance had been met. Pain threshold was described as the point at which they would first label the pressure as painful. Pain tolerance was described as the point at which the pain was no longer tolerable. Expressers were assured that, at the second bell, administration of the pressure would immediately cease, and their pain would quickly dissipate. Expressers then watched as the secondary experimenter demonstrated the pain induction task on the primary experimenter. Expressers were asked if they had any remaining questions before continuing to the video recording task. We note that lab-based assessment of pain threshold and tolerance is complex, as these constructs are affected by emotion inductions (Carter et al., 2002), performance expectations or instructions (e.g., gender expectations; Robinson et al., 2003), and manipulations of threat and insecurity (Chen & Jackson, 2019; Chou et al., 2016). Thus, we attempted to carefully control the lab environment (e.g., physical environment, experimenters, instructions); however, as readers may note below (Table 3), threshold and tolerance values varied widely.

There were four portions of the video recording task: (1) neutral expressions, (2) posed-unrehearsed pain expressions (posed expressions of pain prior to the experience of authentic pain), (3) authentic pain expressions, and (4) posed-rehearsed pain expressions (posed expressions of pain after the experience of authentic pain). The first portion of the video recording task captured expressers exhibiting a neutral expression for 30 seconds. In the second portion of the video recording task (posed pain expressions), expressers attempted to simulate painful expressions while the pressure algometer was placed on their left hands but no pressure was applied. They were instructed to ring the bell once at their fake pain threshold and a second time at their fake pain tolerance. The primary experimenter issued the following instructions before beginning the task[3]: "During this task, the pressure algometer will be placed on your left hand, but no pressure will be administered. During this task, you will ring the bell with your right hand twice: once at your *faked* pain threshold—that's when you're *faking* that the pressure is first experienced as painful and a second time at your *faked* pain tolerance—that is when you are *faking* that you can no longer withstand the pain. This portion of

[2] There is some evidence that people are more sensitive to pain administration on their nondominant hand (e.g., Özcan et al., 2004). Experimenters were asked to log if expressers were left-handed; no such reports were made.

[3] Experimenters were provided a script and memorized the script prior to beginning data collection. However, experimenters did not read the script during session and exact wording varied slightly across participants.

the task will conclude once the second bell is rung. Your goal is to convince whomever is watching the video that you are actually undergoing the pain administration task. We encourage you to try to be as convincing as possible."

In the third portion of the video recording task, expressers engaged in the pain induction task to create an authentic pain video. The pressure algometer was placed on the fifth metacarpal of the left hand, and the secondary experimenter gradually increased pressure. Expressers were instructed to ring the bell with their right hand first at their pain threshold and a second time at their pain tolerance. Prior to the pain manipulation, these terms were again defined for expressers. At each bell (threshold and tolerance), the secondary experimenter stated aloud the amount of pressure withstood in newtons (N). The primary experimenter recorded this value. These values are included in the D-PASS codebook for each expresser. A maximum value of 250 N was set to protect against injury (Bernstein & Claypool, 2012). At the second bell, the secondary experimenter immediately removed the pressure algometer, discontinuing the painful stimulus. The primary experimenter issued the following instructions before beginning the task: "During this portion of the task, increasing pressure will be administered to your left hand. During this task, you will ring the bell with your right hand twice: once at your pain threshold—that's when you first experience the pressure as painful—and a second time at your pain tolerance—that's when you can no longer withstand the pain. During this task, pressure will continue to increase until one of two events occurs: (1) your pain tolerance is met—meaning the pain is no longer tolerable—and you ring the bell for a second time or (2) pressure reaches a previously designated cutoff. This cutoff is set as a safety precaution. Once you ring the bell or this maximum pressure cutoff has been met, we will immediately discontinue the administration of pressure. Please freely express your pain during this time, avoiding exaggeration or suppression."

In the fourth portion of the video recording task, expressers repeated the procedure for the posed pain expression. The instructions from the primary experimenter matched those from the first posed expression. A second posed pain expression was collected to enable examinations of whether recent experiences of authentic pain may influence posed expressions of pain (e.g., whether posed pain expressions are more convincing following an authentic pain experience). Following the conclusion of the video recording task, expressers were escorted to another room where they completed questionnaires and were debriefed, thanked, and compensated. After debriefing and compensation, participants were asked to provide consent for the researchers to (1) cut, edit, and analyze their videos, and (2) distribute their video clips for use in future research. All participants signed both video consent forms enabling their session recordings to be cut, edited, and shared as a research resource.[4]

Phase 2: Stimulus preparation and video editing

Video editing

Neutral still images The 30-second neutral expressions were used to create a static image clip of each expresser. Neutral still images were used in face expression analyses (described below) and to collect normed appearance ratings of each expresser (described below). These neutral still images are also included in database materials for use by future researchers.

Pain videos Authentic and posed pain expression video clips were created from the session recording. For these videos, we aimed to capture expressers' most intense facial expressions and to standardize clip duration so that video duration would not be a cue to pressure administered. All audio was removed from video clips. Thus, authentic and posed pain videos are identical in length and contain no auditory cues.

Phase 3: Automated FaceReader FACS analysis

FaceReader 7.0 by Noldus was used to analyze videos frame by frame (Noldus Information Technology, Wageningen, Netherlands). FaceReader works by first identifying a face using a Viola–Jones algorithm (Viola & Jones, 2001), then models the expresser face using an algorithmic approach based on the active appearance method (Cootes & Taylor, 2001), and lastly, classifies facial expressions based on an artificial neural network (Bishop, 1995). FaceReader detects seven emotions (happiness, sadness, anger, surprise, fear, contempt, and disgust), neutral expression (i.e., lack of emotion), valence (negative to positive), and intensity on the basis of the Facial Action Coding System (Ekman & Friesen, 1976). For each frame of video, the basic emotions, valence, arousal, and AUs are scored on a scale of 0–1. For AUs and emotions, 0 indicates no emotion or AU is present, and 1 indicates its maximum intensity. Intensity can also be scored as discrete categories of Trace (.00–.16), Slight (.16–.26), Pronounced (.26–.58), Severe (.58–.90), and Maximum (.90–1.0) (Ekman et al., 2002). FaceReader software calculates valence as the difference between pleasant and unpleasant emotion intensities, while arousal is an index of overall AU activation. Previous

[4] One participant asked that their videos not be shown to participants at their home institution for at least 1 year; this request was recorded in our log and honored.

research has found FaceReader to be valid and reliable when compared to human coders (den Uyl & Kuilenberg, 2005; Lewinski et al., 2014; Terzis et al., 2010). Moreover, FaceReader can recognize facial expressions of emotion with high accuracy, ranging from 84.8% for disgust to 95.9% for happiness (Loijens et al., 2015). A sizable limitation of FaceReader is that its training and validation largely relied on White individuals. Thus, FaceReader's utility for more diverse samples is an open question. Although in the current work we use FaceReader to characterize our database, we believe that the D-PASS could be useful in future research to systematically test concerns regarding the limitations and generalizability of FaceReader or similar programs designed to assess human expressions.

