

Digital Representation of Emotions through Social Media: A Systematic Review on Tracking Emotions

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Systematic Review

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Abstract

The present systematic review aims to synthesise the existing evidence on tracking the digital representation of emotions through social media platforms, thereby providing scope for identifying users' emotional vulnerability and emotional psychopathology. Emotions are central to human experience, and their expression has undergone a major shift with the rise of digital media platforms. Social media currently serve as a primary medium of communication and emotional exchange. The PRISMA, 2020 guidelines were followed in this systematic review. The review was conducted on four databases, including Scopus, Web of Science, PubMed, and APA Psycnet. The final list consists of 28 articles, specifically focusing on emotional representation through social media, published in English and selected based on the inclusion and exclusion criteria. The findings show an acceleration in interdisciplinary research on emotional representation and digital media, with 90% of studies published after 2022. The most widely researched social media platform from the reviewed research articles was Twitter, with predominantly textual analysis using linguistic and semantic markers. A strong association was found from the reviewed articles on the recognition of the emotional patterns and the early detection of mood disorders and suicidal ideation. The review indicates the function of social media as an emotional expression outlet and a diagnostic mirror of the users' affective and psychological processes.

Introduction

Emotions were found to be central to human lived experiences. The explanations given to emotions from the early researchers were specifically in association with the physiological reactions or arousal. James-Lange, in the late 19th century, proposed and stated that emotions follow the physiological responses (Lang, 1994). Furthermore, Cannon in the early 20th century, stated the limitations of the James-Lange theory and suggested that emotions and physiological response pathways proceed in parallel without one following the other (Dror, 2013). Schachter and Singer introduced the dimension of cognitive labelling, leading to specific emotions (Cherry, 2025). However, the recent advancement in the study and concept of emotions has given the newest and most diversified dimensions and explanations to emotions.

The Modular or Discrete category approach and Dimensional approach of emotions are the two broad paradigms that dominate the theoretical landscape of emotions. The Modular approach to emotions views emotions as distinct modules or specific categories, focusing on emotions as states that take into account their triggers and features, such as anger, happiness, fear, and others. On the other hand, the dimensional approach considers emotions as varying along a continuous axis, such as valence (positive vs negative), arousal (high vs low), predominantly treating emotion as a process (Harmon-Jones et al., 2017). However, this paper adopts a more integrative and functional definition of emotion proposed by APA, which explains emotions as a complex reaction pattern that includes experiential, behavioural, and physiological components through which one tries to deal with a significant triggering event of life.

The definitions of emotion provided by each theoretical perspective predominantly explain the internal manifestation and formation of emotion; likewise, it is essential to understand and identify the patterns and ways through which emotions are represented externally. Emotion representation could be defined as the expression, communication, and sharing of emotions externally, through verbal or nonverbal means. The verbal emotional communication includes spoken or written forms of emotional representation, and the non-

verbal emotional representation includes facial expression, body language, voice tone, and artistic and symbolic representation. With the emergence and advancement of digital communication, emotional representation also shifted towards digital forms, such as text, images, symbols, and so on. In this advanced digital era, social media acts as a primary medium for emotional representation (Kapoor et al., 2018). Social media could be defined as a digital communication platform that facilitates interaction, content dissemination, and relationship-building among individuals and groups. The social media platforms support the exchange of information, emotions, and social meanings through various modes such as texts, images, emojis, hashtags, audio and video. It enables continuous social interaction across personal, professional, and socio-cultural contexts (Kapoor et al., 2018).

Social media is found to be a central mode of communication in the present generation, ranging from text messages to face-to-face through video interaction (Kaplan & Haenlein, 2010). It provides an open platform for users to build connections, express themselves, and engage in emotional exchange through multiple modalities. Self-presentation and self-disclosure are the mechanisms that facilitate social media's functioning at the heart of social media, providing opportunities for users to curate, share, and reveal personal information online (Kaplan & Haenlein, 2010). The social media platform features enable and facilitate the subtle ways of emotional actions and emotional expressions to a large extent (Steinert & Dennis, 2022). Currently, emotional representation has become a part of social media culture. They, along with the mitigation of private emotions, also facilitate social interaction. We generally prefer to broadcast or present positive emotional expression in public, and negative emotions, on the other hand, are mostly presented ironically, satirically or through an indirect mode, providing a collective outlet (Steinert & Dennis, 2022).

