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Abstract:

The pressing need for objective measures in evaluating chronic pain in research and practice highlights the role that neuro information systems (NeuroIS) research plays in designing smart clinical decision support systems. A first step in such a research agenda involves identifying practical stimuli-task paradigms that can reliably detect chronic pain from physiological measures such as eye movements. In this study, we propose and test a new stimuli-task paradigm. Our results show that our proposed stimuli-task paradigm can detect differences in the information-processing behavior of people with and without chronic pain. The results also show that our proposed stimuli-task paradigm can reliably predict self-reported subjective pain experience from eye movements. These findings provide support for our proposed stimuli-task paradigm. They also show that the eye-tracking variables that we selected to test our proposed paradigm are effective in capturing the impact of chronic pain on visual attention, suggesting that eye movements have the potential to serve as reliable biomarkers of chronic pain. Hence, our results support the potential for eye movements to aid in efforts to develop smart information systems that can detect the presence and/or the severity of chronic pain from an individual's ocular behavior.

Keywords: Eye Tracking, Decision Support Systems, Chronic Pain, Cognitive Behavior

Fiona Nah was the accepting senior editor for this paper.

1 Introduction

As digital goods and services address increasingly more human needs, continual market demand for innovation drives competition in today's digital economy (Djamasbi & Strong, 2019). One way to address this market demand involves developing smart devices that can provide useful services with outstanding user experiences. Advances in technology provide the opportunity to unobtrusively collect physiological measures, such as eye movements, without any burden on users. Hence, neuro information systems (NeuroIS) research, which uses physiological measures to detect changes in user experience and/or behavior (Bačić & Henry, 2022; Mirhoseini et al., 2022; Loos et al., 2022; Jia et al., 2021), plays an increasingly critical role in designing smart products (Fehrenbacher & Djamasbi, 2017; Shojaeizadeh et al., 2019).

One domain that can benefit from developing smart products that use sensor-based technologies is chronic pain, which refers to "a distressing experience associated with actual or potential tissue damage" that lasts more than three months (Crofford, 2015; Merskey, 1986). As one of the most common chronic conditions (Zelaya et al., 2020; Yong et al., 2022), chronic pain represents a major health problem with severe personal, societal, and economic negative consequences (Zelaya et al., 2020; Phillips, 2006; Yong et al., 2022).

Providing effective treatment for chronic pain requires a comprehensive understanding of the pain experience. Healthcare professionals typically assess chronic pain by collecting self-reported ratings that capture a patient's level of pain intensity and the degree to which pain interferes with the patient's physical and day-to-day activities (McCahon et al., 2005; Rose et al., 2018). While self-reported ratings provide an opportunity for individuals to convey their point of view, they lack the necessary objectivity to obtain a more balanced (objective and subjective) view of the pain experience (Borsook et al., 2011). Because objectivity in chronic pain assessment can provide major improvements in the effective treatment of chronic pain (Borsook et al., 2011; Xu & Huang, 2020), a NeuroIS research agenda focusing on developing smart information systems that can detect chronic pain objectively via physiological measures could provide significant value to both research and practice. Our study provides a first step in such a research agenda.

The NeuroIS literature shows that eye movements can reliably measure and detect changes in a person's information-processing and decision behavior (Fehrenbacher & Djamasbi, 2017; Shojaeizadeh et al., 2019). Because chronic pain impacts attention (Phelps et al., 2021) and eye movements provide moment-to-moment information about changes in attention, one can reasonably argue that eye movements may serve as physiological measures for detecting chronic pain. For example, smart clinician support systems that could create chronic pain reports from objective eye movements would be useful to clinicians in providing a more comprehensive understanding of their patients' chronic pain experience. One can find support for this argument in various eye-tracking studies that show eye movements can capture objective information-rich differences in visual attention to pain stimuli between people with and without chronic pain (e.g., Alrefaei et al., 2022; Fashler & Katz, 2016; Gaffiero et al., 2019).

Developing an effective stimuli-task paradigm is a fundamental step in the NeuroIS research agenda that focuses on detecting chronic pain from eye movement behavior. A systematic review of chronic pain studies (Chan et al., 2020) indicates that the commonly used stimuli-task paradigm may not be suitable for designing smart NeuroIS for detecting chronic pain from eye movement data. According to Chan et al. (2020), the stimuli-task paradigm that researchers have widely used to examine the impact of chronic pain on visual attention has produced mixed results. One reason could be that the commonly used stimuli-task paradigm does not offer enough opportunities for capturing the complex and dynamic nature of attention because it engages people in relatively simple cognitive activities that are completed in fixed short time intervals.

Hence, in our study, we propose and test a new stimuli-task paradigm that naturally provides more chances for capturing nuances in visual attention. Grounded in theories that explain the interruptive function of pain on information processing (Eccleston & Crombez, 1999; Todd et al. 2015), we argue that engaging people in completing pain-related surveys provides a sensitive stimuli-task paradigm for detecting differences in visual information-processing behavior of people with and without chronic pain. Because completing surveys engages people in a more complex cognitive activity than the tasks that many chronic pain studies have used, our proposed stimuli-task paradigm offers more opportunities to observe the impact of chronic pain on cognition. Our proposed stimuli-task paradigm naturally increases the prospect of observing the interruptive function of pain on attention because it does not impose a time limit. By using the same surveys that clinicians use to collect subjective pain measures to evaluate chronic pain, our proposed stimuli-task paradigm represents a practical and ecologically valid choice for the NeuroIS research agenda that focuses on developing feasible solutions for detecting chronic pain from visual information-processing behavior.

2 Background

2.1 Eye Tracking to Detect Visual Behavior

Video-based eye-tracking has become increasingly popular in NeuroIS research due to its ability to unobtrusively measure visual behavior (Djamasbi, 2014). Video-based eye-trackers capture a person's gaze on a visual display by recording and measuring the changes in the person's pupil position at any given time. These devices, typically mounted beneath a visual display (e.g., the computer monitor that presents the stimuli), shine invisible infrared light onto a person's eyes. The reflection of this light produces a small bright light on the eye surface (glint) and makes detecting the pupil easier. The infrared (IR) sensing video camera embedded in the eye-tracking device captures this reflection. Using the glint's position relative to the pupil center, eye-tracking software calculates a person's gaze point on stimuli (Nyström et al., 2013). Video-based eye trackers capture gaze data continuously with high sampling rates (e.g., 60 to 600 HZ) and, hence, represent an excellent tool for capturing the dynamic nature of attention.

Researchers typically process the raw gaze stream that eye trackers collect to identify gaze points that form fixations and saccades. Fixations refer to a group of stable gaze points in both spatial and temporal proximity. Grounded in the "eye-mind" assumption (Just & Carpenter, 1980), researchers widely agree that such gaze point clusters represent attention to stimuli (Djamasbi, 2014; Rosch & Vogel-Walcutt, 2013; Poole & Ball, 2005). Saccades refer to small, rapid gaze points that occur between fixations (Goldberg & Kotval, 1999). While people do not process visual information during saccadic eye movements, saccadic eye movements provide valuable information about how people shift their attention from one focal point to another (Djamasbi, 2014; Jacob & Karn, 2003).

2.2 Chronic Pain and Attentional Bias

Chronic pain is a complex and debilitating phenomenon that exerts a significant impact on memory. People who endure chronic pain often encounter difficulties in suppressing or eliminating painful memories. This cognitive process may culminate in heightened selective attention toward pain-related information (Phelps et al., 2021; Todd et al., 2015). Such selective attention, called attentional bias, refers to the tendency to pay attention selectively to information that relates to one's concern(s) (Keogh et al., 2001).