Prior to analysis, each expresser's own neutral expression was used to calibrate videos to correct for any potential face structure or expresser-specific biases in FaceReader coding. For example, some people look happy, angry, or sad, even though they are showing a neutral or "resting" expression (Hester, 2019). By calibrating participants' videos to their own neutral expression, FaceReader can correct for these person-specific biases toward both certain facial expressions and emotional expression intensities. FaceReader was unable to calibrate five expressers (i.e., 15 videos). FaceReader coding with calibration was not completed for these targets, as indicated by "FALSE" in the codebook variable "calibrated"; for all other videos ($n_{targets} = 100$; $n_{videos} = 300$), calibration was successful as indicated by "TRUE." The five second video clips from each authentic and posed pain video were then analyzed frame by frame to detect AUs typically associated with pain: AU04, AU06, AU07, AU09, AU10, AU12, AU20, AU25, AU26, AU43 (see Table 2; Craig et al., 1992; Gallant & Hadjistavropoulos, 2017). Across all available video frames for each video of each expresser, the mean of each AU was calculated and then summed to create a composite *pain expression intensity score*. We also analyzed all other AUs available in FaceReader (i.e., AU01, AU02, AU05, AU14, AU15, AU17, AU18, AU23, AU24, AU27). Again, the mean of each AU was calculated and then summed to create a composite *non-pain expression intensity score*. FaceReader individual AU outputs as well as the pain and non-pain composite scores for each expresser's three videos (i.e., two posed and one authentic videos) are included in the database codebook. It is important to note that not all frames were successfully coded by FaceReader in all videos. For example, for P045's first posed pain video, only 74.2% of frames were successfully coded and contribute to FaceReader outputs. In the codebook, we provide information about the total number of frames in each video (i.e., total frames), the number of frames that were *not* successfully coded (i.e., missing_frames), and the proportion of frames successfully coded (i.e., prop_frames_coded). Calibration and coding failures appear to be primarily the result of low light on the face (i.e., insufficient contrast, brightness, or diffuse frontal lighting) and inadequate face information (e.g., expresser is wearing a hat, looks down, or turns to the side).

Table 2 Description of each action unit (AU) coded by FaceReader

Action unit	Description
AU01	Inner brow raiser
AU02	Outer brow raiser
AU04	Brow lowerer
AU05	Upper lid raiser
AU06	Cheek raiser
AU07	Lid tightener
AU09	Nose wrinkler
AU10	Upper lid raiser
AU12	Lip corner puller
AU14	Dimpler
AU15	Lip corner depressor
AU17	Chin raiser
AU18	Lip puckerer
AU20	Lip stretcher
AU23	Lip tightener
AU24	Lip pressor
AU25	Lips part
AU26	Jaw drop
AU27	Mouth stretch
AU43	Eyes closed

Phase 4: Collection of neutral expression trait rating

Rater participants

We recruited a naïve sample of 177 undergraduate participants (referred to as raters) to rate the expressers on numerous traits based on their neutral images alone. Of the 177 raters, 120 identified as women, 54 as men, and one as other (one did not disclose their gender, and one did not respond). Most raters identified as White (130 White, 12 Asian, 12 Latino/a, 11 bi- or multiracial, two American Indian or Alaska Native, two Black, one Native Hawaiian or Pacific Islander, one Middle Eastern, one Turk, four did not wish to disclose, and one did not respond) and ranged in age from 18 to 31 ($M_{age} = 19.53$, $SD_{age} = 1.74$).

Procedure

The raters viewed a random subset of 30 neutral still images and rated each expresser on seven traits (i.e., trustworthy, dominant, warm, competent, attractive, threatening, and baby-faced), four social categorization indices (i.e., Afrocentric [Black], Eurocentric [White], feminine, and masculine), and six emotions[5] (i.e., fearful, angry, happy, disgusted, sad, and surprised). For each set of questions, raters were asked, "To what extent does this person appear … " followed by the rating prompt. All ratings were on a scale from 1 (*not at all*) to 9 (*extremely*). The rating categories were presented in a fixed order (traits followed by social categorizations and then emotions); however, items within each rating category were presented in a random order. After the rating task, raters reported their own demographic information including age, race, ethnicity, gender, and nationality.

Phase 5: Collection of pain detection accuracy

During creation of the D-PASS, several research groups requested access to the posed and authentic pain videos. Additionally, members of the author team conducted studies using the D-PASS stimuli. In exchange for use of the D-PASS stimuli prior to completion of this database, we requested that researchers report back any accuracy data collected from dichotomous choice (e.g., real vs. fake) pain detection tasks using D-PASS videos. For each relevant study conducted, researchers were asked to (a) provide a brief overview of the study sample[6] (i.e., number of participants, recruitment platform) and (b) indicate the total number of participants who viewed each video alongside the count of participants that correctly judged each video's veracity (allowing for calculation of video-level accuracy). Each study featured only a subset of D-PASS videos selected for the specific purposes of the study, but we include data from these participants to include the maximum number of observations. To ensure that we had at least some accuracy data for all D-PASS videos, we gathered an additional sample, reported here, to assess pain detection accuracy (i.e., proportion of correct responses) for all videos in the database. In this additional sample, 191 college students (133 White/European American, 26 Asian, 13 Bi- or multiracial, 13 Latino/a, two Black/African American, one American Indian/Alaska Native, one Native Hawaiian/Pacific Islander, one Middle Eastern, and one did not wish to disclose) viewed a subset of the videos and for each video made a "real" or "fake" classification. Data from our study was aggregated with that of other research teams to provide the most comprehensive accuracy data currently possible. In total, we aggregated video-level accuracy data from ten separate studies and 2016 participants. Of these ten studies, three are published with openly available data (Lloyd et al., 2022), and seven are unpublished. These experiments featured five mTurk samples ($N=900$), four university student samples ($N=991$), and one medical provider sample ($N=125$). We aggregated the accuracy[7] data for each video across the ten studies and included these data in the video-level codebook.

Database characterization & validation

Characterizing the database

The D-PASS database includes 315 video clips and 105 neutral still images from 105 unique expressers; each expresser contributed two posed pain video clips, one authentic pain video clip, and one neutral image. These stimuli are accompanied by a detailed codebook divided into two levels of analysis: expresser-level analysis and video-level analysis. The codebook includes detailed descriptions of each variable, including how each variable was assessed and the scaling of each variable.

