Review of the Current State of Emotion Research in Library and Information Science (Postprint)

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Abstract

[目的/意义] By reviewing the current status and development trajectory of emotion research in library and information science, this study aims to identify core authors and important literature within this domain, summarize relevant research frameworks and characteristics, and forecast future research trends.[方法/过程] This study analyzes emotion research literature in library and information science from databases such as Web of Science, LISA, and Google Scholar, employs HistCite software to mine and analyze citation data, and constructs an emotion research framework using content analysis methodology.[结果/结论] Emotion research in library and information science is in a period of rapid development, with research on emotions in human-computer interaction and IT utilization, as well as in information behavior, being directions of considerable interest to library and information science scholars, and identification of user sentiment orientation in social network environments representing a hotspot research direction. Emotion research in library and information science also faces challenges requiring breakthroughs, including lagging theoretical development and mixed terminology and classification systems.

Full Text

Preamble

A Review of Current Status of Emotion Research in Library and Information Science

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Abstract:
[Purpose/Significance] This study systematically analyzes the status and historical development of emotion research in Library and Information Science (LIS) to identify core authors and key literature within this thematic scope, summarize relevant research frameworks and characteristics, and project future research trends. [Method/Process] Using LIS emotion research literature from Web of Science, LISA, and Google Scholar as the analytical objects, this study employs HistCite software for citation data mining and analysis, and adopts content analysis to construct an emotion research framework. [Result/Conclusion] Emotion research in LIS is in a period of rapid development, with human-computer interaction and IT utilization, as well as emotion research in information behavior, being directions that LIS scholars emphasize. User emotion tendency identification in social network environments represents a hot research direction. However, LIS emotion research still faces challenges such as lagging theoretical development and mixed terminology and classification systems that need to be overcome.

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In early LIS research, emotion as a factor in understanding user information behavior did not receive much theoretical attention. Since the 1960s, with the continuous development of cognitive psychology and other disciplines, the cognitive information processing theory advocated incorporating cognition, emotion, and motivation into the analytical framework of human behavior. The Theory of Reasoned Behavior posits that individual behavioral intention is determined by behavioral attitude and subjective norms. Emotion is an important factor affecting individual beliefs and attitudes, which in turn influences perception, judgment, decision-making, and creativity. LIS scholars have fully absorbed rich theoretical achievements from related disciplines, with research focus gradually shifting from "system-centered" to "user-centered," beginning to explore emotional factors affecting user information behavior. LIS scholars propose that human physiological needs, psychological (or emotional) needs, and cognitive needs interact to jointly trigger user information-seeking behavior, and have investigated factors that stimulate user emotions in information retrieval environments, as well as the interrelationships among emotion, cognition, and information retrieval behavior.

The rise of affective computing and emotional design in the 1990s propelled exploration of emotion recognition and sentiment tendency prediction during user-information system interactions. Subsequently, with the proliferation of search engines and social media networks, users' channels for producing, acquiring, and processing information have become increasingly diverse, and the information value derived from sentiment analysis has grown richer. Faced with this new social information environment, traditional cognition-based behavioral models cannot fully capture users' rich emotional responses, urgently requiring

LIS scholars to propose more systematic and comprehensive emotion analysis frameworks. This paper aims to systematically review the development trajectory and research characteristics of emotion research in the LIS field, summarize existing problems and development directions, and provide reference for future LIS emotion research.

2 Literature Acquisition and Analysis

This study selected Web of Science, LISA, and Google Scholar as data sources, restricting the subject area to Information Science & Library Science. The search query limited topic terms to TS=("emotion" *or* " *sentiment*" or "affect" *or* " *mood*" or "feeling" *or* " *sensation*" or "flow theory" or "affective load" or "anxiety" *or* " *enjoyment*"), with document type set as "Article" and cutoff date of December 31, 2020. After data cleaning to remove publications with unclear dates or out-of-scope content, a total of 3,161 documents were obtained.

