User Emotion and Influencing Factors Based on Facial Expression Recognition in Exploratory Search (Postprint)

Authors: Huang Kun, Zheng Mingxuan, Luo Shichao, Jin Jian

Date: 2023-04-01T00:00:00+00:00

Abstract

[Purpose/Significance] Integrating facial expression recognition technology, this study examines the relationship between emotions during the search process and related factors, explores the relationship between emotions during the search process and search interaction behaviors and experiences, and provides references for user emotion recognition and prediction based on search interaction behaviors, as well as insights for improving user experience during search interaction processes. [Method/Process] Through experimental research, 48 participants were recruited and divided into two groups to complete three designated tasks under time-limited and time-unlimited conditions, respectively, while collecting users' facial expression data, behavioral data, and relevant self-reported data. [Results/Conclusion] The research findings indicate: during the search process, neutral emotions exhibited by users accounted for the highest proportion (58.03%), followed by negative emotions (29.88%), with positive emotions appearing least frequently (12.10%); the higher the proportion of non-neutral emotions, the worse the post-search experience, conversely, the higher the proportion of neutral emotions, the better the post-search experience. The time-limited group exhibited significantly higher proportions of sadness, disgust, surprise, and happiness compared to the time-unlimited group; simultaneously, the proportion of neutral emotions was significantly lower than in the time-unlimited group. Users in the high task-difficulty perception group displayed more disgust and anger emotions, and fewer neutral emotions. Non-neutral emotions were more likely to occur during page-switching scenarios. The more neutral emotions during the search process, the better the user' s post-search experience, while the proportions of both negative and positive emotions showed a negative correlation with post-search experience.

Full Text

A Study on User Emotions and Influencing Factors Based on Facial Expression Recognition in Exploratory Search

Huang Kun, Zheng Mingxuan, Luo Shichao, Jin Jian
School of Government, Beijing Normal University, Beijing 100875

Abstract:
[**Purpose/Significance**] This study integrates facial expression recognition technology to examine the relationship between emotions during the search process and related factors, and explores the connections between search process emotions, search interaction behaviors, and user experience. The findings provide references for the automatic recognition and prediction of user emotions based on search interaction behaviors, and offer insights for improving user experience during search interactions. [**Method/Process**] Through experimental research, 48 participants were recruited and divided into two groups to complete three designated tasks under time-limited and non-time-limited conditions. Facial expression data, behavioral data, and related self-report data were collected. [**Results/Conclusions**] The results indicate that during the search process, neutral emotions accounted for the highest proportion (58.03%), followed by negative emotions (29.88%), while positive emotions appeared least frequently (12.10%). A higher proportion of non-neutral emotions during the search process correlated with poorer post-search experience, whereas a higher proportion of neutral emotions correlated with better post-search experience. The time-limited group exhibited significantly higher proportions of sadness, disgust, surprise, and happiness compared to the non-time-limited group, while showing significantly lower proportions of neutral emotions. Users with high task difficulty perception displayed more disgust and anger, and fewer neutral emotions. Non-neutral emotions were more likely to occur during page-switching scenarios. More neutral emotions during the search process led to better post-search experience, while both negative and positive emotion proportions showed negative correlations with post-search experience.

Keywords: emotion; facial expression recognition; exploratory search; influencing factors
Classification Number: G252.7
DOI: 10.13266/j.issn.0252-3116.2022.05.010

Search is a common activity in daily life, learning, and work. When facing open, uncertain, and ambiguous search needs, people often experience different emotions that may influence their search behavior, performance, and experience. Positive and optimistic emotions often motivate users to continuously explore and progress, while negative emotions such as frustration, anxiety, and anger may undermine user confidence and lead them to stop or abandon the search process [1]. To promote effective information search activities, researchers in information behavior, human-computer interaction, and information retrieval have been exploring the emotional characteristics of users during information search activities. In 2006, G. Marchionini first proposed exploratory search to describe an open, continuous, and multi-faceted information search problem context, where the search process is characterized by opportunism, iteration, and multi-strategic features [2]. Unlike traditional "question-answer" search, users in exploratory search have vague information needs at the initial stage. Due to a lack of knowledge about the search object, they must adjust their search goals through multiple interactions for investigation and learning, with uncertainty also existing at the termination point [3]. Therefore, people are more likely to experience emotions during exploratory search due to the iterative process, increased search duration, and individual and external factors, which in turn affect interaction behavior.

The information search process is accompanied by emotional experiences, where positive and negative emotions during search influence attention, memory, performance, and judgment [4]. Although the cognitive perspective has dominated the field of information behavior, the affective perspective has gradually gained attention with the rapid development of affective computing and Kansei engineering technologies. A number of studies incorporating affective factors have emerged in information behavior research, with specialized attention to emotional issues such as information anxiety and affective load in different contexts [5]. Emotional experiences are diverse, extensive, and differentiated [6], and the causes of their generation and their impact on search interaction behaviors, as well as individual differences, require further investigation and revelation. This study combines facial expression recognition technology to focus on the relationship between emotions during the search process and related factors, and explores the relationship between search process emotions and search interaction behaviors and experience, providing references for the automatic recognition and prediction of user emotional states based on search interaction behaviors, and serving the optimization of the search interaction process.