Expresser-level codebook

The expresser-level codebook includes demographic information about each expresser (i.e., age, race, gender), each expresser's recorded pain threshold and tolerance, and trait ratings of each expresser's neutral still image. Descriptive statistics for variables included in the expresser-level codebook are provided in Table 3 (demographic variables excluded).

Video-level codebook

The video-level codebook includes information about the corresponding expresser's demographic characteristics (i.e., race, gender), category of pain expressed (i.e., posed-unrehearsed, authentic, posed-rehearsed), mean accuracy for the video in pain detection tasks, proportion of "real" responses ("real bias" or "truth bias") in pain detection tasks, and FaceReader outputs. FaceReader outputs include intensity

[5] We did not include pain in our emotion rating task. We aimed to collect ratings of basic emotions and regrettably did not consider including pain.

[6] We did not request more detailed demographic information and thus are unable to report on participant characteristics such as age, race, or gender.

[7] Accuracy was calculated as the proportion of raters with correct responses. Accuracy $= \frac{\text{Number of correct responses}}{\text{Number of total responses}}$

Table 3 Descriptive statistics from expresser-level codebook

Variable	Mean	SD	Range	Possible values
Pain threshold (PA)	46.10	20.33	15.00–108.00	0–250 Newtons
Pain tolerance (PA)	94.36	39.38	29.90–242.20	0–250 Newtons
Trustworthy (NIR)	4.40	0.71	2.84–6.26	1 “Not at all” – 9 “Extremely”
Dominant (NIR)	4.22	0.80	2.43–5.97	1 “Not at all” – 9 “Extremely”
Warm (NIR)	3.80	0.85	2.06–6.47	1 “Not at all” – 9 “Extremely”
Competent (NIR)	5.05	0.52	3.49–6.33	1 “Not at all” – 9 “Extremely”
Attractive (NIR)	4.28	0.91	2.71–7.04	1 “Not at all” – 9 “Extremely”
Threatening (NIR)	3.07	0.69	1.70–4.61	1 “Not at all” – 9 “Extremely”
Baby-faced (NIR)	3.39	0.82	1.54–5.68	1 “Not at all” – 9 “Extremely”
Afrocentric (NIR)	4.33	3.39	1.00–8.84	1 “Not at all” – 9 “Extremely”
Eurocentric (NIR)	5.28	3.42	1.02–8.87	1 “Not at all” – 9 “Extremely”
Feminine (NIR)	4.62	3.07	1.12–8.53	1 “Not at all” – 9 “Extremely”
Masculine (NIR)	4.94	3.06	1.28–8.73	1 “Not at all” – 9 “Extremely”
Fearful (NIR)	1.92	0.35	1.32–2.89	1 “Not at all” – 9 “Extremely”
Angry (NIR)	2.88	0.87	1.16–5.07	1 “Not at all” – 9 “Extremely”
Happy (NIR)	2.37	0.98	1.25–6.40	1 “Not at all” – 9 “Extremely”
Disgusted (NIR)	2.70	0.70	1.21–4.55	1 “Not at all” – 9 “Extremely”
Sad (NIR)	2.74	0.67	1.28–5.00	1 “Not at all” – 9 “Extremely”
Surprised (NIR)	1.77	0.36	1.18–3.10	1 “Not at all” – 9 “Extremely”

Parentheses indicate measurement type: PA = pressure algometry; NIR = neutral image rating (average ratings by naïve evaluators)

scores for 20 unique AUs, an estimate of seven emotion intensities (e.g., happy, sad), an aggregate of all pain- and non-pain-related AUs, and metrics of calibration and coding success (e.g., proportion of frames successfully coded). Mirroring past pain detection work, mean accuracy for a video in the pain detection task was near chance, 49.30% (*SD* = .12). Participants used the “real” and “fake” response options with equivalent frequency, 50.45% real responses (*SD* = .11). Table 4 provides descriptive statistics for a subset of FaceReader variables.

Validation of the D-PASS database

We now address two critical questions in the pain expression and pain authenticity detection literature to illustrate that past findings can be replicated using D-PASS stimuli. Although we do not elaborate upon these questions comprehensively, we sought to provide evidence that D-PASS videos have utility for pain authenticity and pain expression research.

Do the D-PASS authentic and posed videos contain pain expression signal?

Of primary interest in evaluating validity of the D-PASS is whether the authentic and posed pain video clips contain pain expression signal (i.e., are the pain-relevant muscle movements generated in D-PASS video clips similar to those identified in previous pain databases [posed and authentic]). Thus, we compared the expression intensity of pain-related action units to the intensity of non-pain action units from our FaceReader analyses within each video clip. Overall, D-PASS video clips contained more intense pain AUs ($M = .06$, $SD = .06$) than non-pain AUs ($M = .02$, $SD = .03$), $t(303) = 13.53$, $p < .001$, 95% CI [0.04, 0.05], $d = 0.78$,

Table 4 Select FaceReader descriptive statistics from video-level codebook

Video level		
Variable	Mean	SD
Percent frames coded	.75	.41
Mean pain AUs	.06	.06
Mean non-pain AUs	.02	.03
Neutral	.64	.25
Happy	.16	.22
Sad	.08	.13
Angry	.05	.08
Surprised	.02	.05
Scared	.02	.04
Disgusted	.05	.09

Table 5 Pain AUs vs. non-pain AUs within the D-PASS database

Video Type	Pain AUs *Mean* (*SD*)	Non-pain AUs *Mean* (*SD*)	*t*	*df*	*p*	*d*
Overall	.06 (.06)	.02 (.03)	13.53	303	<.001	0.78
Authentic videos	.07 (.07)	.02 (.04)	6.71	100	<.001	0.67
Posed videos (all)	.06 (.06)	.02 (.03)	12.30	202	<.001	0.86
Posed-unrehearsed	.06 (.05)	.02 (.03)	9.21	100	<.001	0.92
Posed-rehearsed	.06 (.06)	.02 (.03)	8.24	101	<.001	0.82

suggesting the presence of pain signal within our videos. This analysis, alongside separate comparisons by video type (authentic, posed-unrehearsed, posed-rehearsed), are presented in Table 5. In sum, all the types of video clips in the D-PASS database included pain expression, evidenced by the higher quantity of pain AUs than non-pain AUs.

Are real and fake pain expressions distinguishable?