Subsequently, HistCite software was used to calculate publication metrics. Citation analysis methods were employed to identify highly cited literature, excavate core research teams, and conduct citation clustering analysis to reveal the developmental trajectory of emotion research. The analysis primarily utilized statistical indicators such as Local Citation Score (LCS, reflecting a publication's influence within the discipline), Total Local Citation Score (TLCS, total citations for an author or institution within the dataset), and Total Global Citation Score (TGCS, total citations across the entire database). Based on this, comprehensive content coding analysis was performed on highly cited literature and the latest publications retrieved from LISA and Google Scholar to summarize the emotion research framework and characteristics.

3 Statistical Analysis Results

3.1 Developmental Stages of Emotion Research in LIS

Statistical results show that since the first publication in 1935, emotion research in LIS has roughly experienced three periods: 1935-1990 as the initial budding stage with few annual publications, where LIS scholars' emotion research was relatively independent (TLCS was zero in most years). However, some representative achievements emerged during 1981-1990, explaining the theoretical evolution of emotion and viewing emotional response as a dynamic rather than static process, while exploring how emotion affects identity cognition, social interaction, life experience, and library anxiety, laying the foundation for subsequent research.

1991-2005 was a slow development period, with annual publication volume beginning to rise gradually. TLCS and TGCS no longer had zero years, indicating increased mutual reference within the LIS discipline and growing external attention to research results. After 2005 represents the rapid growth period, with significant increases in publication volume and consistently high TLCS and TGCS.

Notably, TLCS and TGCS began to show a clear declining trend after 2016, partly due to citation delays and possibly due to the dilution effect from the substantial increase in empirical research on web text sentiment analysis, as shown in Figure 1 [Figure 1: see original paper].

3.2 Core Research Teams, Representative Works, and Publishing Journals

By combining the top 40 authors ranked by TLCS and TGCS, merging their co-authorship relationships, and screening for those with at least two collaborative publications, 10 major research teams and their representative works with highest LCS were identified (see Table 1). M. Thelwall' s team has conducted extensive research on sentiment detection methods for social network texts, becoming the most influential research team. Other teams focus on topics including sentiment analysis in social media, direct and indirect effects of emotion on IT use, while emotion theory and methodology research have also become focal points. For example, I. Lopatovska and I. Arapakis summarized theories, methods, and current status of emotion research in LIS; Swiss psychology professor K.R. Scherer studied the definition, classification, and measurement of emotion, with his research receiving high recognition in LIS. R. Savolainen' s team focused on the role of emotion in user information-seeking behavior, finding that emotion can serve as a motivational factor often related to users' cognition and environment.

Analysis of authors' disciplinary backgrounds reveals that emotion research in LIS features multidisciplinary participation and collaborative research. In addition to LIS scholars from information systems, webometrics, management information systems, and information science, contributions also come from non-LIS disciplines such as computer science, psychology, business administration, and enterprise management. Chinese scholars from City University of Hong Kong' s School of Information Systems and Wuhan University' s School of Information Management rank in the top 3 for institutional publication volume, though research remains relatively dispersed. Zhang Changli' s team from Jilin University explored Chinese text sentiment polarity detection from sentence to full-text level, representing another highly influential achievement.

The top 10 journals by publication volume are shown in Table 2 . In addition to journals like Information Processing & Management and International Journal of Information Management, three medical background journals appear, indicating that health information research is an important direction in LIS, as analyzing users' emotional reactions when acquiring and processing health information has attracted considerable scholarly attention.

3.3 Citation Chronological Cluster Analysis

This study utilized HistCite' s citation chronology component to cluster highly cited literature and discover research development trajectories. LCS reflects the importance of a publication within the field. This paper selected the Top 40 LCS-ranked literature (the software' s default threshold is 30; larger thresholds produce poor visualization effects) to construct a citation chronology diagram (see Figure 2 [Figure 2: see original paper]). Each circular node represents a publication, with circle size indicating citation frequency and arrows pointing to cited literature. The chronology diagram contains 40 nodes and 44 links. Excluding 7 isolated nodes, 33 connected nodes formed three relatively clear clusters spanning 1992-2016.

(1) Cluster One: Emotion Research in Information Retrieval Behavior. This cluster' s publications are earliest, mainly concentrated in 2005-2009, formed through citation relationships centered around I. Lopatovska and I. Arapakis' s research (node 845), with relatively sparse connections between nodes. The top 4 LCS-valued publications in this cluster are all review articles summarizing concepts, theories, and research methods of "emotion" and the current status of emotion research in LIS. Other empirical studies focus on factors triggering various emotional experiences during information retrieval (online or offline), relationships between emotion and cognitive variables, and emotion' s mechanism of action. Scholars' disciplinary backgrounds and research content in this cluster exhibit typical LIS characteristics.