Attentional bias toward pain-related stimuli can manifest as an increased vigilance toward painful stimuli or a decreased ability to disengage from such stimuli (Keogh et al., 2001). However, individuals with chronic pain do not always demonstrate their tendency towards selective attention (i.e., attentional bias) by demonstrating heightened focus on pain-related stimuli. In some instances, studies indicate individuals with chronic pain exhibit attentional bias by avoiding pain-related stimuli rather than by paying extra attention to them (Chan et al., 2020; Fashler & Katz, 2016, 2014; Gaffiero et al., 2019; Vervoort et al., 2013).

Chronic pain studies have reported diametrically opposing attentional biases (heightened attention to vs. avoidance of pain stimuli) that can be elucidated using theories that seek to explain the interruptive function of pain with regard to attentional information processing (Eccleston & Crombez, 1999; Todd et al., 2015). These theories suggest that pain-related characteristics such as pain intensity influence the impact of pain on cognition. When individuals experience severe chronic pain, the appraisal process of their pain experience is more likely to result in heightened attention toward the pain. In contrast, when individuals experience less severe chronic pain, the appraisal process may prompt them to seek interruptions, such as shifting attention from the pain to a task at hand, as a distraction strategy to escape the pain (Eccleston & Crombez, 1999).

2.3 Stimuli-task Paradigm

The stimuli-task paradigm relates to using the context of stimuli and tasks to collect behavioral data. Stimuli refer to experimental materials that one prepares for a study (e.g., webpages, dashboards). Task refers to the activity involving the stimuli that participants complete during a study (e.g., retrieving information, making decisions). The stimuli-task paradigm plays a significant role in behavioral research, particularly in NeuroIS research that relies on eye-tracking sensors, as it provides the context for understanding user behavior (e.g., perceptions and evaluations). Additionally, the mere arrangement of content on visual stimuli (e.g., structure and format) as well as what people are asked to do with the visual stimuli (e.g., review the content or look for specific information) has a major impact on eye-movement patterns with which the presented information is processed (e.g., Djamasbi & Hall-Philips, 2014; Djamasbi et al., 2009; Cyr et al., 2009).

2.4 Stimuli-task Paradigm in Chronic Pain Literature

The stimuli-task paradigm in the chronic pain literature allows one to examine differences in attentional bias toward pain-related information. The most commonly used stimuli-task paradigm in this literature is the stimuli presentation paradigm using the dot-probe task (Cardoso et al. 2021). It predominantly relies on measuring reaction time to visual probes (Asmundson et al., 2005; Fashler & Katz, 2014, 2016; Franklin et al., 2018; Keogh et al., 2001; Vervoort et al., 2013). In this paradigm, one typically determines reaction time to visual probes by presenting participants with a pair of cues displayed laterally on a screen (e.g., words or images on the right and left sides of the screen). After a short period (e.g., 1500-2500 milliseconds), one then presents a new screen to participants. This screen displays a single dot where one of the two cues appeared on the prior screen. Participants must then identify where the dot appears on the screen (e.g., left or right side of the screen) as soon as possible typically by using a keyboard press or a mouse click. One can then use the reaction time (the amount of time that it takes a participant to recognize the dot's location) to measure attention to the cue on the previous screen that appeared in the same location as the dot (see Figure 1). The faster the reaction time, the more heightened the attention to the cue that the dot replaced.

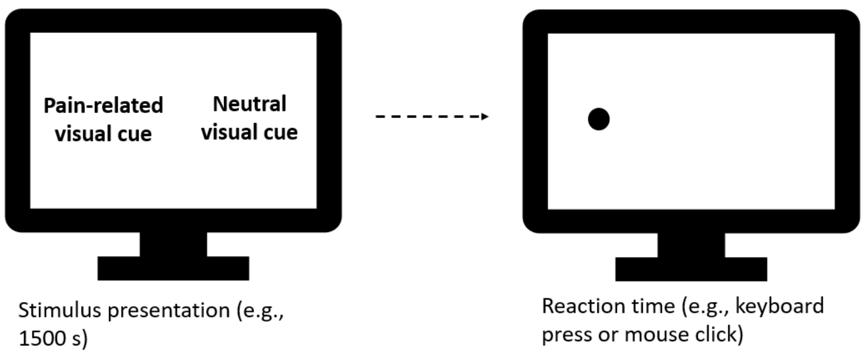

Figure 1. Measuring Attention with Reaction Time in a Dot-probe Task

More recently, researchers have used eye tracking in free-viewing tasks (i.e., presenting participants with images in short time intervals) and dot-probe tasks to directly measure attention by tracking visual engagement with or shift of focus away from stimuli (Fashler & Katz, 2014, 2016; Gaffiero et al., 2019; Mahmoodi-Aghdam et al., 2017; Vervoort et al., 2013; Yang et al., 2012). In addition to serving as a way to directly measure visual attention, moment-to-moment eye movements are likely to provide a more accurate representation of the dynamic nature of attention in chronic pain research (Crombez et al., 2015). Studies in the chronic pain literature that captured attention via both reaction time and eye tracking have demonstrated the value of eye tracking. While these studies have found no significant differences in reaction time between chronic pain individuals and controls, they show significant differences in eye-movement behavior between the two groups (Thigpen et al., 2018).

Despite being touted as the gold standard for capturing attentional bias (Gaffiero et al., 2019), a recent systematic literature review (SLR) of studies that use eye tracking to examine pain-related attentional processes (Chan et al., 2020) shows that using gaze behavior to investigate the impact of chronic pain on information-processing behavior is still in its infancy. For example, the literature search in the SLR paper (Chan et al., 2020) resulted in only 24 papers. Among the 24 papers identified by the SLR paper, only 11 investigated the impact of chronic pain on attentional processes. Of these 11 papers, nine examined the interruptive function of chronic pain on attention by comparing the ocular behavior of people with and without chronic pain. Because we focus on comparing the viewing behavior of those who suffer from chronic pain and those who do not suffer from pain, we summarize what the latter nine papers found in Table A1 in the Appendix. We direct readers to Chan et al. (2020) for more information about the 24 papers they reviewed (e.g., methodology, results) (pp. 5-10).

Table A1 shows that studies that have compared gaze behavior between people with and without chronic pain have produced mixed findings. A study's ability to effectively detect differences in viewing behavior of people with and without chronic pain depends largely on how successfully the stimuli-task paradigm can capture the nuances of visual behavior that are caused by the interruptive function of pain on attention

(Chan et al., 2020). All studies in Table A1 utilize the commonly used stimuli presentation paradigm in pain literature. Hence, the reported results in Table A1 indicate that the commonly used stimuli presentation paradigm in pain literature has not always successfully detected differences in viewing behavior between people with and without chronic pain (see Appendix A).

One reason could be that this paradigm cues participants indirectly to think about their pain experience. This approach may make the stimuli-task paradigm less personally relevant to participants (Chan et al., 2020). Another reason could be the short, fixed exposure times used in this paradigm. All reviewed studies summarized in Table A1 used fixed short periods (e.g., 500-4000 milliseconds) to capture attentional bias toward visual stimuli. Given the complex and dynamic nature of attention, such fixed short times provide only a narrow window for capturing important nuances in information-processing behavior. The mixed results could also be due to relatively simple visual stimuli (e.g., single words and/or images) and relatively simple tasks (e.g., viewing the stimuli and/or reporting whether a dot appears on the left or right side of the screen) used in the stimuli presentation paradigm.