Of additional interest, we examined perceiver pain detection accuracy for D-PASS video clips. Previous work suggests untrained human perceivers struggle to discern between authentic and posed expressions of pain, with reported accuracy rates between 49% and 52% in forced choice paradigms (Bartlett et al., 2014; Littlewort et al., 2009). Consistent with past work, perceivers viewing D-PASS video clips struggled to discern pain authenticity with average accuracy at 49.30% ($M = .49$; $SD = .12$), which did not differ from chance performance, $t(314) = -1.05$, $p = .297$, 95% CI [−0.02, 0.01], $d = 0.06$. Also, perceivers used the response options in the pain detection task (i.e., "Real" and "Fake") with equal frequency, $t(314) = 0.67$, $p = .506$, 95% CI [−0.01, 0.02], $d = 0.04$.

Although untrained human perceivers struggle to discern real from fake pain, researchers have leveraged FACS coding (either via trained experts or automated systems like FaceReader) to identify differences between authentic and posed expressions of pain. For example, some authors argue that posed pain expressions tend to be more exaggerated than authentic pain expressions, with greater pain-related and non-pain-related AUs, longer peak intensity, longer duration, and a more sequential rather than mixed presentation of facial actions (Craig et al., 1991; Hill & Craig, 2002). These are mixed conclusions in past pain authenticity detection work regarding which AUs differentiate between authentic and posed expressions of pain. However, one of the more consistent effects is that the brow lowerer (AU04) is more frequently and more intensely displayed in posed (vs. authentic) pain expressions (Craig et al., 1991; Hill & Craig, 2002; Larochette et al., 2006; Littlewort et al., 2009).

We conducted independent samples *t*-tests comparing real and fake D-PASS videos on FaceReader outputs including the six basic emotion values, the neutral expression value, pain and non-pain aggregate scores, and all individual AUs available via FaceReader. We observed only four significant differences: authentic pain expressions (relative to posed pain expressions) contained less anger signal ($M_{authentic} = .03$; $SD_{authentic} = .05$; $M_{posed} = .06$; $SD_{posed} = .09$; $t(293.61) = -3.50$, $p < .001$, $d = 0.36$) and less intense activation of AU43–eyes closed ($M_{authentic} = .15$; $SD_{authentic} = .24$; $M_{posed} = .22$; $SD_{posed} = .30$; $t(237.04) = -2.60$, $p = .010$, $d = 0.30$), but greater activation in AU6–cheek raiser ($M_{authentic} = .10$; $SD_{authentic} = .20$; $M_{posed} = .05$; $SD_{posed} = .13$; $t(145.18) = 2.31$, $p = .023$, $d = 0.32$) and AU25 – lips part ($M_{authentic} = .13$; $SD_{authentic} = .22$; $M_{posed} = .05$; $SD_{posed} = .13$; $t(136.21) = 3.08$, $p = .002$, $d = 0.44$)[8]. In partial agreement with past work, we found evidence of differences between real and fake expressions on a subset of AUs (i.e., cheek raiser AU06, lip part AU25, and eyes closed AU43) and indicators of emotionality (i.e., anger). However, there were notable departures from past work in that we neither observed an effect of brow lower (AU4; although directionally effects are aligned with past work [$M_{real} = .03$, $SD_{real} = .10$; $M_{fake} = .05$, $SD_{fake} = .12$]) nor consistent evidence of *greater* pain and non-pain AU expressivity in fake (relative to real) expressions.

Recently, researchers have leveraged computer vision and machine-learning approaches to develop automated pain authenticity detection systems. These automated systems tend to exhibit superior pain authenticity accuracy of 72–88% compared to human perceivers' accuracy of 49–52% (Bartlett et al., 2014; Littlewort et al., 2009). Further, these automated systems simultaneously evaluate multiple ways in which real and fake expressions of pain differ from one another, including consideration of the dynamics of the expression (e.g., timing, sequence) rather than just frequency and intensity. Dynamics are considered by some to be more informative than overall output values from FACS coding (Bartlett et al., 2014). Specifically, Bartlett et al. (2014) leveraged a computer vision system (i.e., Computer Expression Recognition Toolbox) to provide evidence that AU26 (jaw

[8] Degrees of freedom fluctuate due to unequal variances across authentic and posed pain videos.

drop/mouth opening) is the single most useful AU in discerning real and fake pain in their study. However, no *overall output* differences emerged for AU26 between real and fake expressions, implying that the critical differences may be attributed to dynamics (e.g., duration of AU activation, time intervals between AU activation). Although a more comprehensive analysis of AU dynamics is not within the scope of the current work, the D-PASS database can serve researchers examining these topics and will enable refining and validating of existing automated pain detection systems.

Discussion and conclusion

The current work introduced a new pain authenticity database, the Denver Pain Authenticity Stimulus Set (D-PASS). The D-PASS is composed of 315 authentic and posed pain videos collected from 105 unique individuals (two posed and one authentic from each expresser). To our knowledge, the D-PASS is among the largest and most racially diverse pain authenticity stimulus set openly accessible to academic researchers.

The relatively large number of stimuli allow for consideration of expresser-level variability in analyses and more advanced statistical approaches (e.g., signal detection analyses). Further, the inclusion of a large number of Black and White expressers enables investigations into the role of race in pain expression, perception, and authenticity detection. Because of the evidence of racial inequality in pain judgments and pain care (Bonham, 2001; Burgess et al., 2006; Drwecki et al., 2011; Green et al., 2003; Hoffman et al., 2016), this resource offers opportunities for researchers to advance our scientific understanding of these important racial disparities (e.g., whether perceivers exhibit less empathy in response to Black relative to White individuals' expressions of pain; whether perceivers rate Black individuals' expressions of pain as less intense than White individuals'; see Drwecki et al., 2011 and Mende-Siedlecki et al., 2019 for existing examinations of these questions).

In addition to providing access to authentic and posed pain video clips, supporting materials including FACS metrics for each video (controlling for neutral images of the expresser), expressers' pain threshold and pain tolerance values, mean pain detection performance by naïve perceivers who viewed the videos (e.g., accuracy), neutral images of each expresser, and face characteristic rating data for neutral images of each expresser (e.g., attractiveness, trustworthiness) are available. These additional metrics can provide pilot data for novel investigations of intergroup bias (e.g., whether White perceivers evaluate Black expressers' neutral face images as less trustworthy than White expressers), pain authenticity detection (e.g., whether existing automated pain detection systems are more accurate than human perceivers at discerning real from fake expressions), or questions intersecting intergroup and emotion sciences (e.g., whether Black and White individuals differ in intensity or pattern of pain expression). Addressing these questions is beyond the scope of the current manuscript, but they illustrate the promise of the D-PASS as a resource for future research.