2 Related Research

In the field of information search behavior research, scholars have focused on the emotional states and changes accompanying users during the search process. Researchers have explored this from both macro and micro perspectives of search, with some attempting to use facial expression recognition technology to identify user emotions during search.

Professor I. Arapakis from the School of Computing Science at the University of Glasgow conducted a series of studies between 2008-2009 applying expression recognition technology to interactive information search. I. Arapakis et al. [7] used facial expression recognition technology to investigate the role of emotion in the information-seeking process. The study recruited 24 participants to complete three search tasks of varying difficulty, recording their facial expressions with a camera during tasks and using the eMotion model for frame-by-frame recognition. Results showed that task type significantly affected unpleasant stimuli but not emotional intensity or the degree of independent emotion concealment. However, no significant correlates were found for user emotions during search based on facial recognition. Subsequently, I. Arapakis et al. [8] attempted to use user facial expressions to explore optimization paths for multimedia recommendation systems, developing a recommendation system for user experiments and using support vector machines to analyze facial emotions corresponding to each search action. Results indicated significant emotional changes across different task types during search and content viewing actions, but no significant association between emotional stimuli (referring to search or viewing behaviors) and specific emotions across tasks. I. Arapakis et al. [9] attempted to predict search result topical relevance through facial expressions and peripheral physiological signals, extracting features from both and analyzing them with support vector machines and K-nearest neighbor methods. The model achieved 66.5% accuracy, demonstrating the feasibility of expression-based search result relevance prediction.

I. Lopatovska from Rutgers University completed her doctoral dissertation titled "Emotional Aspects of the Online Information Retrieval Process" [10] in 2009, and subsequently published two papers in 2011 and 2014 based on facial expression recognition technology, exploring basic emotional states and their relationship with search behaviors when users interacted with digital libraries and information retrieval systems. In 2011, Lopatovska [11] used facial expression recognition to study the association between searchers' facial expressions and their search behaviors. The study recruited 36 participants for two search tasks of different difficulty levels, recording facial expression changes and search behaviors. Twelve search behavior indicators were collected, including left mouse clicks, double-clicks, scrolling, and page switching. Facial values were quantified as the mean of expression recognition results every three seconds within 15 seconds before and after user actions. Results showed multiple significant associations between user behavior indicators and facial expressions; for example, left mouse clicks increased user sadness and disgust, while middle mouse clicks increased joy and surprise. In 2014, Lopatovska [12] used the same dataset to examine relationships between primary emotions, secondary emotions, mood, and search behaviors during online information search. The study used facial expression recognition to measure primary emotions, emotion words extracted from post-search interviews for secondary emotions, and PANAS data completed before and after tasks for mood. Search behaviors focused on eight indicators including task completion time, unique query counts, and Google page views. Using canonical correlation analysis (CCA) to explore associations between primary emotions and behavioral indicators, although no statistically significant models were found, structural correlation coefficients still indicated certain relationships between primary emotions and search behaviors.

M.Y. Zanganeh et al. [13] from Islamic Azad University also used facial expression recognition technology to explore the role of affective factors in PhD students' online information search. The study recruited 50 participants from Iranian universities, requiring each to complete [task]. Using CCA for data analysis, results showed that for personal characteristics, user satisfaction with search results, web search frequency, search experience, interest in search tasks, and familiarity with similar searches positively correlated with happiness. For search process behaviors, users with more happiness spent more time searching and viewing results, visited more URLs, and performed more queries, while users with more anger and disgust made fewer attempts during search. The study noted that the more thoroughly users browsed during search, the more emotional feedback they received; interested users with positive emotions like happiness gained more positive feedback, increasing self-efficacy and motivation to persist.