(2) Cluster Two: Human-Computer Interaction Emotion Experience Research. Publications in this cluster mainly span 2006-2011, including the earliest publication (J. Webster, J.J. Martocchio, "Microcomputer playfulness: development of a measure with workplace implications," 1992), formed through citation relationships around S. Gregor' s research (node 1163). S. Gregor' s team introduced neuroscience into HCI emotion research, classifying emotion response types under dimensional perspectives into Hedonic valence, Arousal, and Dominance, constructing a rule network composed of three emotion systems (physiological, linguistic, behavioral) - an important theoretical and methodological innovation in emotion analysis. J. Webster' s study (node 82) serves as this cluster' s "origin," using questionnaires with five different subject groups to discover that microcomputer playfulness correlates with "computer attitude, computer anxiety, computer competence, and computer efficacy" but not with gender or age, suggesting more attention should be paid to positive rather than negative impacts of human-computer interaction. The highest LCS publication comes from A. Beaudry and A. Pinsonneault's research (node 781), which, based on IT adoption theory, emotion appraisal tendency framework, and adaptation models, found through interviews and questionnaires that emotion relates indirectly to IT use through adaptation behaviors (e.g., seeking instrumental/social support, venting, psychological distancing), with limited direct relationships.

(3) Cluster Three: Network Text Sentiment Detection. Publications in this cluster have a relatively later average publication date, concentrated in 2009-2016, closely related to the rise and development of social networks. Citation relationships among literature are interwoven, with denser connections between nodes. Research contexts involve rich scenarios such as political activities, online marketing, and hot public opinion events in social media, detecting user sentiment tendencies to serve organizational competitive strategies. M. Thelwall team' s empirical research represents typical work, using hybrid classification and data mining methods for sentiment polarity classification of social media texts and movie product reviews, then developing and improving the SentiStrength algorithm for text sentiment intensity detection. However, this algorithm uses sentiment intensity lexicons with limited detected words. In response, H. Saif' s team developed the SentiCircles algorithm that dynamically detects sentiment intensity and polarity of words in context. S. Stieglitz and L. Dang-Xuan' s research (node 1043) bridges this cluster, exploring the relationship between emotion and information diffusion in social media environments. Using sentiment polarity analysis and regression methods, they comprehensively analyzed relationships among user political orientation, communication format, user activity dimensions, and emotions (positive/negative), finding that emotional Twitter messages are retweeted more and faster than neutral messages.

The remaining 7 isolated nodes are mostly interdisciplinary empirical studies, including Chinese text sentiment polarity detection (node 703), polarity shift correction (node 1438), and self-training-based sentiment analysis methods (node 846). Although these isolated nodes didn' t connect with others to form clusters, their unique research perspectives and methods remain highly valuable for research and learning.

3.4 LIS Emotion Research Framework and Characteristics

To reveal general approaches in LIS emotion research, this study employed content analysis. Based on highly cited literature and their references extracted in Section 3.3, combined with the latest literature retrieved from LISA and Google Scholar, key information was extracted and coded according to the "information activity context - stimulus event - emotional response" and "research theory - research question - research method" frameworks, resulting in the LIS emotion research framework shown in Figure 3 [Figure 3: see original paper].

3.4.1 User Information Activity Contexts and Emotional Cues LIS user emotion research relies on rich user information activity contexts, covering micro-level individual information activities such as information retrieval, information dissemination, IT system use, online shopping, and healthcare; meso- and macro-level social events such as government tweets, political elections, and social hot events. Emotion research in information behavior and human-computer interaction generally follows the "stimulus - response - behavioral tendency or outcome" framework. Emotional stimulus cues refer to specific factors that trigger user emotions. For example, in IT use contexts, emotional cues involve deploying new systems, computer playfulness, and IT use paradigms; in online shopping contexts, website characteristics (e.g., visual features, music) are important stimulus factors. Different information activity contexts contain different emotional stimulus cues that trigger rich user emotional responses.