2.5 Our Proposed Stimuli-task Paradigm

We conjecture that a more context-rich visual stimulus and a more demanding task will likely provide more opportunities for capturing the interruptive function of chronic pain on information-processing behavior. We find support for our conjecture in a recent eye-tracking study that used pain-related surveys as visual stimuli and the process of completing the surveys (i.e., assessing one's pain-related health symptoms) as the experimental task. This study found significant differences between people with and without chronic pain in the number of times they attended to survey option labels (i.e., not at all, a little bit, somewhat, quite a bit, very much) (Alrefaei et al., 2022). The results of this study suggest that completing pain-related surveys may serve as a powerful stimuli-task paradigm for capturing nuances in ocular behavior that represent attentional bias. Individuals will likely perceive such a stimuli-task paradigm as personally relevant because it engages them directly in appraising their health symptoms. It provides a context-rich environment for making decisions (i.e., choosing an option among alternatives that best reflects one's experience of a health symptom) without imposing fixed short time limits. The rich decision-making context of such a stimuli-task paradigm along with constraint-free exposure time provides more opportunities for capturing the dynamic nature of attention. Hence, we hypothesize that:

H1: Completing pain-related surveys provides a sensitive stimuli-task paradigm for capturing differences in attentional bias between people with and without chronic pain.

The above-stated hypothesis examines the sensitivity of pain-related survey stimuli-task paradigm in detecting presence/absence of chronic pain. Our next hypothesis extends the above examination by testing whether this stimuli-task paradigm is sensitive enough to predict subjective pain experience from objective eye movement data. Our reasoning is grounded in the pain literature that asserts the interruptive nature of chronic pain on information-processing behavior depends on the severity of pain experience (Eccleston and Crombez, 1999; Moriarty, McGuire, and Finn, 2011; Todd et al., 2015). While H1 examines whether the pain-related survey stimuli-task paradigm can detect the presence/absence of chronic pain due to attentional bias, we extend that examination to test whether this stimuli-task paradigm has enough sensitivity to predict subjective pain experience from objective eye-movement data. Our reasoning for this examination is based on the pain literature that asserts the interruptive nature of chronic pain on information-processing behavior depends on the severity of the pain experience (Eccleston & Crombez, 1999; Moriarty et al., 2011; Todd et al., 2015). Specifically, we hypothesize:

H2: Completing pain-related surveys provides a sensitive stimuli-task paradigm for predicting subjective pain intensity scores from objective eye movements.

Hence, we hypothesize that the proposed stimuli-task paradigm is effective in detecting the presence/absence of chronic pain (H1) and in predicting the degree to which people perceive pain using their objective eye movements (H2).

3 Methodology

To test our hypotheses, we conducted an eye-tracking experiment that was approved by our institutional review board. In the following sections, we explain the methodology that we used to test our hypotheses. We provide details about the visual stimuli and the task that we used in our study. We also explain the process by which we recruited participants for our study and collected experimental data. Then, we provide the specification for the eye-tracker that we used in our study and discuss the variables that we used to capture visual information-processing behavior. We explain how we organized the collected data into chronic-pain and pain-free datasets and discuss how we analyzed the data to test our hypotheses.

3.1 Visual Stimuli and Task

We used three pain-related measures (pain interference, physical function, and pain intensity) from the Patient-Reported Outcomes Measurement Information System (PROMIS) 29+ v2 profile. The National Institutes of Health (NIH) devised the PROMIS measures to provide healthcare professionals and researchers with a standardized national resource for monitoring and evaluating well-being (Cella et al., 2010; Rose et al., 2018). PROMIS measures evaluate many different symptoms across diverse health domains, such as physical function, anxiety, fatigue, depression, cognitive function, ability to participate in social roles, sleep disturbance, pain interference, and pain intensity. Because healthcare providers commonly use PROMIS measures in clinical settings as the conventional means to assess chronic pain, they provide a practical stimuli-task paradigm for detecting differences in information-processing behavior of those who suffer from chronic pain and those who do not suffer from pain.

The task in our study required participants to complete the three pain-related measures in PROMIS 29+ v2 profile that we used as visual stimuli (i.e., pain interference, physical function, and pain intensity). The pain interference measure captures the degree to which pain has interrupted one's daily activities in the past seven days using four questions:

1) "How much did pain interfere with your day to day activities?"
2) "How much did pain interfere with work around the home?"
3) "How much did pain interfere with your ability to participate in social activities?"
4) "How much did pain interfere with your household chores?"

The physical function measure assesses the degree to which pain restricts one's physical activities via four questions:

1) "Are you able to do chores such as vacuuming or yard work?"
2) "Are you able to go up and down stairs at a normal pace?"
3) "Are you able to go for a walk of at least 15 minutes?"
4) "Are you able to run errands and shop?"

The pain intensity measure assesses the severity of pain experience in the past seven days by asking a single question: "How would you rate your pain on average?". The questions in pain interference and physical function measures use a five-point scale. Higher rating values for pain interference and physical function measures indicate more intense symptoms. The pain intensity measure uses an 11-point scale that ranges from 0 to 10. On this scale, a rating of 0 indicates no pain, while 10 indicates the worst pain imaginable.

3.2 Participant Recruitment and Data Collection Process

Using a flyer placed on various community spaces in and outside a northeastern U.S. university, we recruited 48 adults to participate in our study (see Table 1). We required individuals with an interest in participating in our study to answer a screening question about their chronic pain health status. Based on the provided definition for chronic pain (i.e., an intense pain experience (4 or higher on a 0-10 Likert scale) that persists at least for three months), the screening question required participants to self-identify as 1) someone with chronic pain, 2) someone who does not experience pain, 3) or someone with a pain experience between the two previous conditions.

We then scheduled participants for individual experimental sessions at the university laboratory. The data-collection process took place over 12 weeks. Before presenting the stimuli (pain-related surveys), we calibrated the eye tracker for each participant. This calibration process took less than a minute. We then collected participants' eye movements when they completed the experimental task (the surveys). After completing the task, participants took part in an exit interview. During this interview, we verified the participants' health status. Once again, we provided participants with the definition of chronic pain and asked them to self-identify their pain status based on three categories: suffering from chronic pain, pain-free, or having a health status between chronic pain and being pain-free. At the end of the experimental session, we provided each participant with a US$20 Amazon gift card.

We could not calibrate the eye tracker for one participant, which concurs with prior studies that have reported that a small number of participants may not be able to complete the calibration process successfully (Fehrenbacher & Djamasbi, 2017).

The chronic pain participants in our study reported a diverse range of pain types. The prevalent types of pain reported included back pain, neck pain, and knee pain. Additionally, they reported other forms of pain such as leg pain, headache, shoulder pain, eye pain, muscle pain, and wrist pain. Note that some participants experienced multiple chronic pain conditions, and some had received a medical diagnosis for at least one chronic pain condition (see Table 1).

Table 1. Participant Demographics

Number of participants	47. We recruited 48 participants but eliminated the data for one due to calibration issues
Gender	Male (n = 20), Female (n = 26), Other (n = 1).
Age range	18 to 65 (mean = 25.60 years, SD = 12.49)
Chronic pain status	Chronic pain (n = 21), pain-free (n = 22), in-between (n = 4)
Chronic pain types	Back pain (n = 7/21), neck pain (n = 4/21), knee pain (n = 4/21), leg pain (n = 3/21), headache (n = 2/21), shoulder pain (n = 2/21), eye pain (n = 1/21), muscle pain (n = 1/21), and wrist pain (n = 1/21). Some participants reported experiencing multiple chronic pain conditions; some reported that they had received a medical diagnosis as a chronic pain patient.

3.3 Apparatus

We used Tobii Pro Spectrum 600 Hz to collect participants' eye movements in our study. We processed participants' raw gaze data with the IVT filter that Tobii Pro Lab software version 1.162.32461 (x64) provides. We set the threshold for the IVT filter to 30°/s. We set the minimum duration for fixations to 100ms (Liu et al., 2021). We presented visual stimuli to participants via a desktop computer. We captured participants' eye movements unobtrusively as they completed the task with an eye-tracking machine attached to the monitor with a 1920 x 1080 resolution and a 23.8-inch screen size.