Previous studies combining facial expression recognition technology to detect user emotions during search have also integrated eye movement data to analyze emotions during web browsing, though such studies combining physiological measurements remain limited. More studies have used questionnaires, interviews, and experiments, employing psychological scales such as the Positive and Negative Affect Schedule (PANAS) [14], PTSD questionnaires [15], State-Trait Anxiety Inventory (STAI) [16-18], and Geneva Appraisal Questionnaire (GAQ) [19], as well as domain-specific anxiety scales [20] and affective load scales [1,21]. Some researchers have used think-aloud protocols, analyzing verbal reports from search experiments to determine emotional polarity [22], or had participants recall and describe their emotional states during information interaction in natural interview settings or by reviewing recordings in laboratories [23]. Despite different emotion collection methods, research questions are similar, focusing on emotions and their changing characteristics during search, and relationships between emotions, cognition, and behavior. Many researchers have based their work on C.C. Kuhlthau' s Information Search Process (ISP) model [24] to explore information search process characteristics among different groups (children, undergraduates, graduate students), analyzing relationships between affect, cognition, and behavior across stages of initiation, selection, exploration, formulation, collection, and presentation. Other researchers have examined influencing factors of user emotions during search, such as task type [25], perceived task difficulty [26], time pressure [27], task division in collaborative search [28-29], self-efficacy [30], and search system factors and efficiency [31-32]. However, most of these studies collected emotions through pre- and post-search measurements, with limited monitoring of emotions during the process. The aforementioned expression-based studies focused more on emotion-behavior relationships and less on factors influencing emotions. Facial expression recognition technology offers advantages of economy and minimal interference [33], and has been increasingly applied across domains for user emotion recognition, such as teacher-student interaction in remote education [34-35], anti-fatigue driving in transportation [36], and patient emotion measurement in medicine [37]. Therefore, this study uses expression recognition technology, treating facial expression recognition results as measurements of user emotions during search, focusing on the distribution characteristics of process emotions and their relationships with user tasks, time pressure, and search interaction behaviors to explore influencing factors and mechanisms.

3 Research Design

3.1 Research Questions

This laboratory study investigates user emotion characteristics and influencing factors during exploratory search tasks based on P. Ekman' s seven basic emotion types [38] and facial expression data collection. Specific research questions include:

1. What are the distribution characteristics of users' basic emotions during the search process?
2. Do task cognitive complexity, time constraints, and difficulty perception significantly affect user emotions during search?
3. Are there significant correlations between user search behaviors/experience and emotions during search?

3.2 Task Design

K. Athukorala et al. [39] categorized typical exploratory search tasks into three types: knowledge acquisition, comparison, and planning tasks. Knowledge acquisition tasks require open-ended collection of information on specific topics; comparison tasks involve gathering information about two or more topics and analyzing similarities and differences; planning tasks involve collecting and integrating overview information about new domains to prepare for future activities. These three task types reflect different cognitive complexities of understanding, analysis, and creation [40-41]. Therefore, this study designed three search tasks as shown in Table 1 .

3.3 User Emotion Recognition

This study collected user emotions through both expression recognition and self-report methods. Since affect (feelings) typically refers to subjective experiences during emotion processes, emotion generally refers to attitudes and experiences toward objective events, and mood reflects mild to moderate affect lasting longer than emotions [42], this study used facial expression recognition to collect emotions during search and the PANAS questionnaire for self-reported mood before and after search [14,43], following previous research [7,9-10,13], to examine relationships between process emotions and pre/post-search mood.

3.3.1 Expression-Based Emotion Measurement Facial expression recognition is an affective computing technology that judges facial emotions from facial images under psychological theory guidance. P. Ekman and W.V. Friesen proposed the Facial Action Coding System (FACS) in 1978 [38], categorizing facial emotions into seven types: fear, anger, disgust, happiness, sadness, surprise, and neutral, with emotions determined by encoding combinations of facial muscle movements. In affective analysis research, emotions are often summarized into three categories: positive, negative, and neutral [44].

Based on preliminary investigation, the commercial API provided by the AI open platform FACE++ [45] was selected for emotion recognition. Face++ is a commercial AI open platform developed by Megvii Technology, widely used in China for various facial recognition services. This study developed a Python program to split recorded expression videos. Since user expressions typically last 5-10 seconds [46], one frame per second was extracted. The API was then called to obtain probability values for the seven emotion types for each expression image, with the emotion type showing the highest probability considered the expression for that frame.

To test FACE++' s recognition accuracy on this study' s expression images, a manual annotation comparison experiment was conducted. First, five expression images were randomly selected from each of the 144 sessions of 48 participants, totaling 720 images. Two graduate students, trained in FACS theoretical framework annotation rules, manually annotated the images. During annotation, results were compared, and disagreements were discussed until consensus was reached. Finally, using manual annotations as the benchmark, FACE++' s annotation accuracy on this dataset was 71.67%. According to performance standards in expression recognition research [47], accuracy above 70% is acceptable, so FACE++ was used for analyzing user expressions in this study.

3.3.2 PANAS-Based Emotion Measurement To obtain users' emotions before and after search tasks, this study also used the PANAS (Positive and Negative Affect Schedule) scale for self-report evaluation. Developed by D. Watson et al. in 1988 [48], this psychological measurement scale categorizes emotions into positive and negative types. D. Watson et al. noted that individual affective experience structure can be described by two independent dimensions of positive and negative affect [49], which forms the theoretical basis of PANAS. This study used the PANAS scale revised by Qiu Lin et al. [50], consisting of 18 words representing positive and negative emotions rated on a five-point Likert scale.