Being a central and significant part in human life, emotions were identified to be foundational. Hence, it is important to understand how emotions are represented in the recent advanced digital era. Understanding emotions as an internal process of the emotional representation is significant in developing knowledge of emotions from a psychological perspective with a communication lens, which is further expanded with the rise of digital media. Digital emotional representation is a significant new layer of recognising and tracking the patterns of emotions and their variations. Research indicates the crucial role of social media platform design in shaping emotional expression and interactions (Steinert & Dennis, 2022). The study further introduces emotional affordances, which refer to the features in social media as that facilitate specific emotional expressions, such as like and dislike buttons, reaction emojis, comments tab, share function, and automated suggestions (Steinert & Dennis, 2022). The notion of emotional architecture facilitated by social media platforms suggests that social media platforms are not merely neutral conduits for communication or emotional expression, but an active environment that shapes the emotional flow of users (Jorgenson, 2019). Digital media enables in the transformation of emotional experiences and emotional expression patterns through hashtags, viral campaigns, and symbolic outrage, through which emotions can rapidly circulate and inspire coordinated actions (Manikonda et al., 2018). The emotional architecture of social media facilitates both the expression and amplification of emotions. The emotional affordances and architecture introduced through the digital media creates the emotional condition in addition to their mediation role in interaction and emotional expression. Understanding the dual nature of social media by decoding the patterns of emotional expression and amplification among users could provide a wider scope for human-computer interaction through the emotional spectrum.

Rationale

The focus of the recent research was found increasingly in the area of emotional expression through social media; even then, the field remains widely fragmented. Studies in this area have limited scope with confined integration of theoretical framework. Further, the methodological rigour remains inadequate (Schreiner et al., 2019). Hence, the present systematic review aims to provide a structured and transparent synthesis of existing research papers on emotional representation through social media contexts, to address the gaps mentioned above. The two key questions covered in this systematic review are;

1. How do individuals represent different states and processes of emotions through varying modes of social media communication forms?
2. What are the characteristics and platform-specific variations based on specific emotional representation?

The current study seeks to deepen the understanding of the psychosocial dynamics of emotional representation in digital/online environments. It further provides direction for interdisciplinary research, thereby guiding digital well-being interventions and support systems for the design of emotionally supportive social media platforms and its healthy usage.

Methodology

A systematic review design was followed as per the PRISMA guidelines (2020) for synthesising and reviewing research articles. It aimed at finding evidence from authentic research articles in exploring the psychosocial dynamics of emotional representation through social media platforms. Four databases, including Scopus, PubMed, Web of Science, and APA PsycNET, were reviewed in this systematic review.

Inclusion & Exclusion criteria

Peer-reviewed research articles published in the English language were considered in this systematic review, which investigated emotional representation from posts or comments shared through social media platforms. Eligible studies examining emotional expression or perception across diverse socio-demographic groups ranging from adolescence to adulthood, considering all forms of users, involving active, passive or observational users. Adolescence is a critical period, characterised by identity formation, emotion regulation development and heightened peer influence. Social media plays a major role in emotion representation and social comparison of this group (Steinberg, 2014). The adults group generally demonstrates a stable and mature emotion regulation and variations in their motivations for social media usage, which also helps in making an understanding across developmental stages. The quantitative, qualitative, or computational studies, were considered to capture a comprehensive range of research evidence on the same. Case studies, secondary literature, or studies focusing on offline media were excluded. Literature published in languages other than English were also excluded.

Search Strategy

A strategic search was conducted across four databases (SCOPUS, APA PsycNET, PubMed, and Web of Science) from October 2024 to November 2024 with keywords such as "social media", "emotional

representation", "emotional states", and "emotion". Boolean operators and database-specific filters were utilised to refine search results by date (last 10 years) and language (English). The selection process comprised independent screening by reviewers based on title and abstract, followed by a full-text review for eligibility. The final selection of studies was made based on their relevance to the representation of emotions through social media, judged by independent reviewers. Any disagreements were resolved by reaching a consensus.