3.4.2 LIS Emotion Research Theories and Research Questions Regarding research theories, LIS scholars have extensively borrowed emotion-related theories from psychology based on information behavior theory and IT use theory. For emotion definition and composition, there is the emotion component theory. For emotion generation, cognitive appraisal theory and somatic theory are widely borrowed. For emotion classification, discrete emotion theory, continuous emotion theory, and flow theory are involved. For emotion mechanisms, S-O-R theory, emotion function theory, emotion event theory, and emotion appraisal tendency theory are borrowed. LIS scholars rarely propose complete emotion theoretical models, such as D. Nahl' s affective load theory. Most researchers embed emotion factors into information behavior cognitive models or IT technology adoption models, such as C.C. Kuhlthau' s ISP model, T.D. Wilson' s information behavior model, and A. Beaudry and A. Pinsonneault' s user adaptation model.

3.4.3 Emotion Response Measurement Dimensions and Research Methods Currently, LIS scholars measure user emotion states across three systems: linguistic, physiological, and behavioral, employing corresponding methods. For example, self-report methods (e.g., questionnaires) measure users' subjective emotional experiences; text automatic processing methods like data mining and machine learning combined with emotion lexicons extract and classify emotions from large linguistic datasets; neurophysiological signal processing methods measure users' bodily emotion states; observation and facial recognition methods capture behavioral emotion responses.

Overall, LIS user emotion research content and methods exhibit the following characteristics:

(1) Ambiguity in Emotion Definition and Classification. The ambiguity stems from emotions' subtle and changeable nature, and because conceptualizing emotion research requires natural language, which itself is fuzzy and constantly evolving, making consensus difficult. Despite long-standing research on emotion' s meaning and nature, the academic community still lacks consensus on what "emotion" is. P.R. Kleinginna et al. summarized over 100 emotion definitions. K.R. Scherer proposed using design features to define "emotion," distinguishing it from "preferences," "attitude," "mood," etc., across dimensions including event focus, appraisal-driven nature, synchronized response, change speed, behavioral impact, and intensity. LIS user emotion research uses mixed terminology, with interchangeable emotion vocabulary further blurring conceptual definitions.

Currently, LIS emotion classification methods mainly fall into two categories: discrete and continuous perspectives. Discrete classification uses natural language emotion vocabulary to express individual emotions, divided by polarity into positive (joy, pleasure, interest) and negative (boredom, sadness, fear); by complexity into basic and complex emotions. For example, M. Power and T. Dalgleish proposed five basic emotions: sadness, happiness, anger, fear, and disgust. A. Beaudry and A. Pinsonneault developed a composite emotion framework through primary and secondary appraisal based on user adaptation models and emotion appraisal theory. Continuous classification is a structured description of subjective feelings, positing that emotions have multiple attributes, each with negative and positive endpoints. Main two-dimensional methods include "valence-arousal" and "energy-tension"; three-dimensional methods include "intensity-similarity-polarity," "valence-control-activation," and "pleasure-arousal-dominance." Flow theory uses a three-dimensional system of "control-focus-cognitive enjoyment" to construct flow emotional states. Continuous classification lacks the intuitiveness of discrete emotion expression but provides interval data for statistical analysis.

(2) Multi-level Nature of Emotion Influencing Factors. Two representative views exist on emotion generation: cognitive appraisal theory and somatic theory. Cognitive appraisal theory posits that emotion originates from evaluative perception of person-environment relationships, with cognitive activity as the prerequisite for emotion generation. Somatic theory suggests bodily reactions trigger psychological emotional responses, subsequently generating corresponding motivation and behavioral outcomes. Emotion function theory views emotion as goal-oriented states. Appraisal tendency framework theory holds that emotion has long-term effects on user attitudes, judgments, beliefs, decisions, and behaviors, assuming each emotion carries motivational properties influencing subsequent events and actions until the emotional stimulus is resolved.