3.4 Eye-tracking Metrics

We used three eye-movement metrics that have been used in the pain literature to capture attention: fixation duration, saccade frequency, and visit duration (Fashler & Katz, 2014, 2016; Skaramagkas et al., 2021; Yang et al., 2012). Fixation duration (FD) refers to how much time the eye remains relatively still on a stimulus. Saccade frequency (SF) captures how many times people change their focus when looking at a stimulus. Visit duration (VD) refers to the total amount of time people view a stimulus, including the time they spend engaging with the content (via fixations) and the time they spend changing their focus (via saccades).

We captured these three eye-movement metrics for multiple areas as is customary in eye-tracking research (Djamasbi, 2014). We divided each visual stimulus (i.e., pain interference, physical function, and pain intensity) into two major areas of investigation (AOIs) that pertained to our study. The first AOI delineated the part of the stimulus that contained the questions in the pain-related surveys (Question AOI). The other AOI covered the part of the stimulus that contained possible answers to those questions (Answer AOI). The amount of time that users take to visit an AOI represents attention to that AOI (Djamasbi, 2014). An AOI visit includes both fixation gaze points, which represent engagement with the AOI content, and saccadic gaze points, which represent one or more shifts in focus in that AOI. The eye-tracking pain literature has used both engagement and shift in focus to examine attentional bias toward stimuli (Fashler & Katz, 2014, 2016; Skaramagkas et al., 2021; Yang et al., 2012).

Because the stimuli-task paradigm in our study did not use a fixed time limit, we normalized the eye-tracking variables used in our study (Shojaeizadeh et al., 2019). To do so, we defined a third AOI that contained the entire screen (Screen AOI). We then calculated fixation duration, saccade frequency, and visit duration for Question and Answer AOIs as the percentage of their total values captured in Screen AOI. For example, we determined the ratio of fixation duration in Question AOI by calculating FD for Question AOI divided by FD for Screen AOI, the ratio of saccade frequency in Question AOI by calculating SF for Question AOI divided by SF for Screen AOI, and the ratio of visit duration in Question AOI by calculating VD for Question AOI divided by VD for Screen AOI (see Figure 2).

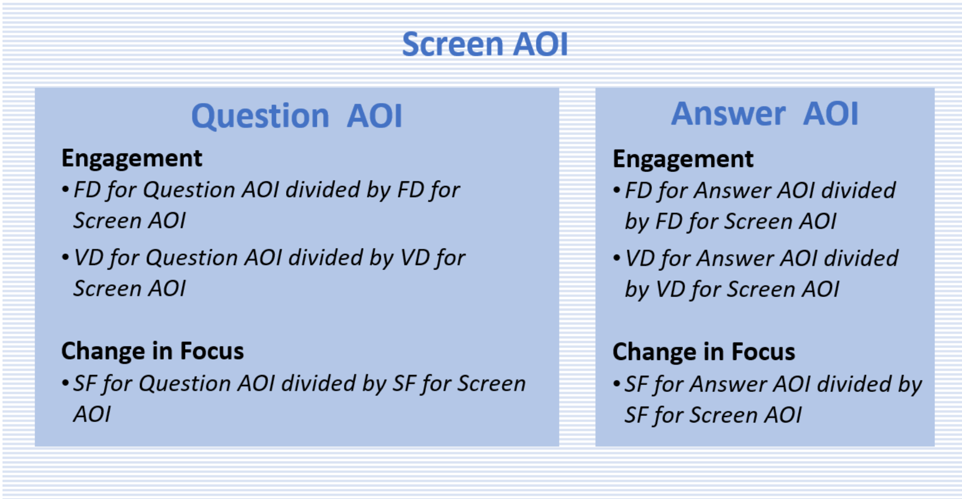

Figure 2. Areas of Investigation (AOI) and Eye-tracking Data Calculated for Each AOI (FD = Fixation Duration, VD = Visit Duration, SF = Saccade Frequency)

3.5 Dataset

The eye-tracking dataset included the participant's eye-movement data for the Question and Answer AOIs on each of the three PROMIS measures that we used as visual stimuli (i.e., six AOIs per participant). In addition to eye-movement behavior, the dataset for each participant also included the participant's self-reported scores for those three PROMIS pain measures. We then organized the collected datasets into chronic-pain (n = 21), pain-free (n = 22), and in-between (n = 4) groups based on participants' self-identified health status that we solicited at the time they registered for participation and confirmed during the exit interview portion of the experiment. To examine the impact that chronic pain has on eye movements due to attentional bias, we analyzed only the datasets for those who self-identified as having chronic pain and those who declared themselves as pain-free (n = 43). As Table 2 shows, this process resulted in a total of 258 eye-movement datasets (43 participants multiplied by six AOIs).

Table 2. Eye-movement Dataset

Number of visual stimuli (3)	Pain interference, physical function, and pain intensity
Number of AOIs on each stimulus (2)	Question AOI and Answer AOI
Number of eye-movement datasets (258)	43 participants (21 chronic pain, 22 pain-free) * 6 AOIs

3.6 Analysis of the Hypotheses

We used eye-movement data to assess differences in attentional engagement and change in focus between participants with and without chronic pain (H1). To conduct this assessment, we examined differences in fixation duration, saccade frequency, and visit duration between participants with and without chronic pain for the Question and Answer AOIs on each of the three visual stimuli (pain interference, physical function, and pain intensity).

From the self-reported ratings, we used only the one that captured pain intensity because we needed participants' ratings for this measure to investigate a possible association between their objective eye-movement data and their subjective pain intensity scores (H2). To examine this possibility, we conducted a backward regression that used the following equation for each stimulus:

Pain Intensity Score = b0 + b1 fixation duration in Question AOI + b2* fixation duration in Answer AOI + b3* saccade frequency in Question AOI + b4* saccade frequency in Answer AOI + b5* visit duration in Question AOI + b6* visit duration in Answer AOI* (1)

4 Results

In this section, we report the results of testing our hypotheses. We start by reporting the results for H1 and then discuss the results for H2 for each of the three visual stimuli used in our study, pain interference, physical function, and pain intensity.

4.1 Hypothesis 1

4.1.1 Pain Interference Stimulus

Figure 3 shows the results of the comparison of fixation duration, saccade frequency, and visit duration in the Question and Answer AOIs between the two groups (chronic pain, pain-free) for the pain interference stimulus. Participants in the chronic-pain group exhibited significantly ($p = 0.00$) shorter fixation duration (52%) in the Question AOI than participants in the pain-free group (61%), significantly ($p = 0.04$) fewer saccadic eye movements (60%) in the Question AOI than participants in the pain-free group (68%), and significantly ($p = 0.02$) shorter visit duration (49%) in the Question AOI than the pain-free group (58%).

We observed the opposite viewing behavior in the Answer AOI in contrast to the viewing behavior in the Question AOI. People in the chronic-pain group had significantly ($p = 0.00$) longer fixation duration (42%) in the Answer AOI than participants in the pain-free group (26%), significantly ($p = 0.00$) more saccades (28%) in the Answer AOI than the pain-free group (15%), and significantly longer visit duration (37%) in the Answer AOI than the pain-free group (25%).

In summary, the above results, which show significant differences in engagement (fixation and visit duration) and change in focus (saccades) between the two groups, support our first hypothesis for the pain interference stimulus.