Limitations

Despite many strengths, the D-PASS has several limitations. First, the D-PASS includes expressers who largely identified as Black or White. Black people in the United States are neither the only racial minority group experiencing pain treatment inequities (Cintron & Morrison, 2006; Green et al., 2003) nor the only racial minority group underrepresented in research resources (e.g., emotional expression stimulus sets). Further, the D-PASS does not include a representative sample of Black and White Americans. Expressers were recruited from a small college town, and most expressers were college students. It is possible that pain expression norms may vary by region, community type (urban, suburban, rural), socioeconomic status, among other factors. It is also possible that subcultural dialects or display norms might independently or interactively influence pain expression and perception, and the D-PASS is not well suited to address such issues. Similarly, the D-PASS is age-restricted (range: 17–28). Claims made from the database may not generalize to children or older adults. Although some pain expression stimulus sets do include children (Larochette et al., 2006; Yan et al., 2020) or older adults (Kunz et al., 2008), concerns regarding stimulus numbers, racial diversity, inclusion of authentic and posed pain, and accessibility remain relevant. In pursuit of more inclusive science practices, future resources should extend pain expression and pain authenticity databases to include greater representation of individuals varied in age, race, ethnicity, gender, and other social group memberships (e.g., socioeconomic status).

A second limitation pertains to the severity or intensity of pain expressions captured. In the current work, we opted for a pain task that offered tight control in stimulus creation (e.g., surrounding environment, expectation setting), allowed for measurement of pain threshold and tolerance, and enabled protection of human participants. The pain administration task (i.e., pressure algometry) used in the current work elicits only minor and temporary painful experiences when compared with pain experiences incurred in a lifetime, in healthcare settings, or in response to injuries. Although pressure algometry is argued to be a valuable analogue to musculoskeletal pain problems (Birnie et al., 2014), temporary pain from bone pressure may be an unsatisfying parallel for researchers interested in examining intense expressions or experiences of pain (e.g., lacerations, dislocations, pain experienced during childbirth). Previous work indicates that more intense experiences of pain (e.g., more serious injuries) provide more intense expressions and thereby cues to authenticity (Galin & Thorn, 1993). Although it is unlikely researchers could ethically induce intense authentic expressions of pain in the lab among healthy expressers, some researchers have found creative solutions to creating more intense pain authenticity databases. Craig et al. (1991) created videos of patients experiencing pain while undergoing painful physiotherapy exercises and videos of those same patients faking pain, while Lloyd et al. (2022) aggregated images of soccer players who either experienced serious injury during play or were expressing feigned pain to gain advantage on the field (i.e., "flopping" or "diving"). Future research would benefit from building upon these creative solutions to address challenges in stimulus creation (ethical and practical) to create more intensive pain authenticity databases.

Conclusion

In this manuscript, we present the Denver Pain Authenticity Database (D-PASS) as a new resource that offers opportunity to refine existing and develop novel theories in pain and intergroup sciences. The D-PASS videos and corresponding data (i.e., codebook) can be accessed by academic researchers at https://digitalcommons.du.edu/lsdl_dpass/1/.

References

Anderson, K. O., Green, C. R., & Payne, R. (2009). Racial and ethnic disparities in pain: Causes and consequences of unequal care. *The Journal of Pain, 10*(12), 1187–1204. https://doi.org/10.1016/j.jpain.2009.10.002

Bartlett, M. S., Littlewort, G. C., Frank, M. G., & Lee, K. (2014). Automatic decoding of facial movements reveals deceptive pain expressions. *Current Biology, 24*(7), 738–743. https://doi.org/10.1016/j.cub.2014.02.009

Baum, C., Schneider, R., Keogh, E., & Lautenbacher, S. (2013). Different stages in attentional processing of facial expressions of pain: A dot-probe task modification. *The Journal of Pain, 14*(3), 223–232. https://doi.org/10.1016/j.jpain.2012.11.001

Belin, P., Fillion-Bilodeau, S., & Gosselin, F. (2008). The montreal affective voices: A validated set of nonverbal affect bursts for research on auditory affective processing. *Behavior Research Methods, 40*(2), 531–539.

Bernstein, M. J., & Claypool, H. M. (2012). Social exclusion and pain sensitivity: Why exclusion sometimes hurts and sometimes numbs. *Personality and Social Psychology Bulletin, 38*(2), 185–196. https://doi.org/10.1177/0146167211422449

Birnie, K. A., Caes, L., Wilson, A. C., Williams, S. E., & Chambers, C. T. (2014). A practical guide and perspectives on the use of experimental pain modalities with children and adolescents. *Pain Management, 4*(2), 97–111. https://doi.org/10.2217/pmt.13.72

Bishop, C. M. (1995). *Neural networks for pattern recognition*. Clarendon Press.

Bonham, V. L. (2001). Race, ethnicity, and pain treatment: Striving to understand the causes and solutions to the disparities in pain treatment. *The Journal of Law, Medicine & Ethics, 29*(1), 52–68. https://doi.org/10.1111/j.1748-720X.2001.tb00039.x

Burgess, D. J., Van Ryn, M., Crowley-Matoka, M., & Malat, J. (2006). Understanding the provider contribution to race/ethnicity disparities in pain treatment: Insights from dual process models of stereotyping. *Pain Medicine, 7*(2), 119–134. https://doi.org/10.1111/j.1526-4637.2006.00105.x

Carter, L. E., McNeil, D. W., Vowles, K. E., Sorrell, J. T., Turk, C. L., Ries, B. J., & Hopko, D. R. (2002). Effects of emotion on pain reports, tolerance and physiology. *Pain Research and Management, 7*, 21–30. https://doi.org/10.1155/2002/426193

Chen, S., & Jackson, T. (2019). Causal effects of challenge and threat appraisals on pain self-efficacy, pain coping, and tolerance for laboratory pain: An experimental path analysis study. *PLoS One, 14*(4), e0215087. https://doi.org/10.1371/journal.pone.0215087

Chou, E. Y., Parmar, B. L., & Galinsky, A. D. (2016). Economic insecurity increases physical pain. *Psychological Science, 27*(4), 443–454. https://doi.org/10.1177/0956797615625640

Cintron, A., & Morrison, R. S. (2006). Pain and ethnicity in the United States: A systematic review. *Journal of Palliative Medicine, 9*(6), 1454–1473. https://doi.org/10.1089/jpm.2006.9.1454

Cootes, T. F., & Taylor, C. J. (2001). Constrained active appearance models. In *Proceedings eighth IEEE international conference on computer vision. ICCV 2001, 1* (pp. 748–754). https://doi.org/10.1109/ICCV.2001.937601

Craig, K. D., Hyde, S. A., & Patrick, C. J. (1991). Genuine, suppressed and faked facial behavior during exacerbation of chronic low back pain. *Pain, 46*(2), 161–171. https://doi.org/10.1016/0304-3959(91)90071-5

Craig, K. D., Prkachin, K. M., & Grunau, R. V. E. (1992). The facial expression of pain. In *Handbook of pain assessment* (pp. 257–276). The Guilford Press.