Researchers have found that individual factors such as age, gender, information literacy level, and emotional capacity significantly affect user emotional responses. M. Thelwall et al. manually coded 1,000 MySpace comments, finding women express more positive emotions than men. S. Gregor et al.' s rule network experiment based on three-order emotion systems found user information literacy can reduce negative emotions in information activities. J. Kracker reached similar conclusions in an information retrieval controlled experiment. I. Lopatovska and C. Cool found individual differences in emotion expression capacity in online search studies - one subject' s face expressed 57 strong emotions while another expressed only 9 during the same search duration.

Interpersonal factors also affect user emotions. M.K. Stein et al. found in a faculty productivity software use survey that positive IT tool discussions among users generate feelings of accomplishment, while complaints or insufficient interaction cause loss. A. Beaudry and A. Pinsonneault reached similar conclusions.

Environmental factors involve cultural context, task difficulty, and information system characteristics. R. Savolainen argued that emotion phenomena intertwine with cognitive and environmental factors in user information-seeking behavior motivation research. C.S. Wu et al. found warm colors have higher arousal capacity than cool colors, and fast-tempo music stimulates user pleasure more than slow-tempo music, with certain colors providing cognitive cues in specific cultural contexts. Task difficulty and outcomes also affect user emotional experiences. J. Hyldegård found uncertainty about retrieval tasks increases frustration in collaborative information behavior research. Z. Guo's team discovered that in online learning contexts, students' balance between challenge and skill, goal clarity, timely feedback, and presence significantly affect flow experience.

(3) Complexity of Emotion Mechanisms. Scholars have analyzed emotion triggers and pathways from different theoretical perspectives. Environmental psychology theory posits direct and indirect links between environments (physical and social) and emotion generation. Emotion function theory considers emotion as goal-oriented states. Appraisal tendency framework theory assumes emotion has long-term impacts on user attitudes, judgments, beliefs, decisions, and behaviors, with each emotion carrying motivational properties influencing subsequent events until resolution.

Most studies show positive emotions promote users' information approach intention or sharing behavior, while negative emotions increase avoidance intention. Z. Jiang and I. Benbasat found in flow research that higher user engagement and exploratory emotions help product understanding and increase return intention. S.M. Zavattaro et al. analyzed U.S. local government tweets using a government social media interaction framework, finding positive emotional tweets better promote citizen engagement (retweets, comments). C.S. Wu and L. Deng both found pleasure positively affects user approach behavior (browsing, purchasing), though L. Deng further discovered calm users in task-oriented environments are more willing to browse webpages, while entertainment-oriented environments show higher browsing intention when users feel more pleasant. J. Gwizdka and I. Lopatovska found pre-search anxiety or unpleasantness prompts students to access more pages, view results, revisit, and save bookmarks, leading to more satisfactory results, indicating negative emotions may also produce approach effects. Thus, different emotion types' mechanisms and effects require context-specific verification.

Some scholars study emotion's indirect effects. A. Beaudry and A. Pinsonneault found bank customer managers' emotional responses to new IT technologies indirectly affect IT use patterns through adaptive behaviors (e.g., seeking tutorials, social support), with limited direct effects. C.H. Hsiao et al. found in mobile social app continuance intention research that users' value perception (usefulness, hedonic emotion, social influence) positively affects satisfaction and usage habits, indirectly promoting continuance intention.

(4) Methodological Diversity and Integration. LIS emotion research methods include self-report, experimentation, data mining, neurophysiological signal analysis, and observation, with increasing integration of multiple methods. For example, J.F. Nunamaker et al. designed an information kiosk integrating various physiological sensors to collect facial expressions, voice, body temperature, and other signals for emotion recognition. S. Gregor et al. combined EEG measurement with self-report methods for contextual interpretation. Speech analysis concepts have been applied to emotion lexicon construction, and computer logs (a special observation method) extract social media users' comments, retweets, and likes. J. Kim et al. combined control, hypothetical scenario, and questionnaire methods to study computer abuse behavior tendencies under negative event stimuli (demotion, pay cuts, conflicts).