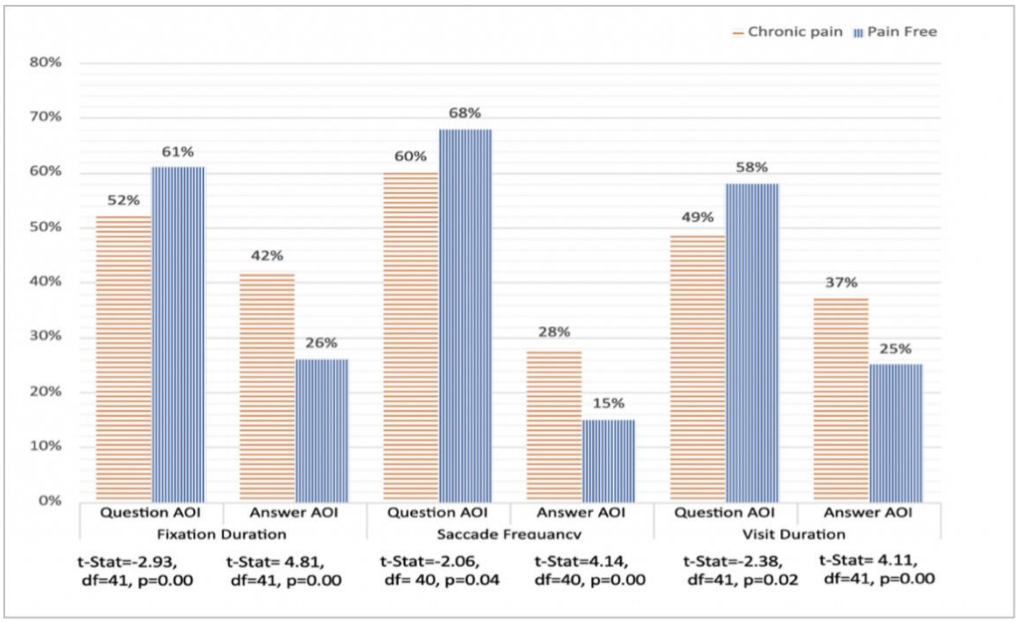

Figure 3. T-test Results for H1 for the Pain Interference Stimulus

4.1.2 Physical Function Stimulus

Similar to viewing trends that we detected in the pain interference stimulus, we observed reverse behavior patterns between the two groups in Question and Answer AOIs for the physical function stimulus. Compared to the pain-free group, people in the chronic pain group showed less intense engagement and change of focus in the Question AOI and exhibited more intense viewing behavior than the pain-free group in the Answer AOI. We found that the chronic-pain group had significantly ($p = 0.03$) shorter fixation duration (43%) in the Question AOI than the pain-free group (48%), had significantly ($p = 0.02$) fewer saccadic eye movements (33%) than the pain-free group (53%) in the Question AOI, and had significantly ($p = 0.04$) shorter visit duration in the Question AOI (41%) than pain-free group (46%) (see Figure 4).

Fixation duration in the Answer AOI was significantly (p = 0.00) longer for the chronic pain group (50% vs. 43%). Also, the chronic pain group had significantly (p = 0.02) more saccadic eye movement in the Answer AOI (58% vs. 33%). We observed the same behavior pattern for visit duration in the Answer AOI. The chronic pain group had longer visit duration (45%) than the pain-free group (40%); however, the result was not significant at the 0.05 level (0.08).

Our analysis shows significant differences in engagement and change in focus between people with and without chronic pain. Hence, our analysis supports H1 for the physical function stimulus.

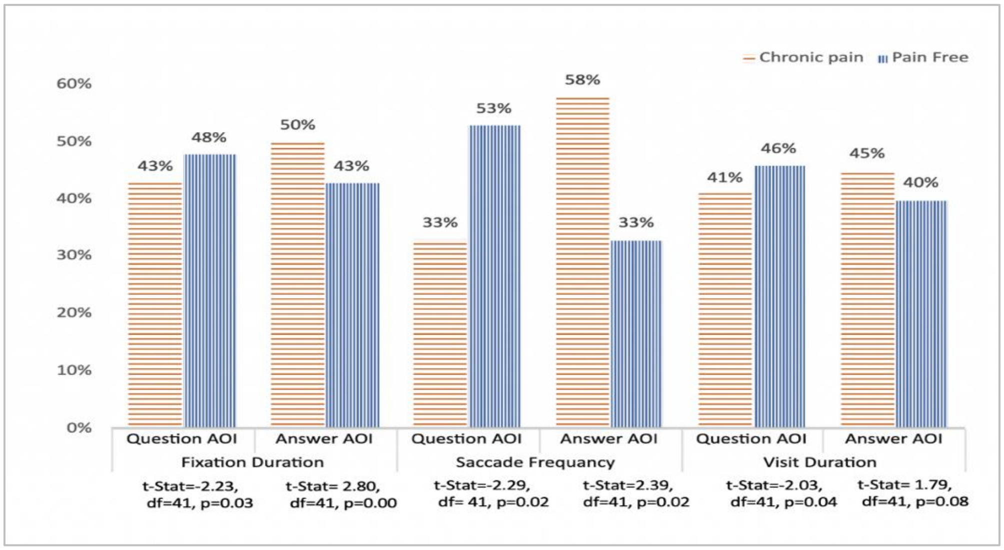

Figure 4. T-test Results for H1 for the Physical Function Stimulus

4.1.3 Pain Intensity Stimulus

Figure 5 shows the differences in fixation duration, number of saccades, and visit duration in each AOI between the two groups. Unlike the patterns observed in previous stimuli (pain interference and physical function), participants in the chronic pain group demonstrated longer fixation durations, more frequent saccadic eye movements, and longer visit durations in both Question and Answer AOIs than participants in the pain-free group. The differences between the two groups, however, did not reach significance. Hence, we did not find support for H1 for the pain intensity visual stimulus.

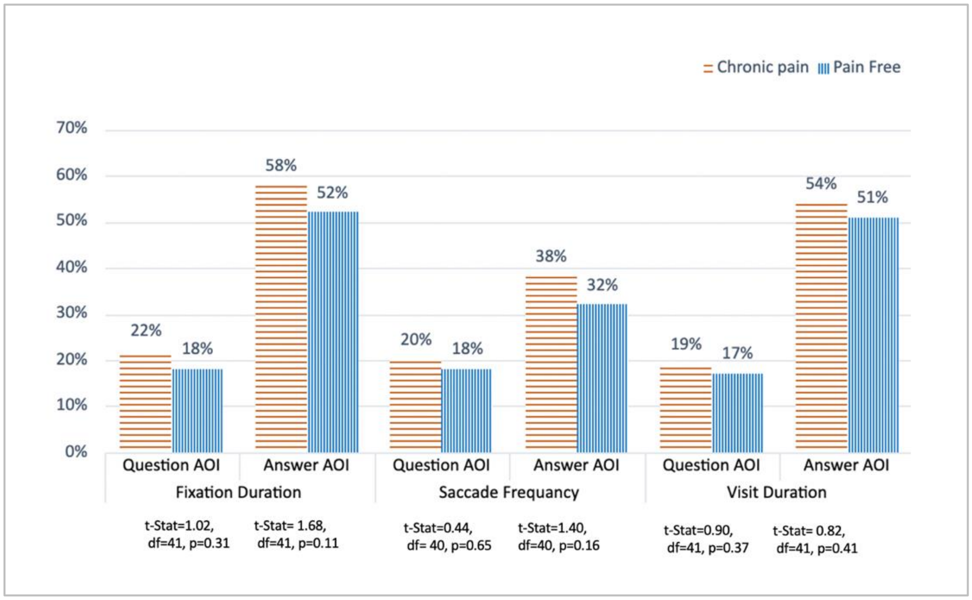

Figure 5. T-test Results for H1 for the Pain Intensity Stimulus

4.2 Hypothesis 2

4.2.1 Pain Interference Stimulus

To assess the potential for fixation duration, frequency of saccades, and visit duration in the Question and Answer AOIs in the pain interference stimulus to predict the self-reported pain intensity scores, we conducted a backward regression analysis. Table 3 displays the results from the last step of the backward regression analysis where we removed the independent variable with the largest p-value in each iterative step. The findings in Table 3 reveal a robust positive association between objective eye movements and subjective pain-intensity scores. Specifically, the results show that participants' fixation duration in both AOIs and the number of saccadic eye movements in the Answer AOI explained 51% of the variance in self-reported pain intensity ratings. This positive association between the dependent and independent variables indicates that the longer fixation duration (engagement) in both AOIs and the more saccadic eye movements (change in focus) in the Answer AOI, the higher the pain intensity score ($p < 0.001$). These results show that participants' eye movements indicating engagement and change in focus predicted their subjective pain experience. Hence, these results support H2 for the pain interference stimulus.