3.4 Search Behaviors

For overall behavioral feature coding, this study referenced existing research [51-53], comparing, summarizing, and inducting to form a complete behavioral indicator system for user search processes. The system categorizes user behaviors into six types: query features, viewing features, click features, saving features, hover features, and dwell features, with specific indicators shown in Table 2 .

Additionally, based on the primary functions of different pages during search, pages were categorized into six types as shown in Table 3 .

3.5 Data Collection

This study randomly recruited 48 university students (16 male, 32 female; 33 undergraduates, 15 postgraduates) from seven universities including Beijing Normal University, Beijing University of Chemical Technology, and Beijing University of Posts and Telecommunications, covering 24 majors.

Based on preliminary experiments, the 48 participants were randomly divided into two groups: a time-limited group (24 participants) and a non-time-limited group (24 participants). The time-limited group was required to complete each task within 10 minutes, stopping when time expired, while the non-time-limited group had no time constraints. Task order followed a Latin square design. At the experiment' s start, participants completed a background information questionnaire covering demographics, information literacy, and search experience. Before each task, they completed the PANAS questionnaire. During task execution, facial video data was collected through front-facing cameras, and screen recordings were made using Bandicam. After each search task, participants completed questions about search experience, including PANAS self-reports, search result evaluations (usefulness, relevance, confidence, and satisfaction), and perceived task difficulty.

Data collection yielded 126,589 seconds of video, from which 126,589 frames were extracted at one frame per second. Using Face++ commercial services, 125,576 images were successfully processed, achieving a recognition efficiency of 99.20%. The remaining 0.80% of frames were excluded due to faces being out of frame or excessive occlusion.

4 Data Analysis

4.1 Emotion Characteristics Across Different Tasks

4.1.1 Cognitive Complexity Based on the frequency percentages of the seven emotions, as shown in Figure 1 [Figure 1: see original paper], neutral emotion appeared most frequently at 58.03%, significantly higher than the other six emotions. This was followed by sadness (14.71%), anger (8.51%), surprise (6.72%), happiness (5.38%), disgust (4.96%), with fear being the least frequent (1.70%). Overall, nearly 60% of search time involved neutral emotions, with the remaining time showing various emotions including sadness, anger, surprise, happiness, and disgust. Negative emotions (sadness, anger, disgust, fear) accounted for 29.88% in total, higher than positive emotions (12.10%).

Chi-square tests on emotion percentages across the three tasks showed that despite different cognitive complexities, differences in emotion distribution were not significant, as shown in Table 4 .

4.1.2 Time Constraints Mann-Whitney U tests for time constraints showed that under time-limited conditions, proportions of sadness, disgust, happiness, and surprise were significantly higher than in non-time-limited conditions, while neutral emotion proportion was significantly lower, as shown in Table 5 . This indicates that time-limited users exhibited more non-neutral emotions during search.

4.1.3 Task Difficulty Perception Based on pre- and post-search task difficulty evaluations, 144 user search sessions were divided into three groups: low difficulty (score < 3), medium difficulty (score $= 3$), and high difficulty (score > 3). Kruskal-Wallis tests analyzed emotion differences across these groups, as shown in Tables 6 and 7 .

Results showed that regardless of pre- or post-search difficulty perception, both anger and disgust appeared significantly more frequently in difficult tasks than in easier tasks, while neutral emotions were significantly less frequent in high post-search difficulty perception tasks.

4.2 Search Interaction Behaviors and User Emotions

4.2.1 Search Behaviors Based on expression recognition results, the seven emotions were categorized into neutral, positive, and negative. Correlation analysis between search behaviors and these three emotion polarities was conducted. Table 8 lists behavior indicators showing significant correlations with search process emotions.

Indicators significantly correlated with neutral emotion showed that more average document page visits per query and less SERP dwell time as a proportion of total task time correlated with more neutral emotions during search. Indicators significantly correlated with positive emotion showed that shorter first queries relative to average query length, fewer unique SERP page visits per query, and higher average document page ranking correlated with more positive emotions. Indicators significantly correlated with negative emotion showed that more mouse hovers per query and higher SERP dwell time proportion correlated with more negative emotions.

4.2.2 Page Dwell Behavior Building on specific search behavior analysis, this study also analyzed page dwell scenarios. Table 9 shows dwell times across page types.

Further comparison of emotions across different pages (Table 10) revealed that neutral emotions during document browsing and document editing were significantly higher than during query formulation and SERP pages. The latter two page types showed significantly lower neutral emotions than browsing and output pages, with SERP pages showing the highest proportion of negative emotions and relatively high positive emotions. This may relate to greater uncertainty faced during query formulation (regarding search terms and strategies) and SERP evaluation processes.

4.2.3 Page Switching Behavior Users displayed neutral emotions most of the time during search, but approximately 40% of the time showed non-neutral emotional states. Observation of facial emotion videos revealed that page-switching scenarios easily captured positive and negative emotions. Therefore, this study further analyzed the timing of all non-neutral emotions relative to page switching.