Data Extraction

Data collection involved the extraction of the following information from eligible studies by reviewers: general information (title, authors, year of publication), study characteristics (research design, social media context (platform(s), type of data - text, images, videos), type of emotions, representation characteristics (linguistic, symbolic, semantic features), and findings (main outcomes, implications, and research gaps). The filtration and extraction process lasted from November 2024 to June 2025. A narrative synthesis was performed to categorise findings based on the type of emotions, SMPs, representation style (e.g., textual vs. visual) and outcomes.

Results

The systematic review followed the PRISMA 2020 guidelines across four databases, including Scopus, PubMed, Web of Science, and APA PsycNET. The initial search resulted in a total of 421 articles. After the removal of 19 duplicates and 7 non-research articles from the list, a total of 395 research articles were screened for title and abstract. A total of 325 articles were removed after title and abstract filtration, and 70 articles were sorted for full-text retrieval, with 66 articles having full text accessed for eligibility. The primary reason for the exclusion of articles after reviewing the full text is due to the lack of clear focus on emotional representation ($n = 34$), and lack of clear distinct eligibility ($n = 4$). The final list consists of 28 articles which met all the inclusion and exclusion criteria. The detailed flow chart in the study selection is given in Fig. 1.1, the PRISMA flow chart.

The characteristics and summary of the 28 included studies are given in Table 1.1. Studies were spread across different nations, but a major focus was found with Asian countries (from China (31%), in collaboration with India (17%) & Saudi Arabia (10%), and the USA (24%)) as mentioned in Table 1.1. The chronological distribution of studies spikes after 2022, which accounts for 90% of studies as given in Table 1.1. The most frequently studied social media, according to these studies, was Twitter (25%), followed by Reddit (10%). The majority of the studies focused on analysing textual data through linguistic and semantic analysis (95%). Some of the studies used emojis and symbolic analysis (5%). The majority of participants across the

28 reviewed studies fall into adulthood, belonging to 19 to 64 years of age group (84.3%), and adolescence 13 to 18 years of age group (11.2%), and the remaining in late adulthood.

The review and synthesis of research articles indicates that a higher range of emotional representations were expressed and segregated through the verbal mode, more specifically through textual contents which were determined predominantly using linguistic (41%), semantic (39%) and lexical (19%) markers given in Fig. 1.3. Linguistic markers were frequently used in emotional words and phrases, narrative self-disclosure, pronoun

usage, informal language and slang. These linguistic patterns potentially represent immediate emotional responses, sustained emotional distress, and so on. The semantic markers were found to capture the underlying emotional meaning and intent beyond surface-level words and meaning. It indicates emotional states and thematic meaning based on subtle emotions such as anxiety, uncertainty or vulnerability could be inferred, and the emotional shifts over time were also being interpreted. This supports the contextual determination of emotions. Lexical markers used in emotional segregation are based on word frequency, emotional polarity, and affective lexicons. Even though the lexical markers were less likely to be used, but it remains essential in emotional valence and polarity with strength of emotion determination. The representation of emotions through social media was observed with the combination of explicit linguistic expression and implicit semantic meaning, supported by the lexical indicators.

The specific emotional representation and characteristics were found to highly vary based on the social media platform on communication affordances, user roles, and content domains of the major themes identified and shown in Fig. 1.4. The microblogging platforms such as Twitter, facilitate short, immediate emotional expression and high emotional intensity. It covers the themes, including public health, misinformation and breaking news. The influencers and celebrity-driven platforms such as Instagram indicate emotional amplification for social reach, users mirror disclosed emotions, and high emotional engagements. The community or support-oriented social media platforms show a more elaborate and reflective emotional representation, encouraging empathy and understanding facilitation. Support oriented social media features a more reflective emotional representation, encouraging empathy and facilitating understanding among users. In the support-based community online forums, highly arousing emotional expressions are less likely to dominate visibility, as they focus mainly on encouraging empathetic validation and coping. (Berger, & Milkman, 2012; Barak et al., 2008).