De Ruddere, L., Goubert, L., Stevens, M., & de C. Williams, A. C., & Crombez, G. (2013). Discounting pain in the absence of medical evidence is explained by negative evaluation of the patient. *PAIN, 154*(5), 669–676. https://doi.org/10.1016/j.pain.2012.12.018

den Uyl, M. J., & Kuilenberg, H. (2005). The FaceReader: Online facial expression recognition | semantic scholar https://www.semanticscholar.org/paper/The-FaceReader%3A-Online-facial-expression-Uyl-Kuilenburg/a12478d732da627c37924e4f96239ecd0675a76e.

Dildine, T. C., & Atlas, L. Y. (2019). The need for diversity in research on facial expressions of pain. *Pain, 160*(8), 1901–1902. https://doi.org/10.1097/j.pain.0000000000001593

Drwecki, B. B., Moore, C. F., Ward, S. E., & Prkachin, K. M. (2011). Reducing racial disparities in pain treatment: The role of empathy and perspective-taking. *PAIN, 152*(5), 1001–1006. https://doi.org/10.1016/j.pain.2010.12.005

Ekman, P., & Friesen, W. V. (1976). Measuring facial movement. *Environmental Psychology and Nonverbal Behavior, 1*(1), 56–75. https://doi.org/10.1007/BF01115465

Ekman, P., Friesen, W. V., & Hager, J. C. (2002). *The facial action coding system: A technique for the measurement of facial movement*. Consulting Psychologists Press.

Elfenbein, H. A. (2013). Nonverbal dialects and accents in facial expressions of emotion. *Emotion Review, 5*(1), 90–96.

Elfenbein, H. A., Beaupré, M., Lévesque, M., & Hess, U. (2007). Toward a dialect theory: Cultural differences in the expression and recognition of posed facial expressions. *Emotion, 7*(1), 131–146. https://doi.org/10.1037/1528-3542.7.1.131

FeldmanHall, O., Dalgleish, T., Evans, D., & Mobbs, D. (2015). Empathic concern drives costly altruism. *NeuroImage, 105*, 347–356. https://doi.org/10.1016/j.neuroimage.2014.10.043

Fordyce, W. E. (1976). *Behavioral methods for chronic pain and illness*. CV Mosby.

Friesen, J. P., Kawakami, K., Vingilis-Jaremko, L., Caprara, R., Sidhu, D. M., Williams, A., Hugenberg, K., Rodriguez-Bailón, R., Cañadas, E., & Niedenthal, P. (2019). Perceiving happiness in an intergroup context: The role of race and attention to the eyes in differentiating between true and false smiles. *Journal of Personality and Social Psychology, 116*(3), 375–395. https://doi.org/10.1037/pspa0000139

Galin, K. E., & Thorn, B. E. (1993). Unmasking pain: Detection of deception in facial expressions. *Journal of Social and Clinical Psychology, 12*(2), 182–197. https://doi.org/10.1521/jscp.1993.12.2.182

Gallant, N. L., & Hadjistavropoulos, T. (2017). Experiencing pain in the presence of others: A structured experimental investigation of older adults. *The Journal of Pain, 18*(4), 456–467. https://doi.org/10.1016/j.jpain.2016.12.009

Goldstein, E., Elliott, M. N., Lehrman, W. G., Hambarsoomian, K., & Giordano, L. A. (2010). Racial/ethnic differences in patients' perceptions of inpatient care using the HCAHPS survey. *Medical Care Research and Review, 67*(1), 74–92. https://doi.org/10.1177/1077558709341066

Gray, H. M., Mendes, W. B., & Denny-Brown, C. (2008). An in-group advantage in detecting intergroup anxiety. *Psychological Science, 19*(12), 1233–1237. https://doi.org/10.1111/j.1467-9280.2008.02230.x

Green, C. R., Anderson, K. O., Baker, T. A., Campbell, L. C., Decker, S., Fillingim, R. B., Kaloukalani, D. A., Lasch, K. E., Myers, C., Tait, R. C., Todd, K. H., & Vallerand, A. H. (2003). The unequal burden of pain: Confronting racial and ethnic disparities in pain. *Pain Medicine, 4*(3), 277–294. https://doi.org/10.1046/j.1526-4637.2003.03034.x

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics* (Vol. 1). New York: Wiley.

Gruss, S., Geiger, M., Werner, P., Wilhelm, O., Traue, H. C., Al-Hamadi, A., & Walter, S. (2019). Multi-modal signals for analyzing pain responses to thermal and electrical stimuli. *Journal of Visualized Experiments, 146*, 1–12. https://doi.org/10.3791/59057

Haque, M. A., Bautista, R. B., Noroozi, F., Kulkarni, K., Laursen, C. B., Irani, R., & Moeslund, T. B. (2018). Deep multimodal pain recognition: a database and comparison of spatio-temporal visual modalities. In *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition* (FG 2018) (pp. 250–257). IEEE.

Hassan, T., Seus, D., Wollenberg, J., Weitz, K., Kunz, M., Lautenbacher, S., Garbas, J.-U., & Schmid, U. (2021). Automatic detection of pain from facial expressions: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 43*(6), 1815–1831. https://doi.org/10.1109/TPAMI.2019.2958341

Hein, G., Silani, G., Preuschoff, K., Batson, C. D., & Singer, T. (2010). Neural responses to ingroup and outgroup members' suffering predict individual differences in costly helping. *Neuron, 68*(1), 149–160. https://doi.org/10.1016/j.neuron.2010.09.003

Hester, N. (2019). Perceived negative emotion in neutral faces: Gender-dependent effects on attractiveness and threat. *Emotion, 19*(8), 1490–1494. https://doi.org/10.1037/emo0000525

Hill, M. L., & Craig, K. D. (2002). Detecting deception in pain expressions: The structure of genuine and deceptive facial displays. *Pain, 98*(1), 135–144. https://doi.org/10.1016/S0304-3959(02)00037-4

Hoffman, K. M., & Trawalter, S. (2016). Assumptions about life hardship and pain perception. *Group Processes & Intergroup Relations, 19*(4), 493–508. https://doi.org/10.1177/1368430215625781

Hoffman, K. M., Trawalter, S., Axt, J. R., & Oliver, M. N. (2016). Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites. *Proceedings of the National Academy of Sciences, 113*(16), 4296–4301. https://doi.org/10.1073/pnas.1516047113