For window selection around page switches, this study referenced Lopatovska' s [11] work, which analyzed expressions 15 seconds before and after mouse actions in 3-second windows, finding that left-clicks (typically causing page switches) slightly decreased neutral emotions while slightly increasing surprise and sadness. This study categorized non-neutral emotion timing into near page-switching and during page browsing. Since emotions typically last 5-10 seconds [46] and average page dwell time was about 14 seconds, windows of 3-7 seconds were tested. Results showed that using a 5-second window, differences in non-neutral emotion distribution between page-switching and non-switching processes were significant (Table 11).

Statistics showed 14,586 pre- and post-switch windows were extracted, capturing non-neutral emotions in 10,576 windows (72.51%). For non-page-switching processes, 10,031 windows were extracted with non-neutral emotions in 5,569 windows (55.52%). Non-neutral emotions occurred more frequently around page switches.

4.3 Relationships Between Search Process Emotions and Pre/Post Emotions/Experience

Relevance, usefulness, confidence, and satisfaction are four common search experience evaluation indicators. Pearson analysis results are shown in Table 12 .

Results showed significant associations between search result evaluations and search process emotions. Relevance, usefulness, and confidence were significantly associated with negative and neutral process emotions but not positive emotions, negatively correlating with negative emotions and positively correlating with neutral emotions. Satisfaction was significantly associated with all three emotion types, negatively correlating with both positive and negative emotions, and positively correlating with neutral emotions. Overall, more neutral emotions during search led to higher post-search experience evaluations, while more negative emotions lowered evaluations. Positive emotions also negatively affected post-search satisfaction.

5 Discussion

Based on the findings, search process emotions correlate with task context and pre/post emotions, particularly regarding emotion changes across different pages and page-switching processes. Therefore, understanding user emotion perception and its influencing factors can help infer user cognitive states behind behavioral manifestations, thereby improving the affective support functions of information search systems. Several aspects warrant further attention:

First, deeper research on search process emotions and their types is needed. Since primary emotions from facial recognition, secondary emotions from self-reports, and mood from scales cannot substitute for each other [12], and given the degree to which expressions reflect emotions and mood and their interrelationships require further exploration, future research could focus more on specific emotions in search contexts, such as search anxiety and result satisfaction.

Second, analysis of typical scenarios should be strengthened. More granular research on scenarios representing cognitive changes is needed, such as whether user emotions change during search processes with supportive system features [70] or professional assistance [71], or exploring emotional experience differences across search engines. Stable relationships between emotions and behaviors should be explored to build predictive models of emotional states and changes based on behaviors.

Third, emotion recognition methods should be enriched to characterize process emotions from multiple angles, such as using user-computer distance and eye position on screen [72] to assess task focus, incorporating postural expressions like clenched fists or bowed heads [73], and using physiological signals from smart wristbands as subjective emotion measurement indicators [74] for more comprehensive emotion characterization.

6 Conclusion

This experimental study recruited 48 participants divided into two groups completing three tasks under time-limited and non-time-limited conditions, collecting facial expression, behavioral, and self-report data. Results show that neutral emotions dominated the search process (58.03%), followed by negative emotions (29.88%), with positive emotions being least frequent (12.10%). The time-limited group showed significantly higher proportions of sadness, disgust, surprise, and happiness, and significantly lower neutral emotions compared to the non-time-limited group. High task difficulty perception groups exhibited more disgust and anger, and fewer neutral emotions. Non-neutral emotions were more likely to occur during page-switching scenarios. More neutral emotions during search correlated with better post-search experience, while both negative and positive emotion proportions correlated negatively with post-search experience.

The main limitations include the limited sample size and reliance solely on facial expression recognition for process emotion measurement, as not all emotions are reflected in expressions. Future research should test findings with non-student populations and larger samples to establish more stable relationships between process expressions and search interaction behaviors, building more systematic models of emotion change patterns to inform emotion prediction and intervention based on search interaction behaviors.

References

[1] NAHL D. Measuring the affective information environment of Web searchers[J]. Proceedings of the Association for Information Science and Technology, 2004, 41(1): 191-197.

[2] MARCHIONINI G. Exploratory search: from finding to understanding[J]. Communications of the ACM, 2006, 49(4): 41-46.

[3] WHITE R W, ROTH R A. Exploratory search: beyond the query-response paradigm[J]. Synthesis lectures on information concepts retrieval and services, 2009, 1(1): 1-98.

[4] SCOTT B, CLIFFORD N, KEVIN H. Computers that care: investigating the effects of orientation of emotion exhibited by an embodied computer agent[J]. International journal of human-computer studies, 2005, 62(2): 161-178.