Table 1.1
Study characteristics

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
1	Happiness, stress, a bit of vulgarity, and lots of discursive conversation: A pilot study examining nursing students' tweets about nursing education posted to Twitter	2015	Canada	Richard G. Booth	Tweets about nursing courses, classes and clinical work were analysed using thematic analysis with five thematic clusters	Informal social media expression and need for digital professionalism among nursing students
2	Language-agnostic deep learning framework for automatic monitoring of population-level mental health from social networks	2022	Thailand	Thanapon Noraset, Krittin Chatrinan, Tanisa Tawichsri, Tipajin Thaipisutikul, Suppawong Tuarob	Proposes a language-agnostic deep learning framework as a feasible alternative to traditional methods for gathering mental health data across diverse populations.	Effective low-resource language framework for social media-based mental health monitoring
3	Deep parallel contextual analysis framework-based emotion prediction in community wellness communications on social media	2024	China	Feng Liu, Kun Hou, Yang Dong	Introduces the DPCAF framework, which uses dual word embedding techniques to better capture semantic information in short texts for wellness communications.	Deep contextual framework improving emotion prediction in short social media texts
4	A Deep Learning Framework for News Readers' Emotion Prediction Based on Features From News Articles and Pseudo Comments	2023	China	Xu Mou, Qinke Peng, Zhao Sun, Ying Wang, Xintong Li, Muhammad Fiaz Bashir	Proposes a block emotion attention network (BEAN) that merges article content with "pseudo-comments" to predict reader emotions, even when actual reader feedback is missing.	A hybrid framework enhancing emotion prediction in news articles through comment integration

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
5	Differing Content and Language Based on Poster-Patient Relationships on the Chinese Social Media Platform Weibo: Text Classification, Sentiment Analysis, and Topic Modelling of Posts on Breast Cancer	2024	Japan & New Zealand	Zhouqing Zhang, Kongmeng Liew, Roeline Kuijer, Wan Jou She, Shuntaro Yada, Shoko Wakamiya, Eiji Aramaki	Weibo posts on breast cancer fine-tuned through two step with Chinese BERT classification to identify poster-patient relationships determined using sentiment analysis using linguistic inquiry and word count	Influence of poster–patient relationship on emotional expression in health-related social media posts
6	Emotion Topology: Extracting Fundamental Components of Emotions from Text Using Word Embeddings	2024	Poland	Hubert Plisiecki, Adam Sobieszek	Go Emotions dataset of Reddit of communities with a minimum 10k comments with emotion taxonomy developed through manual annotations.	Word embedding approach for mapping valence–arousal dimensions in textual emotion analysis
7	Increased Online Aggression During COVID-19 Lockdowns: Two-Stage Study of Deep Text Mining and Difference-in-Differences Analysis	2022	Taiwan	Jerome Tze-Hou Hsu, Richard Tzong-Han Tsa	A two-stage study combining Deep Text Mining (training a BERT model to detect anger, offensive language, and hate speech) with a Difference-in-Differences (DID) econometric analysis to establish causal links between lockdowns and aggression.	Rise in aggressive social behaviours during COVID-19 lockdown and its policy implications
8	Emotional Expression on Social Media Support Forums for Substance Cessation: Observational Study of Text-Based Reddit Posts	2023	USA	Genevieve Yang, Sarah G. King, Hung-Mo Lin, Rita Z. Goldstein	Reddit posts across 394 forums, quantified and categorised emotion word frequencies in substance cessation of alcohol, nicotine, and cannabis.	Online communities as valuable sources for understanding emotional recovery experiences