Jackson, P. L., Rainville, P., & Decety, J. (2006). To what extent do we share the pain of others? Insight from the neural bases of pain empathy. *PAIN, 125*(1), 5–9. https://doi.org/10.1016/j.pain.2006.09.013

Kappesser, J., & de Williams, A. C. (2002). Pain and negative emotions in the face: Judgements by health care professionals. *PAIN, 99*(1), 197–206. https://doi.org/10.1016/S0304-3959(02)00101-X

Kinser, A. M., Sands, W. A., & Stone, M. H. (2009). Reliability and validity of a pressure algometer. *The Journal of Strength & Conditioning Research, 23*(1), 312–314. https://doi.org/10.1519/JSC.0b013e31818f051c

Kunz, M., Meixner, D., & Lautenbacher, S. (2019). Facial muscle movements encoding pain—A systematic review. *PAIN, 160*(3), 535. https://doi.org/10.1097/j.pain.0000000000001424

Kunz, M., Mylius, V., Schepelmann, K., & Lautenbacher, S. (2008). Impact of age on the facial expression of pain. *Journal of Psychosomatic Research, 64*(3), 311–318. https://doi.org/10.1016/j.jpsychores.2007.09.010

Lamm, C., Decety, J., & Singer, T. (2011). Meta-analytic evidence for common and distinct neural networks associated with directly experienced pain and empathy for pain. *NeuroImage, 54*(3), 2492–2502. https://doi.org/10.1016/j.neuroimage.2010.10.014

Larochette, A.-C., Chambers, C. T., & Craig, K. D. (2006). Genuine, suppressed and faked facial expressions of pain in children. *Pain, 126*(1), 64–71. https://doi.org/10.1016/j.pain.2006.06.013

LeResche, L., & Dworkin, S. F. (1984). Facial expression accompanying pain. *Social Science & Medicine, 19*(12), 1325–1330. https://doi.org/10.1016/0277-9536(84)90020-0

Lewinski, P., den Uyl, T. M., & Butler, C. (2014). Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. *Journal of Neuroscience, Psychology, and Economics, 7*(4), 227–236. https://doi.org/10.1037/npe0000028

Littlewort, G. C., Bartlett, M. S., & Lee, K. (2007). Faces of pain: Automated measurement of spontaneousallfacial expressions of genuine and posed pain. In *Proceedings of the ninth international conference on multimodal interfaces - ICMI '07* (p. 15). https://doi.org/10.1145/1322192.1322198

Littlewort, G. C., Bartlett, M. S., & Lee, K. (2009). Automatic coding of facial expressions displayed during posed and genuine pain. *Image and Vision Computing, 27*(12), 1797–1803. https://doi.org/10.1016/j.imavis.2008.12.010

Lloyd, E. P., Hugenberg, K., McConnell, A. R., Kunstman, J. W., & Deska, J. C. (2017). Black and white lies: Race-based biases in deception judgments. *Psychological Science, 28*(8), 1125–1136. https://doi.org/10.1177/0956797617705399

Lloyd, E. P., Lloyd, A. R., McConnell, A. R., & Hugenberg, K. (2022). Race deficits in pain detection: Medical providers and laypeople fail to accurately perceive pain authenticity among black people. *Social Psychological and Personality Science, 13*(5), 895–905. https://doi.org/10.1177/19485506211045887

Lloyd, E. P., & Hugenberg, K. (2021). Beyond bias: response bias and interpersonal (in) sensitivity as a contributors to race disparities. *European Review of Social Psychology, 32*(2), 201–234.

Loijens, L., Krips, O., van Kuilenburg, H., den Uyl, M., & Ivan, P. (2015). *FaceReader 6.1 reference manual*. Noldus Information Technology.

Lucey, P., Cohn, J. F., Prkachin, K. M., Solomon, P. E., & Matthews, I. (2011). Painful data: The UNBC-McMaster shoulder pain expression archive database. *IEEE International Conference on Automatic Face Gesture Recognition (FG), 2011*, 57–64. https://doi.org/10.1109/FG.2011.5771462

Macmillan, N. A., & Creelman, C. D. (2005). *Detection theory: A user's guide* (2nd ed., (pp. xix, 492).). Lawrence Erlbaum Associates Publishers.

Major, B., Sawyer, P. J., & Kunstman, J. W. (2013). Minority perceptions of whites' motives for responding without prejudice: The perceived internal and external motivation to avoid prejudice scales. *Personality and Social Psychology Bulletin, 39*(3), 401–414. https://doi.org/10.1177/0146167213475367

Matsumoto, D. (1990). Cultural similarities and differences in display rules. *Motivation and Emotion, 14*(3), 195–214. https://doi.org/10.1007/BF00995569

Matsumoto, D. (1993). Ethnic differences in affect intensity, emotion judgments, display rule attitudes, and self-reported emotional expression in an American sample. *Motivation and Emotion, 17*(2), 107–123. https://doi.org/10.1007/BF00995188

Matuszewski, B. J., Quan, W., & Shark, L.-K. (2011). High-resolution comprehensive 3-D dynamic database for facial articulation analysis. *IEEE International Conference on Computer Vision Workshops (ICCV Workshops), 2011*, 2128–2135. https://doi.org/10.1109/ICCVW.2011.6130511

Mende-Siedlecki, P., Qu-Lee, J., Backer, R., & Van Bavel, J. J. (2019). Perceptual contributions to racial bias in pain recognition. *Journal of Experimental Psychology: General, 148*(5), 863–889. https://doi.org/10.1037/xge0000600

Mende-Siedlecki, P., Qu-Lee, J., Lin, J., Drain, A., & Goharzad, A. (2020). The Delaware pain database: A set of painful expressions and corresponding norming data. *Pain Reports, 5*(6), e853. https://doi.org/10.1097/PR9.0000000000000853

Özcan, A., Tulum, Z., Pınar, L., & Başkurt, F. (2004). Comparison of pressure pain threshold, grip strength, dexterity and touch pressure of dominant and non-dominant hands within and between right- and left-handed subjects. *Journal of Korean Medical Science, 19*(6), 874–878. https://doi.org/10.3346/jkms.2004.19.6.874

Pletcher, M. J., Kertesz, S. G., Kohn, M. A., & Gonzales, R. (2008). Trends in opioid prescribing by race/ethnicity for patients seeking care in US emergency departments. *The Journal of the American Medical Association, 299*(1), 70–78. https://doi.org/10.1001/jama.2007.64

Prkachin, K. M. (1992). The consistency of facial expressions of pain: A comparison across modalities. *Pain, 51*(3), 297–306. https://doi.org/10.1016/0304-3959(92)90213-U