Table 3. Regression Result for H2 for the Pain Interference Stimulus

Dependent variable	Independent variable	Parameter estimate	Standard error	Standardized coefficient	T-value	P-value
Pain intensity ratings	Intercept	-15.961	5.572		-2.865	0.007
	Fixation duration in Question AOI**		6.391	0.771	2.581	0.014
	Fixation duration in Answer AOI***		5.774	1.216	4.072	<0.001
	Saccade frequency in Answer AOI*		2.743	0.287	2.263	0.029
	Overall model F = 15.560; $p < 0.001$; $R^2 = 0.545$; adjusted $R^2 = 0.510$					
*p < 0.05; ** p < 0.01; ***p < 0.001						

4.2.2 Physical Function Stimulus

The results of the backward regression for the physical function stimulus showed a strong inverse relationship between fixation duration in the Question AOI and the subjective pain intensity scores; that is, the shorter the fixation duration when reading the questions, the larger the value of pain intensity (see Table 4). The results showed that fixation duration in the Question AOI explained 12 percent of the variance in subjective pain intensity scores ($p = 0.013$). These results showed that a participant's engagement (fixation duration) with the content of the Question AOI predicted the participant's subjective pain intensity rating. While these results support H2, the R^2 for the physical function stimuli (see Table 4) is lower than the R^2 for the pain interference stimuli (see Table 3) reported in the previous section.

Table 4. Regression Result for H2 for the Physical Function Stimulus

Dependent variable	Independent variable	Parameter estimate	Standard error	Standardized coefficient	T-value	P-value
Pain intensity ratings	Intercept	7.764	1.933		4.017	< 0.001
	Fixation duration in Question AOI**	-10.638	4.119	-0.0374	-2.583	0.013
	Overall model F = 6.670; $p < 0.010$; R^2 =0.140; adjusted $R^2 = 0.119$					
*p < 0.05; ** p < 0.01; ***p < 0.001						

4.2.3 Pain Intensity Stimulus

Table 5 displays the last step of the backward regression analysis that was conducted to examine the association between objective eye-movement behaviors and subjective pain intensity ratings for the pain intensity stimulus. As the table shows, the p-value for the independent variable, while close to the accepted threshold, did not reach the required 0.05 value. Hence, this analysis shows that eye movements representing engagement (fixation and visit duration) and change of focus (saccade frequency) on this visual stimulus did not predict participants' subjective pain intensity ratings. In other words, we did not find support for H2 for this visual stimulus.

Table 5. Regression Result for H2 for the Pain Intensity Stimulus

Dependent variable	Independent variable	Parameter estimate	Standard error	Standardized coefficient	T-value	P-value
Pain intensity ratings	Intercept	-0.232	1.627		-0.143	.887
	Fixation duration in answer AOI	5.580	2.858	0.292	1.950	0.058
	Overall model $F = 3.81$; $p = 0.058$; $R^2 = 0.085$; adjusted $R^2 = 0.063$					
*p < 0.05; ** p < 0.01; ***p < 0.001						

4.3 Hypothesis Testing Summary

Table 6 summarizes the results of the study. As shown in Table 6, H1 and H2 are supported for two of the three visual stimuli used in our study, namely, pain interference and physical function.

Table 6. Summary of Results

H1: Completing pain-related surveys provides a sensitive stimuli-task paradigm for capturing differences in attentional bias between people with and without chronic pain.							
Stimulus	**Q_AOI**			**A_AOI**			
	FD	**SF**	**VD**	**FD**	**SF**	**VD**	
Pain interference	†CP<PF	†CP<PF	†CP<PF	†CP>PF	†CP>PF	†CP>PF	Supported
Physical function	†CP<PF	†CP<PF	†CP<PF	†CP>PF	†CP>PF	CP>PF	Supported
Pain intensity	CP>PF	CP>PF	CP>PF	CP>PF	CP>PF	CP>PF	Not supported
H2: Completing pain-related surveys provides a sensitive stimuli-task paradigm for predicting subjective pain intensity scores from objective eye movements. $PIS = b0 + b1 * FDQ\_AOI + b2 * FDA\_AOI + b3 * SFQ\_AOI + b4 * SFA\_AOI + b5 * VDQ\_AOI + b6 * VDA\_AOI$							
Pain interference	$PIS = b0 + b1 * FD_{Q\_AOI} + b2 * FD_{A\_AOI} + b3 * SF_{A\_AOI}$ †$F = 15.560$; $p < 0.001$; $R^2 = 0.545$; adjusted $R^2 = 0.510$						Supported
Physical function	$PIS = b0 + b1 * FD_{Q\_AOI}$ †$F = 6.670$; $p < 0.010$; $R^2 = 0.140$; adjusted $R^2 = 0.119$						Supported
Pain intensity	$PIS = b0 + b1 * FD_{A\_AOI}$ $F = 3.810$; $p = 0.058$; $R^2 = 0.085$; adjusted $R^2 = 0.063$						Not supported
Note: Q_AOI = Question AOI; A_AOI = Answer AOI; FD = Fixation Duration; SF = Saccade Frequency; VD = Visit Duration; CP = Chronic Pain; PF = Pain-Free; PIS = Pain Intensity Score; † = Significant results							

5 Discussion

While the literature provides ample evidence that pain impacts cognition, it suggests that the ability to capture attentional biases that are caused by the interruptive function of pain is largely dependent on the stimuli-task paradigms (Chan et al., 2020). Grounded in the chronic-pain literature, we argue that the stimuli-task paradigms appropriate for NeuroIS research that focuses on designing smart clinician support systems for chronic pain are 1) context-rich and pain-related, 2) related to engaging people directly in appraising their pain experience, and 3) dependent on exposure time, i.e., do not impose short exposure time limits. Stimuli-task paradigms that meet these criteria will likely provide more opportunities for capturing the impact of chronic pain on visual attention. Hence, they are likely to be effective in detecting differences in information-processing behavior between people with and without chronic pain.

To test this argument, we used a task that engaged our study participants directly in appraising their pain experience by asking them to complete three pain-related measures in the PROMIS 29+ profile (i.e., pain interference, physical function, and pain intensity) that required them to summarize their pain-related health symptoms in the past seven days. These three pain-related surveys served as the visual stimuli for the task. We collected participants' eye movements as they completed these surveys.

To prepare the collected data for hypothesis testing, we classified the eye-tracking datasets into two distinct groups based on participants' self-identification as belonging to either the chronic-pain or pain-free groups based on whether they experienced persistent pain for at least three months. Based on our proposed stimuli-task paradigm, we hypothesized that we would be able to detect significant disparities in visual behavior between the chronic-pain and pain-free groups when they completed the experimental task of answering the survey questions.