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
9	Exploring Public Emotions on Obesity During the COVID-19 Pandemic Using Sentiment Analysis and Topic Modelling: Cross-Sectional Study	2024	Switzerland, UK, Pakistan	Jorge César Correia, Sarmad Shaharyar Ahmad, Ahmed Waqas, Hafsa Meraj, Zoltan Pataky	Analyzes 53,414 tweets using the XLM-RoBERTa-base model for sentiment analysis and the BERTopic library for topic modelling.	Negative public sentiment toward obesity highlighting need for informed health communication and policy
10	Guide for the Application of the Data Augmentation Approach on Sets of Texts in Spanish for Sentiment and Emotion Analysis	2023	Chile	Rodrigo Gutiérrez Benítez, Alejandra Segura Navarrete, Christian Vidal-Castro, Claudia Martínez-Araneda	Evaluates Machine Learning and Deep Learning performance using data augmentation (DA) techniques like Easy Data Augmentation (EDA), back-translation (BT), and SentiGAN to expand small Spanish-language datasets.	Data augmentation techniques enhancing sentiment and emotion analysis in Spanish social media texts
11	EMFSA: Emoji-Based Multifeature Fusion Sentiment Analysis	2024	China	Hongmei Tang, Wenzhong Tang, Dixiong Xiao, Zhu, Shuai Wang, Yanyang Wang, Lihong Wang	Proposes a multifeature fusion model (EMFSA) that integrates emoji, topic, and text features. It uses a sentiment- and emoji-masked language model (Senti_MLM) and a cross-attention mechanism to improve accuracy in short social media texts.	Multifeature fusion model leveraging emojis to improve sentiment analysis in short social media texts
12	Emotion-Based Reinforcement Attention Network for Depression Detection on Social Media: Algorithm Development and Validation	2022	China	Bin Cui, Jian Wang, Hongfei Lin, Yijia Zhang, Liang Yang, Bo Xu	Proposes an Emotion-Based Reinforcement Attention Network (ERAN) that uses a TextCNN for deep emotional feature extraction and Reinforcement Learning (RL) to	Deep learning model enhancing depression detection through emotional semantic feature extraction on social media

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
					select specific "depression indicator" posts from a user's history.	
13	An Optimised Deep Learning Approach for Suicide Detection through Arabic Tweets	2022	Saudi Arabia, & Egypt	Nadiah A. Baghdadi, Amer Malki, Hossam Magdy Balaha, Yousry AbdulAzeem, Mahmoud Badawy, Mostafa Elhosseini	Proposes a framework for binary classification (Normal vs. Suicide) of Arabic tweets using Bidirectional Encoder Representations from Transformers (BERT) and Universal Sentence Encoder (USE) models after rigorous Arabic text preprocessing (lemmatization and stemming).	Social media as a tool for tracking depression and mental health trend
14	Computational Linguistics-Based Text Emotion Analysis Using Enhanced Beetle Antenna Search with Deep Learning During the COVID-19 Pandemic	2023	Saudi Arabia, & India	Youseef Alotaibi, Arun Mozhi Selvi Sundarapandi, Subhashini P, Surendran Rajendran	Computational linguistics based mood analysis using enhanced beetle antenna search with deep learning (CLSA-EBASSDL using BERT word embedding classifier using attention based BiLSTM network.	Application of computational intelligence and nature-inspired algorithms for real-world optimisation problems
15	Machine Learning and Natural Language Processing to Assess the Emotional Impact of Influencers' Mental Health Content on Instagram	2024	Spain	Noemi Merayo, Alba Ayuso-Lanchares, Clara González-Sanguino	Created a labelled dataset of influencer's Instagram responses based on mental health posts categorized by emotion laden and applied machine learning algorithms	Emotional impact of mental health disclosures on social media beyond psychopathology detection

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
16	A hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM	2022	India	Harnain Kour, Manoj K. Gupta	Development of a hybrid deep learning model using a feature-rich Convolutional Neural Network (CNN) and a Bi-directional Long Short-Term Memory (Bi-LSTM) network to classify depressive versus non-depressive textual narratives from Twitter data.	Predicting users' mental health conditions through Twitter data analysis
17	Research on the detection model of mental illness of online forum users based on a convolutional network	2023	China, & India	Yuliang Guo, Zheng Zhang, Xuejun Xu	Hierarchical user post feature representation models including Single- Gated LeakReLU- CNN and Multi- Gated LeakReLU- CNN to extract emotional features from user posts and to identify mental illness by analysing online forums.	Improved models for accurate extraction of key emotional features from social media posts
18	Emotion recognition for human–computer interaction using high-level descriptors	2024	India, & Ethiopia	Chaitanya Singla, Sukhdev Singh, Preeti Sharma, Nitin Mittal, Fikreselam Gared	Construction and preprocessing of a labelled speech corpus from diverse social media sources, followed by the application of Deep Learning techniques, specifically Convolutional Neural Networks (CNN), for Speech Emotion Recognition (SER).	Enhanced emotion recognition accuracy in Punjabi speech using an advanced SER approach
19	Meaningful messaging: Sentiment in elite social	2021	USA	Janet M. Box-Steffensmeier, Laura Moses	Analysis of the tone and sentiment in elite social media	Influence of partisanship and emotional tone on crisis