[5] LI Jingjin, HUANG ?, YUAN Xin, et al. Definition and Application of User Affective Factors in the Field of Information Query and Retrieval[J]. Library and Information Service, 2019, 63(7): 63-71.

[6] GUO Tingting, CUI Lixia, WANG Yan. Emotional Complexity: A New Perspective for Exploring Emotional Functions[J]. Advances in Psychological Science, 2011, 19(7): 993-1002.

[7] ARAPAKIS I, JOSE J M, GRAY P D. Affective feedback: an investigation into the role of emotions in the information seeking process[C]//Proceedings of the 31st annual international ACM SIGIR conference on research and development in information retrieval. Singapore: ACM, 2008: 395-402.

[8] ARAPAKIS I, MOSHFEGHI Y, JOHO H, et al. Enriching user profiling with affective features for the improvement of a multimodal recommender system[C]//ACM international conference on image & video retrieval. Santorini: ACM, 2009: 1-8.

[9] ARAPAKIS I, KONSTAS I, JOSE J M, et al. Modeling facial expressions and peripheral physiological signals to predict topical relevance[C]//Proceedings of the 32nd international ACM SIGIR conference on research and development in information retrieval. Boston: ACM, 2009: 728-729.

[10] LOPATOVSKA I. Emotional aspects of the online information retrieval process[D]. New Brunswick: Rutgers The State University of New Jersey, 2009.

[11] LOPATOVSKA I. Emotional correlates of information retrieval behaviors[C]//Affective computational intelligence. Paris: IEEE, 2011: 101-110.

[12] LOPATOVSKA I. Toward a model of emotions and mood in the online information search process[J]. Journal of the Association for Information Science & Technology, 2014, 65(9): 1775-1793.

[13] ZANGANEH M Y, HARIRI N. The role of emotional aspects in the information retrieval from the Web[J]. Online information review, 2018, 42(4):

520-534.

[14] LOPATOVSKA I. Searching for good mood: examining relationships between search task and mood[J]. Proceedings of the American Society for Information Science & Technology, 2009, 46(1): 1-19.

[15] KOO J H. Information seeking within negative affect[J]. Journal of the Korean Society for Library and Information Science, 2016, 50(1): 285-312.

[16] ZHOU Wenjie. Experimental Study on User Anxiety in Digital Information Analysis[J]. Journal of Library Science in China, 2011, 37(6): 58-66.

[17] KRACKER J. Research anxiety and students' perceptions of research: an experiment. part I. effect of teaching Kuhlthau' s ISP model[J]. Journal of the Association for Information Science and Technology, 2002, 53(4): 282-294.

[18] KRACKER J, WANG P. Research anxiety and students' perceptions of research: an experiment. part II. content analysis of their writings on two experiences[J]. Journal of the Association for Information Science and Technology, 2002, 53(4): 295-307.

[19] JIANG Tingting, HE Honghong, ZHANG Zhengnan. Research on the Impact of Search Task Complexity on User Emotions[J]. Knowledge of Library and Information Science, 2016(4): 74-82.

[20] O NWUEGBUZIE A J, JIAO Q G, BOSTICK S L. Library anxiety: theory, research, and applications[J]. Library review, 2004, 56(3): 258-259.

[21] NAHL D. Affective and cognitive information behavior: interaction effects in Internet use[J]. Proceedings of the Association for Information Science and Technology, 2005, 42(1): 246-268.

[22] LAZAR J, JONES A, HACKLEY M, et al. Severity and impact of computer user frustration: a comparison of student and workplace users[J]. Interacting with computers, 2006, 18(2): 187-207.

[23] TENKOPIR C, WANG P, ZHANG Y, et al. Academic users' interactions with ScienceDirect in search tasks: affective and cognitive behaviors[J]. Information processing & management, 2008, 44(1): 105-121.

[24] SHANNON D. Kuhlthau' s information search process[J]. School library media activities monthly, 2002, 19(2): 19-19.

[25] QIU Jin, WU Dan. Affective Research in Collaborative Information Retrieval Behavior[J]. Library and Information, 2011: 1-7.

[26] YUAN Hong, ZHAO Yuxi. Research on User Task Perception and Emotional State in Collaborative Search Behavior[J]. Library and Information Service, 2015, 59(17): 89-98.

[27] CRESCENZI A, CAPRA R, ARGUELLO J. Time pressure, user satisfaction and task difficulty[J]. Proceedings of the American Society for Information Science and Technology, 2013, 50(1): 1-10.

[28] IMAZUMI M, NAKAYAMA S, JOHO H. Effect of explicit roles on collaborative search in travel planning task[C]//Asia Information Retrieval Symposium. Dubai: Springer, 2011: 205-214.

[29] HUANG ?, YUAN Xin, LI Lei, et al. Research on Users' Negative Emotion Perception and Influencing Factors in Collaborative Retrieval from the Perspective of Affective Load[J]. Knowledge of Library and Information Science, 2020(1): 42-51.