Self-report methods require participants to describe emotional experiences, necessitating emotion recognition ability, typically obtained through interviews, diaries, think-aloud protocols, and questionnaires. These methods often borrow emotion scales, divided into discrete and continuous types. Common discrete scales include Izard' s Differential Emotions Scale, CES Consumer Emotion Set, Positive-Negative Affect Schedule (PANAS), State-Trait Anxiety Inventory (STAI), and stress coping scales. Continuous scales constitute "three-dimensional emotion" through valence, arousal, and dominance ratings, though typically only valence and arousal are measured to form "two-dimensional emotion." Common dimensional scales include PAD, SAM, and flow Webster scales. In self-report methods, participants sometimes inaccurately understand scale terminology, causing data bias. I. Lopatovska and I. Arapakis summarized free-report methods allowing participants to freely use words expressing their emotional experiences for finer-grained data.

Experimental research is also common, where researchers provide different information environments and emotional trigger levels by controlling platform interface, audio-visual elements, operation difficulty, and information organization, or design different information behavior tasks (e.g., shopping, retrieval) to create emotion-generating scenarios. For example, D.V. Parboteeah et al. designed a simulated website controlling webpage resolution, icons, and information bars to design different emotional cues, then measured impulse purchase desire through purchase amounts.

Neurophysiological signal methods and observation methods require specific equipment, have high research thresholds, and struggle to disentangle intertwined emotional, psychological, or physiological factors. Researchers attempt to combine multiple methods to meet different research needs. With social network text sentiment analysis becoming a hotspot, computational methods from computer science have been introduced, including sentiment text detection algorithms, machine learning, and data mining, focusing on identifying sentiment polarity or intensity in text datasets. Multiple method integration is emerging, such as J. Kim et al.' s combination of control, hypothetical scenario, and questionnaire methods to study computer abuse under negative stimuli.

Currently, LIS emotion research, particularly in information retrieval behavior, remains dominated by self-report methods, with integrated multi-method research urgently needing enrichment. Scholars focus on factors affecting user emotion, emotion state characteristics, and emotion mechanisms, especially the relationship between emotion and cognition/behavior, emotion-IT system interaction, and sentiment intensity/polarity detection methods. Analysis of emotion triggers, influencing factors, and mechanisms requires further contextual exploration, suggesting the field remains in its early stages.

4 Conclusions and Future Directions

4.1 Conclusions

This paper conducted citation analysis of LIS emotion research literature, organized publication volume and citation metrics to trace the temporal development, identified representative research teams and their major achievements, and performed cluster and content analysis on highly cited and recent literature to map out the emotion research framework in LIS. Overall, LIS emotion research has significantly increased in quantity and influence, with research themes continuously extending around information behavior, human-computer interaction, and social media. In terms of research levels and methods, micro-level analysis focuses on individual emotion triggers and effects in information activities through interviews, questionnaires, and instrument recordings for fine-grained measurement, analyzing associations among emotion, cognition, and information behavior elements within behavioral model frameworks. Macro-level analysis examines associations among public group emotional expressions, event development, participation, and identity identification in large-scale social events. For massive text, image, audio, and video datasets, researchers employ computational sentiment analysis methods from computer science, combining supervised and unsupervised machine learning for automated emotion data extraction and classification.

However, LIS emotion research remains immature, with mixed terminology and classification systems, limited development of emotion theoretical models integrating disciplinary characteristics, and insufficient multi-dimensional integration of emotion measurement across linguistic, physiological, and behavioral systems. Multi-method fusion research is rare; obtaining subjective emotional experiences through individual self-report or measuring/predicting emotional responses through text analysis is more common. Although scholars have proposed various emotion measurement methods, equipment, funding, and technical limitations constrain current practice. LIS emotion research, particularly in information retrieval behavior, remains dominated by self-report methods, with multi-method integrated research urgently needing enrichment. Research questions mainly include factors influencing user emotion, emotion state characteristics, and emotion mechanisms, with particular attention to emotion-cognition-behavior relationships, emotion-IT system interactions, and sentiment intensity/polarity detection methods. Emotion triggers, influencing factors, and mechanisms require further contextual exploration, indicating the field remains in its early stages.

4.2 Future Directions

Emotion is considered a fundamental social phenomenon constituting the basis of various social activities and interactions, playing important roles in socialization processes. Emotion research is a highly comprehensive cross-disciplinary field involving neuroscience, clinical medicine, computer science, philosophy, linguistics, anthropology, and LIS. Some scholars have even discussed whether current research has "moved beyond the behaviorism and cognitivism eras into the affectivism era." Future LIS research can expand across research paradigms, contexts, methods, and content.