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
	media communication with the public on the COVID-19 pandemic				messaging to determine its effect on information spread and public reaction during the pandemic.	communication and message engagement
20	Detecting Substance Use Disorder Using Social Media Data and the Dark Web: Time- and Knowledge-Aware Study	2024	USA, India, & Thailand	Usha Lokala, Orchid Chetia Phukan, Triyasha Ghosh Dastidar, Francois Lamy, Raminta Daniulaityte, Amit Sheth	Utilization of state-of-the-art deep learning models to generate sentiment and emotion from social media posts and crypto market listings to understand users' perceptions and the relationship between substance misuse and mental health.	Detection of Substance Use Disorder through social media and Dark Web data analysis
21	User-based Hierarchical Network of Sina Weibo Emotion Analysis	2023	China	Qian Chen, Xiao Sun, Jiamin Wang, Meng Wang	User based hierarchical network with combination of multi head attention and convolutional neural network to jointly analyse individual Weibo texts and related posts over time, capturing contextual emotional information for improved five category emotion classification.	User-level contextual information improves accuracy in emotional classification,
22	Twitter Perspectives on Cochlear Implantation: Sentiment and Thematic Analysis	2023	USA	Joel S. Feier; Kenny Nguyen; Janet S. Choi	All English language tweets mentioning 'Cochlear implantation', from 2019–2021 collected using custom Python script, analysed for sentiment with VADER tool,	Understanding public positive and negative perceptions of cochlear implantation

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
					and based on positive, negative, liked tweets using thematic analysis.	
23	"Twitter is Really Therapeutic at Times": Examination of Black Men's Twitter Conversations Following Hip-Hop Artist Kid Cudi's Depression Disclosure	2021	USA	Diane B. Francis	The study was conducted in the United States and used thematic analysis to examine a sample of 1,482 tweets from the hashtag #YouGoodMan to identify recurring patterns in Black men's mental health conversations following Kid Cudi's depression disclosure.	Celebrity disclosure facilitates emotional expression online, and depression disclosure through an influencer
24	Topics and Sentiments of Public Concerns Regarding COVID-19 Vaccines: Social Media Trend Analysis	2021	USA	Monselise et al.	Tweets related to COVID-19 vaccines were collected over 60 days and analysed using topic modelling and sentiment analysis to identify key topics and emotions.	Fear as a leading reaction, news events dictate spikes
25	Social media's dark secrets: A propagation, lexical and psycholinguistic oriented deep learning approach for fake news proliferation	2024	China, & Saudi Arabia	Kanwal Ahmed; Muhammad Asghar Khan; Ijazul Haq; Alanoud Al Mazroa; Syam M.S.; Nisreen Innab; Masoud Alajmi; Hend Khalid Alkahtani	A deep learning framework using Graph Convolutional Neural Networks (GCNN) with multi-head attention, incorporating BERT embeddings and psycholinguistic attributes (sentiment, personality, etc.) across user interaction and semantic	1. Disinformers are generally newer users, tweet more frequently, and are more active at night (higher insomnia index). 2. Users with lower popularity (low F2F ratio) are more likely to spread fake news.