[30] WANG Chang, HAN Jianhua, SUN Xiaoning. Research on Influencing Factors of Users' Emotions in Collaborative Information Seeking: Based on Self-Efficacy and Task Complexity[J]. Knowledge of Library and Information Science, 2021(1): 76-84.

[31] GWIZDKA J, LOPATOVSKA I. The role of subjective factors in the information search process[J]. Journal of the Association for Information Science and Technology, 2014, 60(13): 2452-2464.

[32] TAN Jinbo, WANG Guangxin. The Interaction Effect of Learning Emotion and Query Task Type on Web Information Search Experience[J]. Chinese Journal of Distance Education, 2017(9): 19-25, 79.

[33] ANDERSEN R A, NASROLLAHI K, MOESLUND T B, et al. Interfacing assessment using facial expression recognition[D]. Lisbon: University of Warwick, 2014.

[34] GHIJSEN M, NIJHOLT A, POEL M, et al. Facial expression analysis for human computer interaction-recognizing emotion in an intelligent tutoring system[J]. Affective computing, 2004, 2(3): 147-161.

[35] HU Min, QI Ke. Educational Application of Facial Expression Recognition Technology[J]. Education Modernization, 2019, 6(75): 100-102.

[36] PASCHERO M, VESCOVO G D, BENUCCI L, et al. A real-time classifier for emotion and stress recognition in vehicle driver[C]//IEEE international symposium on industrial electronics. Hangzhou: IEEE, 2012: 1690-1695.

[37] YANG Z, KAY A, LI Y, et al. Pose-based body language recognition for emotion and psychiatric symptom interpretation[C]//25th international conference on pattern recognition. ElectrNetwork: IEEE, 2021: 294-301.

[38] EKMAN P, FRIESEN W V. Facial action coding system: a technique for the measurement of facial movement[M]. Palo Alto: Consulting Psychologists Press, 1978.

[39] ATHUKORALA K, DOROTA GÓWACKA, JACUCCI G, et al. Is exploratory search different? a comparison of information search behavior for exploratory and lookup tasks[J]. Journal of the Association for Information Science and Technology, 2016, 67(11): 2635-2651.

[40] ANDERSON L W, KRATHWOHL D R, AIRASIAN P W, et al. A taxonomy for learning, teaching, and assessing: a revision of bloom' s taxonomy of

educational objectives[M]. New York: Longman, 2001.

[41] KELLY D, ARGUELLO J, EDWARDS A, et al. Development and evaluation of search tasks for IIR experiments using a cognitive complexity framework[C]//Proceedings of the 2015 international conference on the theory of information retrieval. Northampton: ACM, 2015: 101-110.

[42] LI Jingjin, HUANG ?, YUAN Xin, et al. Definition and Application of User Affective Factors in the Field of Information Query and Retrieval[J]. Library and Information Service, 2019, 63(7): 63-71.

[43] SCHERER K R. What are emotions? and how can they be measured?[J]. Social science information, 2005, 44(4): 695-729.

[44] CHEN H, GU Y, WANG F, et al. Facial expression recognition and positive emotion incentives system for human-robot interaction[C]//Proceedings of the 13th world congress on intelligent control and automation. Changsha: IEEE, 2019: 407-412.

[45] LI Haoran. Megvii AI Open Platform Face++: Support for Long-Tail Image Applications[J]. Artificial Intelligence, 2019(2): 76-86.

[46] EKMAN P, FRIESEN W V. Unmasking the face[M]. Cambridge MA: Malor Books, 2003.

[47] LI Shan, DENG Weihong. Research Progress on Deep Facial Expression Recognition[J]. Journal of Image and Graphics, 2020, 25(11): 2306-2320.

[48] WATSON D, CLARK L A, TELLEGEN A. Development and validation of brief measures of positive and negative affect: the PANAS scales[J]. Journal of personality and social psychology, 1988, 54(6): 1063-1070.

[49] WATSON D, WIESE D, VAIDYA J, et al. The two general activation systems of affect: structural findings, evolutionary considerations, and psychobiological evidence[J]. Journal of personality and social psychology, 1999, 76(5): 820-838.

[50] QIU Lin, ZHENG Xue, WANG Yanfei. Revision of the Positive and Negative Affect Schedule (PANAS)[J]. Chinese Journal of Applied Psychology, 2008, 14(3): 249-254, 268.

[51] ARGUELLO J. Predicting search task difficulty[C]//European conference on information retrieval. Amsterdam: Springer, 2014: 88-100.

[52] LIU C, LIU J, BELKIN N J. Predicting search task difficulty at different search stages[C]//Proceedings of the 23rd ACM international conference on information and knowledge management. Shanghai: ACM, 2014: 519-578.