To investigate the differences in visual behavior, we compared engagement with the stimuli and the frequency of changes in focus (attentional shifts) between the two groups. Engagement and change in focus are two commonly used visual behaviors for assessing attentional bias in the pain literature (Fashler & Katz, 2014, 2016; Skaramagkas et al., 2021; Yang et al., 2012). We examined the differences in information-processing behavior between the two groups for two relevant AOIs on each stimulus: Question AOIs that covered the question area and Answer AOIs that covered responses to questions on visual stimuli used in our study (see Figure 1). Consistent with previous pain research, we determined differences in engagement between the two groups by examining fixation and visit duration (Alrefaei et al., 2022; Fashler & Katz, 2014, 2016; Vervoort et al., 2013). We determined differences in change of focus by analyzing saccade frequency (Skaramagkas et al., 2021).

H1 posits that our proposed stimuli-task paradigm can detect differences in viewing behavior between people with and without chronic pain. Our analysis supported this hypothesis for two of the three visual stimuli used in our study. Specifically, the results revealed significant differences in how the two groups processed information on the pain interference and physical function stimuli but not on the pain intensity stimulus. One potential explanation for this discrepancy is that the pain intensity stimulus was less contextually rich compared to the other two stimuli, as it featured only one item (as compared to the other two stimuli that had 4 items each). This interpretation aligns with the notion that the more contextually elaborate the stimuli, the greater the prospects for capturing nuances in visual attention.

The detected differences in information-processing behavior for both AOIs of the pain interference and physical function stimuli revealed an interesting trend. People in the chronic-pain group exhibited significantly less cognitive effort (e.g., less intense engagement and fewer changes in focus) than people in the pain-free group when reading the questions. When it came to responding to questions, however, they expended significantly more cognitive effort than people in the pain-free group. It is not surprising that those with chronic pain expended more cognitive effort when responding to the questions. Naturally, people with chronic pain have more pain-related incidences to recall and evaluate compared to people who do not experience pain (Alrefaei et al., 2022). Individuals who experienced pain (compared to those who did not experience pain) may have paid less attention to questions due to avoidance behavior. According to the pain literature, pain intensity level determines vigilance/avoidance behavior toward pain-related stimuli. When people experience severe pain, they exhibit vigilance; when they experience non-severe pain, they exhibit avoidance behavior (Eccleston & Crombez, 1999). To provide insight into the pain intensity levels that participants in the chronic pain group experienced, we examined the participants' ratings for the PROMIS 29+ v2 pain intensity measure. This measure determines subjective pain intensity via a numeric rating scale that comprises 11 points that range from 0 (no pain) to 10 (worst pain imaginable). Ratings in the 7 to 10 range indicate severe pain (Karcioglu et al., 2018). The pain intensity scores in our study show that our participants in the chronic-pain group did not suffer from severe pain ($M = 5.095$, $SD = 1.410$). Hence, our results support the literature that suggests that, when people experience non-severe pain intensity, they engage in avoidance behavior. That is, people in the chronic-pain group may have focused on completing the task (e.g., accurately summarizing pain experience in a single score) to escape from negative thoughts and feelings that reading pain-related questions invoked (Eccleston & Crombez, 1999).

H2 tested whether our stimuli-task paradigm could detect a relationship between participants' subjective pain intensity scores and their objective visual behavior. Specifically, we examined whether eye movements that reflect engagement and change in focus could predict individuals' self-reported pain intensity scores. Our findings revealed significant associations between participants' objective attentional eye-movement behavior, specifically engagement and change in focus, and their subjective pain-intensity score for the pain interference and physical function stimuli. In contrast, we observed no significant associations for the pain intensity visual stimulus. These outcomes concur with our results from testing H1, which underscores the notion that stimuli with more contextual information, such as pain interference and physical function, have greater potential to reveal nuances of attention. Similarly, the obtained results for H2 in our study indicate that context-rich stimuli will likely be more effective in predicting subjective pain intensity scores compared to stimuli with fewer contextual details.

Our results show that pain interference is the most sensitive visual stimulus in our study for detecting differences in engagement and change in focus between participants with and without chronic pain. We found significant differences between the two groups for both engagement and change in focus in both AOIs for this stimulus. Similarly, visual behavior on the pain interference stimulus explained 51 percent of the variance in subjective pain intensity scores. For the physical function stimulus, all but one t-test showed significant differences between the two groups; visual engagement (measured as visit duration) between the two groups in the Answer AOI did not reach significance at the 0.05 level. While we found a significant association between objective eye movements and subjective pain intensity scores, this relationship is weaker for the physical function stimulus compared to the pain interference stimulus (12% vs. 51%).

One reason could be that participants in our study found the items in the pain interference stimuli more relevant than items in the physical function stimuli (Chan et al. 2020). The former focused more broadly on assessing pain interference with daily activities (i.e., “How much did pain interfere with your day to day activities?”, “How much did pain interfere with work around the home?”, “How much did pain interfere with your ability to participate in social activities?”, and “How much did pain interfere with your household chores?”). The latter focused on the impact of pain on relatively more specific physical daily activities (i.e., “Are you able to do chores such as vacuuming or yard work?”, “Are you able to go up and down stairs at a normal pace?”, “Are you able to go for a walk of at least 15 minutes?”, and “Are you able to run errands and shop?”).

Our participants in the chronic-pain group suffered from a diverse range of pain experiences. As a result, the pain questions may not have been relevant to everyone in pain. Questions in the physical function stimuli such as “Are you able to go up and down stairs at a normal pace” or “Are you able to go for a walk of at least 15 minutes?” may be more relevant to those who suffer from back, leg, muscle, and knee pain compared to those who suffer from headache, wrist, shoulder, and eye pain (Chan et al., 2020). Questions in the pain interference stimuli, however, seemed to be relevant to all the reported chronic conditions in our study. Future research needs to examine this possibility.

6 Contributions and Implications

Our study makes important contributions to the NeuroIS literature by proposing and testing a new stimuli-task paradigm that provides more opportunities for capturing differences in visual behavior between people who suffer from chronic pain and people who do not experience pain. In particular, our investigation showed that two of the three visual stimuli in our study not only revealed differences in eye movements that represent engagement and change in focus between people with and without chronic pain but are also sensitive in predicting the pain intensity score regardless of whether a person self-identified as someone who suffers from chronic pain or someone who is pain-free.

We calculated three eye-tracking metrics (fixation duration, saccade frequency, and visit duration) to measure information-processing behavior in our study. We normalized these eye-tracking metrics by calculating the ratios of their total values. Researchers often need to perform such normalization for stimuli-task paradigms that do not impose fixed time intervals (Shojaeizadeh et al., 2019). Our results show that the calculated eye-tracking metrics used in our study were effective in capturing differences in information-processing behavior between people with and without chronic pain. Our results also showed a strong association between participants’ objective visual attention (captured by the eye-tracking metrics that we used) and their subjective pain scores. By doing so, our study provides support and rationale for NeuroIS research that focuses on developing smart information systems for detecting chronic pain experience from eye movement data.

Our study also contributes to the pain literature. Our results suggest that eye movements have the potential to serve as reliable biomarkers of chronic pain. Our study extends the existing stimuli-task paradigms for investigating the interruptive function of pain on attention to include pain-related surveys as visual stimuli and survey completion as the experimental task. Our results also show that the eye-tracking variables that we developed for our proposed paradigm (i.e., FD, SF, VD in Question and Answer AOIs as ratios of their total values) were effective in detecting the impact of chronic pain on visual attention. By offering more opportunities for capturing nuances in information-processing and decision behavior and eye-tracking variables that can effectively capture such nuances, our proposed stimuli-task paradigm can assist pain researchers in exploring and explaining how pain disrupts attention.