Prkachin, K. M., & Mercer, S. R. (1989). Pain expression in patients with shoulder pathology: Validity, properties and relationship to sickness impact. *Pain, 39*(3), 257–265. https://doi.org/10.1016/0304-3959(89)90038-9

Prkachin, K. M., & Solomon, P. E. (2008). The structure, reliability and validity of pain expression: Evidence from patients with shoulder pain. *PAIN, 139*(2), 267–274. https://doi.org/10.1016/j.pain.2008.04.010

Rigg, K. K., March, S. J., & Inciardi, J. A. (2010). Prescription drug abuse & diversion: Role of the pain clinic. *Journal of Drug Issues, 40*(3), 681–701. https://doi.org/10.1177/002204261004000307

Robinson, M. E., Gagnon, C. M., Riley, J. L., & Price, D. D. (2003). Altering gender role expectations: Effects on pain tolerance, pain threshold, and pain ratings. *The Journal of Pain, 4*(5), 284–288. https://doi.org/10.1016/S1526-5900(03)00559-5

Roy, S., Roy, C., Fortin, I., Ethier-Majcher, C., Belin, P., & Gosselin, F. (2007). A dynamic facial expression database. *Journal of Vision, 7*(9), 944. https://doi.org/10.1167/7.9.944

Ruben, M. A., & Hall, J. A. (2013). "I know your pain": Proximal and distal predictors of pain detection accuracy. *Personality and Social Psychology Bulletin, 39*(10), 1346–1358. https://doi.org/10.1177/0146167213493188

Schpero, W. L., Morden, N. E., Sequist, T. D., Rosenthal, M. B., Gottlieb, D. J., & Colla, C. H. (2017). For selected services, blacks and Hispanics more likely to receive low-value care than whites. *Health Affairs (Project Hope), 36*(6), 1065–1069. https://doi.org/10.1377/hlthaff.2016.1416

Schwartzman, R. J., Alexander, G. M., Grothusen, J. R., Paylor, T., Reichenberger, E., & Perreault, M. (2009). Outpatient intravenous ketamine for the treatment of complex regional pain syndrome: A double-blind placebo controlled study. *PAIN®, 147*(1), 107–115. https://doi.org/10.1016/j.pain.2009.08.015

Sheng, F., & Han, S. (2012). Manipulations of cognitive strategies and intergroup relationships reduce the racial bias in empathic neural responses. *NeuroImage, 61*(4), 786–797. https://doi.org/10.1016/j.neuroimage.2012.04.028

Simon, D., Craig, K. D., Gosselin, F., Belin, P., & Rainville, P. (2008). Recognition and discrimination of prototypical dynamic expressions of pain and emotions. *PAIN®, 135*(1), 55–64. https://doi.org/10.1016/j.pain.2007.05.008

Singhal, A., Tien, Y.-Y., & Hsia, R. Y. (2016). Racial-ethnic disparities in opioid prescriptions at emergency department visits for conditions commonly associated with prescription drug abuse. *PLoS One, 11*(8), e0159224. https://doi.org/10.1371/journal.pone.0159224

Terzis, V., Moridis, C. N., & Economides, A. A. (2010). Measuring instant emotions during a self-assessment test: The use of FaceReader. In *Proceedings of the 7th international conference on methods and techniques in Behavioral research* (pp. 1–4). https://doi.org/10.1145/1931344.1931362

Vaughan, K. B., & Lanzetta, J. T. (1980). Vicarious instigation and conditioning of facial expressive and autonomic responses to a model's expressive display of pain. *Journal of Personality and Social Psychology, 38*(6), 909–923. https://doi.org/10.1037/0022-3514.38.6.909

Velana, M., Gruss, S., Layher, G., Thiam, P., Zhang, Y., Schork, D., Kessler, V., Meudt, S., Neumann, H., Kim, J., Schwenker, F., André, E., Traue, H. C., & Walter, S. (2017). The SenseEmotion database: A multimodal database for the development and systematic validation of an automatic pain- and emotion-recognition system. In F. Schwenker & S. Scherer (Eds.), *Multimodal pattern recognition of social signals in human-computer-interaction* (pp. 127–139). Springer International Publishing. https://doi.org/10.1007/978-3-319-59259-6_11

Viola, P., & Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001*, *1*, 1–9. https://doi.org/10.1109/CVPR.2001.990517

Walsh, J., Eccleston, C., & Keogh, E. (2014). Pain communication through body posture: The development and validation of a stimulus set. *PAIN®, 155*(11), 2282–2290.

Walter, S., Gruss, S., Ehleiter, H., Tan, J., Traue, H. C., Werner, P., Al-Hamadi, A., Crawcour, S., Andrade, A. O., & Moreira da Silva, G. (2013). The BioVid heat pain database data for the advancement and systematic validation of an automated pain recognition system. *IEEE International Conference on Cybernetics (CYBCO), 2013*, 128–131. https://doi.org/10.1109/CYBConf.2013.6617456

Weathers, M. D., Frank, E. M., & Spell, L. A. (2002). Differences in the communication of affect: Members of the same race versus members of a different race. *Journal of Black Psychology, 28*(1), 66–77. https://doi.org/10.1177/0095798402028001005

Williams, A. C. D. C. (2002). Facial expression of pain: an evolutionary account. *Behavioral and Brain Sciences, 25*(4), 439–455.

Yan, J., Lu, G., Li, X., Zheng, W., Huang, C., Cui, Z., Zong, Y., Chen, M., Hao, Q., Liu, Y., Zhu, J., & Li, H. (2020). FENP: A database of neonatal facial expression for pain analysis. *IEEE Transactions on Affective Computing, 1–1*. https://doi.org/10.1109/TAFFC.2020.3030296

Zhang, X., Yin, L., Cohn, J. F., Canavan, S., Reale, M., Horowitz, A., Liu, P., & Girard, J. M. (2014). BP4D-spontaneous: A high-resolution spontaneous 3D dynamic facial expression database. *Image and Vision Computing, 32*(10), 692–706. https://doi.org/10.1016/j.imavis.2014.06.002

Zhang, Z., Girard, J. M., Wu, Y., Zhang, X., Liu, P., Ciftci, U., Canavan, S., Reale, M., Horowitz, A., Yang, H., Cohn, J. F., Ji, Q., & Yin, L. (2016). *Multimodal spontaneous emotion corpus for human behavior analysis*. 3438–3446. https://www.cv-foundation.org/openaccess/content_cvpr_2016/html/Zhang_Multimodal_Spontaneous_Emotion_CVPR_2016_paper.html