Sl. No	Title	Year	Country	Author(s)	Methodology	Major findings
					propagation graphs.	
26	Sentiment, we-talk and engagement on social media: insights from Twitter data mining on the US presidential elections 2020	2022	Germany	Linus Hagemann and Olga Abramova	A data mining approach using a dataset of over three million tweets from the 2020 US presidential elections, applying dual process theory to test how affective cues (sentiment) and cognitive cues (insight, causation) impact audience engagement.	Emotional and cognitive cues influence social media engagement, and negative bias attracting users
27	Sentiment Classification of Anxiety-Related Texts in Social Media via Fusing Linguistic and Semantic Features	2024	China	Jianghong Zhu, Zhenwen Zhang, Zhihua Guo, and Zepeng Li	Fuses linguistic and semantic features by using the SC-LIWC dictionary for linguistic extraction and a TextCNN-based model for deep semantic analysis. It uses a novel recursive feature selection algorithm on Sina Weibo data.	Anxiety-related posts are a combination of negative and meaningful highly supporting the incorporation of the fusion model.
28	Revealing the spatial co-occurrence patterns of multi-emotions from social media data	2023	China & USA	Dongyang Wang a, Yandong Wang a,*, Xiaokang Fu a,b, Mingxuan Dou a, Shihai Dong a, Duocai Zhang c	Used BERT based model to classify social media posts into six emotions, applied K- means clustering to analyse special emotion co-occurrence patterns, and employed a Multi Model Logit Model to examine their relationship with land use characteristics.	Significant special co-occurrence patterns of conflicting or consistent emotions in urban space on social media

Themes

Emotional Vulnerability Detection

The theme of Emotional vulnerability covers 36% of the identified themes from reviewed papers. The studies indicate the detection in the segments of emotional vulnerability, including sadness, fear, aggression and other negative emotions. Sentiment analysis, emotion classification, and lexicon-based or deep-learning models were used to segment social media texts. It helps in the early identification of emotional distress and its vulnerability on the development of mood disorders. It further indicates the understanding of platform-specific emotional risk detection and the necessary action.

Emotional Support Sequences

The theme of Emotional support sequences covers 23% of identified themes from reviewed papers, with the dimensions of positive emotions, including happiness, joy, satisfaction and other positive emotions. Emotion recognition models were used in analysing and identifying these segments. It helps in understanding well-being, resilience, and social support patterns. The digital well-being initiatives and potentiality were discussed with positive social media engagement strategies. The positive emotions were identified using polarity-based sentiment models and multi-class emotion classifiers. The algorithm and thematic classification based on the emotional support theme help in identifying segments in fostering wellbeing and protective factors against vulnerability.

Emotion Valence Measurement

The theme of Emotion valence measurement covers 16% of the identified themes from the reviewed papers. Research depicting the classification of emotions based on the range of positivity or negativity using emotional polarity categorization or sentiment classification using supervised machine learning models. It helps in the simplification of large-scale emotional representation patterns and prevalence through social media comparing emotional polarity across time, topic, or population.

Technological Application

The theme of Technological application covers a total of 9% of identified themes from research papers. The specific ML algorithms learning models of LSTM, CNN, Transformer-based, and NLP pipelines were predominantly trained and used in the emotion recognition of social media textual contents. It improves the accuracy and scalability of emotion detection. It further enables in the real time emotion monitoring on social media. The ethical usage of AI has been highlighted based on the training and model performance.

Mental Health Monitoring

The theme of Mental health monitoring covered a total of 7% from identified themes from reviewed papers. It indicates the monitoring of mental health through emotion and sentiment patterns for mental health using computational models. Computational models have been used in emotion detection and sentiment analysis. This do not just assess individual's emotion representation, but is also helpful in monitoring mental health at population level. It promotes interdisciplinary researches that the incorporate computer science with

psychology for the early diagnosis of emotional dysfunctions, including depression, and anxiety using predictive computational models.

Emotional Communication Strategies

The theme of emotional communication strategy covered a total of 5% of identified themes from reviewed papers. It indicates analysis of language, slang and interaction patterns to understand emotional expression. It shows verbal emotional expressions communicated differently across different platforms. It further helps in improving the human-computer interaction and development of empathetic systems, and designing better online communication tools. The linguistic structures, discourse patterns and interaction patterns features indicate examination of differences in emotional expression across platforms and cultures.

Stress Detection

The theme of stress detection covered a total of 4% of themes from the identified reviewed papers. It indicates the analysis of stress through linguistic cues, sentiment shifts, and temporal emotion patterns. The studies identify the stress triggers related to work, crisis, or social events. It further indicates the potential of the early warning systems during emergencies or pandemics. Stress is detected with related keywords, sentiment shifts, and temporal emotion changes using classification ML models trained on stress labelled dataset.