Our study also has practical implications for enhancing efforts to assess chronic pain in clinical settings. Healthcare professionals commonly use pain-related measures in the PROMIS profile in clinical settings to assess pain. By using response to these measures as a stimuli-task paradigm, our results demonstrate that both objective eye movements and subjective ratings can be collected via eye-tracking enabled information systems in advance of routine office visits. One can readily integrate contemporary eye-tracking devices with information systems administering pain surveys in clinical settings and, thereby, acquire high-quality eye-movement data. Additionally, the increasing integration of high-quality eye-tracking devices in consumer-grade computing products represents a promising trend for developing web-based applications that can collect patients' eye movements when they complete pain surveys remotely outside the clinical settings. These developments hold promise for efforts to develop smart clinician support systems that can support the advancement of chronic pain management, which emphasizes the need for more research in this domain.

7 Limitations and Future Research

As with any experiment, our study has strengths and limitations. Among its strengths, we used a relatively more diverse population than previous eye-tracking studies by recruiting participants from within and outside a university campus (e.g., Alrefaei et al., 2022). Having a diverse set of chronic pain types present in our study could be considered as both a strength and a limitation. On one hand, our results show that our proposed stimuli-task paradigm and eye-tracking variables are effective in detecting differences in the information-processing behavior between people with and without chronic pain regardless of their pain types, which attests to the robustness of our proposed stimuli-task paradigm and eye-tracking variables. On the other hand, focusing on the visual behavior of a population that suffers from a specific chronic pain may enable us to detect nuances in information-processing behavior that may be unique to that particular chronic pain condition. Future research needs to provide insight into these interpretations.

Using only three visual stimuli in our study could be viewed as a limitation. The significant results in our study, however, with only three stimuli show that we may be able to detect differences in visual behavior between people with and without chronic pain by using even fewer stimuli, such as by using only one four-item subjective measure that requires people to appraise their pain symptoms on a five-point scale (e.g., pain interference or physical function).

Similarly, using only three eye-tracking variables (fixation duration, saccade frequency, and visit duration) to investigate attention and change in focus could be considered a limitation. Our results, however, conclusively demonstrate that they can successfully detect changes in the visual behavior between people who suffer from chronic pain and those people who are pain-free. Nevertheless, future studies with different pain-related surveys and eye-tracking variables need to verify and extend our results.

Among our key foci, we conducted our study to examine whether one can accurately detect chronic pain status and pain intensity solely via analyzing eye movements. Recent studies show that other objective measures such as mouse movements can reveal how users experience cognitive load and cognitive deliberation when they complete online forms (Weinmann et al., 2021; Kim et al., 2022). Future studies can extend our work by combining eye movements with mouse movements to study how chronic pain impacts information-processing behavior.

8 Conclusion

The pressing need for objective measures in evaluating chronic pain both in research and practical contexts (Borsook et al., 2011) underscores the significance and value of NeuroIS research in the human health domain. Our study shows that subjective pain-related measures that healthcare professionals commonly use in clinical settings can serve as effective visual stimuli for detecting marked differences in the ocular behavior of individuals with and without chronic pain and for predicting how individuals would rate their pain intensity.

Our study also shows that our eye-tracking variables were effective in measuring the ocular behavior for the proposed stimuli-task paradigm. These findings underscore the potential value of NeuroIS research in identifying practical stimuli-task paradigms that healthcare professionals can implement in clinical settings. They also highlight the value NeuroIS research provides in determining eye-movement metrics that can serve as reliable predictors (i.e., biomarkers) of chronic pain. Such research endeavors have the potential to foster efforts to develop cutting-edge machine learning algorithms and intelligent clinician support systems that can automatically detect chronic pain and, thereby, assist clinicians in improving patient care.

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Appendix A: Summary of Eye-tracking Chronic Pain Studies

In their recent systematic literature review, Chan et al. (2020) found few eye-tracking studies that have investigated the impact that chronic pain has on attentional processes. Specifically, they identified only 24 papers that used eye tracking to examine how pain-related stimuli impact attentional processes among which only 11 investigated the impact that chronic pain has on attentional processes. Furthermore, among those 11 papers, only nine examined the interruptive function that chronic pain has on attention by comparing the ocular behavior of people with and without chronic pain. Because we focus on comparing the viewing behavior of those who suffer from chronic pain and those who do not suffer from pain, we summarize what the latter nine papers found in Table A1. Chan et al. (2020) list all 24 papers they reviewed and their details (e.g., methodology, results) (pp. 5-10).

Among the nine studies summarized in Table A1, all used short, fixed exposure times (500-4000ms) to capture reactions to pain-related words or images, and they used the dot-probe task more than any other task.

The findings in the table show mixed results. For example, first fixation duration significantly differed between people with and without chronic pain in a study that used the dot-probe task and a study that used the free viewing task. The same eye-movement metrics, however, did not show significant differences between chronic pain and healthy individuals in five other studies that used either the dot-probe task or the free viewing task. Similarly, first fixation latency significantly differed between people with and without chronic pain in two studies (one used the dot-probe task and the other used the visual search task) but not in other studies that used similar tasks.

Table A1. Characteristics of the Stimulus Presentation Paradigm and their Related Eye-movement Measures that Were Used in Eye-tracking Chronic Pain Studies that Compared the Ocular Behavior of People with and without Chronic Pain

Stimuli presentation	Eye movements	Reference
Task: Dot probe **Visual probe:** Words (2 studies) Images (3 studies) **Exposure time:** 500ms (1 study) 1500ms (1 study) 2000ms (3 studies)	First fixation proportion, first fixation latency, first fixation duration, average fixation duration, total fixation count, average visit duration, total visit count, and total gaze duration. Comparing CP and PF groups: 1 study showed significant differences in first fixation duration. 1 study showed significant differences in first fixation latency and average fixation duration. 1 study showed significant differences in total fixation count. 1 study showed significant differences in total gaze duration. No significant differences were found for the remaining metrics.	Yang et al. (2012), Fashler & Katz (2014, 2016), Franklin et al. (2018), Mazidi et al. (2021)
Task: Free viewing **Visual probe:** Images (2 studies) **Exposure time:** 1000ms (1 study) 4000ms (1 study)	First fixation proportion, first fixation latency, total fixation count, first visit duration, first fixation duration, average fixation duration, and total gaze duration. Comparing CP and PF groups: 1 study showed significant differences in first fixation duration and first fixation proportion. No significant differences were found for the remaining metrics.	Mahmoodi-Aghdam et al., (2017), Liossi et al. (2014)
Task: Cued choice viewing* **Visual probe:** Images (1 study) **Exposure time:** 3000ms (1 study)	First fixation proportion, and total gaze duration. Comparing CP and PF groups: No significant differences were found for the metrics.	Giel et al. (2018)

Table A1. Characteristics of the Stimulus Presentation Paradigm and their Related Eye-movement Measures that Were Used in Eye-tracking Chronic Pain Studies that Compared the Ocular Behavior of People with and without Chronic Pain

Task: Visual search** **Visual probe:** Images (1 study) **Exposure time:** 3000ms (1 study)	First fixation proportion and first fixation latency. Comparing CP and PF groups: The study showed significant differences in first fixation latency and first fixation proportion.	Schoth et al. (2015)
CP= chronic pain; PF= pain free. * In this study, researchers informed participants that a dot (presented on the screen for 1500ms) indicated the position of the emotional picture that would appear on the next screen (this screen included two pictures of the same person), which allowed the researchers to capture participants' strategic attention deployment. Researchers instructed participants to look at the pictures as if they were watching television (i.e., free viewing) ** Researchers asked participants to look for a target image among a set of eight images so the former could capture the latter's attention to pain-related images.		

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