[53] LIU J, LIU C, COLE M, et al. Exploring and predicting search task difficulty[C]//Proceedings of the 21st ACM international conference on information and knowledge management. Maui: ACM, 2012: 1313-1322.

[54] AI Hui, ZHOU Hui, HUANG Yuxia. Cross-Cultural Universality and Differences in Emotion: Implications for Educational Practice[J]. Global Education Outlook, 2015, 44(11): 104-113.

[55] LIM N. Cultural differences in emotion: differences in emotional arousal level between the East and the West-ScienceDirect[J]. Integrative medicine research, 2016, 5(2): 105-109.

[56] SHARMA P, JOSHI S, GAUTAM S, et al. Student engagement detection using emotion analysis, eye tracking and head movement with machine learning[EB/OL]. [2022-01-21]. https://arxiv.org/abs/1909.12913.

[57] WEI Yantao, LEI Fen, HU Meijia, et al. A Review of Research on Student Facial Expression Recognition[J]. China Educational Informationization, 2020(21): 48-55.

[58] D'MELLO S K, GRAESSER A C, PICARD R W. Toward an affect-sensitive AutoTutor[J]. IEEE intelligent systems, 2007, 22(4): 53-61.

[59] MCDANIEL B, D' MELLO S, KING B, et al. Facial features for affective state detection in learning environments[C]//Cognitive science society. 2007: 467-472.

[60] FENG Ying, GAN Yiqun, LIU Zhixiao, et al. Exploring the Relationship between Uncertainty Response Style and Future-Oriented Coping: The Mediating Role of Anticipated Emotion[J]. Acta Scientiarum Naturalium Universitatis Pekinensis, 2015, 51(3): 485-494.

[61] VERONICA G, DEREK R. Coping with uncertainty: the construction and validation of a new measure[J]. Personality and individual differences, 2001, 31(4): 519-534.

[62] LIU Chang, ZHAO Yu, YANG Fan. Research on the Influence of Time Limit and Task Order in Information Retrieval User Experiment Design[J]. Library and Information Service, 2015, 59(1): 99-105.

[63] MAULE A J, HOCKEY G R J, BUDZOLA L. Effects of time-pressure on decision-making under uncertainty: changes in affective state and information processing strategy[J]. Acta psychologica, 2000, 104(3): 283-301.

[64] CHEN S Y, RIEH S Y. Take your time first, time your search later: how college students perceive time in Web searching[J]. Proceedings of the American Society for Information Science and Technology, 2009, 46(1): 1-19.

[65] NAHL D. Measuring the affective information environment of Web searchers[C]//Proceedings of the 67th annual meeting of the American Society for Information Science & Technology. Medford: Information Today, 2004: 191-197.

[66] XU Zhenguo, ZHANG Guanwen, MENG Xiangzeng, et al. Learner Emotion Recognition and Application Based on Deep Learning[J]. e-Education Research, 2019, 40(2): 87-94.

[67] WEHNER C, SCHILS T, BORGHANS L. Personality and mental health: the role and substitution effect of emotional stability and conscientiousness[EB/OL]. [2022-01-21]. https://papers.ssrn.com/sol3/papers.cfm?abstract_{id}=2864838.

[68] QURTUBIA. Analysis of students' emotional stability, parenting style and teaching method on student learning achievement: a case study of junior high school student in jakarta[J]. Asian journal of management sciences & education, 2016, 5(2): 101-109.

[69] KUMAVELU G. Emotional stability of high school students in relation to their selected variables[J]. Journal of emerging technologies and innovative research, 2018, 5(1): 167-169.

[70] QIU Minghui, QIU Yuqi. Research on the Design of Help Functions Supporting Exploratory Queries[J]. Journal of Library and Information Science in Agriculture, 2021, 33(3): 56-67.

[71] ZOU Wei. An Empirical Study on the Influence of University Librarians' Behavior on Reader Participation Based on the SOR Model[J]. Agricultural Library and Information, 2019, 31(10): 76-81.

[72] WHITEHILL J, SERPELL Z, LIN Y C, et al. The faces of engagement: automatic recognition of student engagement from facial expressions[J]. IEEE transactions on affective computing, 2014, 5(1): 86-98.

[73] WALBOTT H G. Bodily expression of emotion[J]. European journal of social psychology, 1998, 28(6): 879-896.

[74] CHEN Zijian, ZHU Xiaoliang. Research on Automatic Recognition of Learners' Emotions Based on Facial Expressions: Appropriateness, Current Status, Existing Problems, and Improvement Paths[J]. Journal of Distance Education, 2019, 37(4): 64-72.

Author Contributions:
Huang Kun: Proposed research topic, designed study, finalized manuscript;
Zheng Mingxuan: Participated in study design, collected and analyzed data, wrote manuscript;
Luo Shichao: Participated in data analysis and discussion revision;
Jin Jian: Participated in study design and discussion of data analysis.

Note: Figure translations are in progress. See original paper for figures.