4.2.1 Integrating Emotion Research Paradigms Current LIS emotion research, despite attracting many scholars, seems to "simmer beneath the surface" and should "rise to the surface" for deep integration with social research paradigms. More comprehensive consideration of emotion and emotional factors should form an integrated "socio-emotional paradigm" research model. Future directions may include continuing to integrate individual-level emotion research paradigms, such as incorporating emotional factors into personal perception paradigms. Individual differences in emotion recognition ability have not been well explained at the Big Five personality level, while broader connections between metacognitive ability and emotional capacity remain worthwhile research directions. Additionally, core concept definitions need improvement and unification. Given the fuzziness of natural language in describing emotion concepts, LIS could attempt to use controlled language to standardize core emotion definitions.

4.2.2 Expanding Emotion Research Contexts Current research primarily focuses on online shopping, political elections, and academic information retrieval contexts. Future research can extend to more diverse information activity scenarios such as healthcare, AI services, voice interaction, disaster prevention, and mobile social applications, exploring user emotion triggers and mechanisms in more complex information environments. Regarding platform selection, current studies mainly use text-based social media platforms like Twitter and Weibo, or e-commerce platforms like Taobao and Amazon. Future research can attempt to select multimodal platforms like Instagram and TikTok as data sources, where LIS scholars have begun making breakthroughs.

Emotion research is a cross-disciplinary topic requiring LIS scholars to strengthen interdisciplinary integration and borrow rich theoretical achievements from multiple disciplines. For example, current LIS research has introduced flow theory, enabling investigation of flow experience effects on different groups in specific contexts to construct multi-level user cognition-emotion-behavior interaction models. Combining experimental research, log mining, and sentiment computing can excavate and analyze users' internal and external emotional expressions, expanding through richer user behavior patterns to test different emotion types' regulatory and feedback mechanisms, thereby promoting more mature LIS emotion research theories and more systematic paradigms.

4.2.3 Enriching Emotion Measurement Methods and Approaches Emotion itself is a difficult psychological attribute to measure. Current emotion measurement relies primarily on self-report (questionnaires, diaries), which risks recall bias and struggles to distinguish intertwined emotion types. Some studies use instruments to detect brain cortex activity, heartbeat, and other neurophysiological responses, but this raises experimental thresholds. Observation methods easily introduce noise. Computer science scholars have developed sentiment lexicons and clustering algorithms based on text automatic processing, using machine learning to improve automated sentiment prediction and identification. Future research can attempt to introduce AI, big data, and other emerging technologies to enhance sentiment detection intelligence and convenience, improving recognition accuracy. Multi-method integration to finely capture and depict multimodal user emotion response data represents a significant future research characteristic.

Computer technology applied to sentiment analysis can automatically extract and classify sentiment from large-scale, multimodal information, continuously modifying and updating algorithms to improve measurement speed and accuracy, placing higher demands on LIS researchers' computer application abilities. Current automatic sentiment measurement technologies have been applied in social media analysis, word-of-mouth marketing, online public opinion analysis, and civic political activities, with future applications expandable to customer service, government governance, risk warning, and decision-making.

4.2.4 Strengthening Research on Emotion Classification, Evolution, and Mechanisms Currently, no systematic and complete user emotion type classification list exists. Most LIS research only analyzes static discrete emotion types in specific contexts, with dynamic, continuous emotion mechanism research needing strengthening. Due to the complexity and variability of emotion triggers, influencing factors, and manifestations, emotion mechanisms lack consistent research conclusions. The relationship between user emotion and cognitive behavior requires in-depth verification combining organizational contexts and cultural environments. Users' emotional capacity is an important component of emotional intelligence (EI), including emotion recognition ability, expression ability, regulation ability, understanding ability, empathy, and emotion style. Exploring multimodal emotion recognition ability assessment methods (ERAM) (silent video, audio, video-with-sound) can effectively measure subjects' emotion recognition ability. LIS emotion research should expand from current "emotion effect research" to "emotion utilization research," focusing more on emotion feedback and compensation mechanisms. Additionally, the relationship between personalized interfaces and user emotion improvement, and how to use multimodal emotion data to perfect information system design, are directions worthy of in-depth research.

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