The common procedures inferred from the research papers based on machine learning and supervised models are represented in a structured and systematic order as follows. The technique begins with the data acquisition through APIs and web scraping tools such as Scrapy. A comprehensive data pre-processing is followed, which includes data cleaning, artefact removal and normalisation. Data augmentation techniques such as random word swapping, synonym replacement, and back translation are applied. The textual data is then translated to numerical representations using feature extraction methods ranging from traditional bag of words to advanced word2vec, Glove, and BERT. The emotion classification or sentiment range was performed using a deep learning framework, including CNN and Bi-LSTM architectures. In addition, it incorporates topic modelling using LDA to uncover latent topicschemes, causal and statistical analysis through Difference in Difference or emotional topology. The performance is further evaluated using standard metrics of precision, recall, and F1 score to ensure accuracy and reliability.

Discussion

The present study aims to synthesise the rapidly growing body of research examining how emotions are digitally represented, detected, and interpreted in social media by youth population. The systematic review indicates that the interdisciplinary dimension of social media and emotion is widely accelerating, as shown by the growing number of research in recent years, as shown in Fig. 1.2. The study specifically focused on identifying how individuals express diverse emotional states and process across different social media modalities and further analysing the platform-specific variations in emotional representation. The systematic review process resulted in a final list of 28 peer-reviewed research articles. The research shows the convergence of psychology, computer science, communication studies, and data science with natural language processing by leveraging the analysis of linguistics and semantics more sequentially. The models, to show high performance in areas including predicting mental health conditions such as mood disorders and

for recognising emotional states more specifically. The review further shows evidence for the methodological advancement moving beyond textual data to visual or auditory multi lingual interpretation. This multicultural expansion is significant in the development of a robust detection system.

A consistent pattern was detected from the 28 reviewed research articles showing the development of the digital environment into a significant ecosystem, in which emotions are expressed and interpreted. The findings indicate that the ML-based approaches of CNN, Bi LSTM, and Reinforcement attention mechanism demonstrate significant capacities in decoding patterns of emotional representation through texts, visual contents or symbols. These techniques further expand the reach and expansion of studies of emotional representations through digital media (Liu et al., 2024). The research evidence shows that emotional recognition is not limited to linguistic or semantic markers, but extends to semantic, syntactic and symbolic cues, such as emojis, hashtags, reaction symbols (Tang et al., 2023). Digital communication channels serve as a significant source for the multi-model structure of emotional representation (Steinert & Dennis, 2022). Social medias were found not just a platform to express emotions, but research shows evidence of them playing an active role in shaping the pattern of emotions based on media culture

The text-based emotion analysis was found to be predominant and widely researched as the majority of research articles from the review uses textual content. Linguistic and semantic markers were predominantly used for analysing the text for detecting emotional patterns (Pliseki & Sobieszek, 2024). The emerging recent models adopt a hybrid and multilingual approach that expands beyond the English language, addressing cultural and linguistic variation in emotional expression (Gutierrez et al., 2024). A strong intersection of emotional representation with mental health was also identified from this review. Emotional language, sentiment polarity and emotional valence were found to reliably indicate the symptoms of mood disorders such as depression or anxiety (Kour & Gupta, 2022). The ethical usage of this user-generated social media data can act as a mirror of the user's emotional process and state. Even then, the technical usage remains a challenge, especially regarding informed consent and user privacy (Steinert & Dennis, 2022).

The thematic analysis of the 28 finally selected articles shows three dominant trends in emotional representation research. The first is regarding the contingent effect or emotional amplification effect is prevalent more specifically during social crisis situations, such as the COVID-19 pandemic, where solidarity became widespread (Hsu, Tsa, 2022). The second trend depicts emotional personalisation driven by the user's algorithmic polarisation reinforces the user's unique affective contents by influencing public discourse and promoting wellbeing (Box- Steffensmeier & Moses, 2021). The third trend is regarding the interdisciplinary researches with the combination of computer science, psychology and language to interpret the complex interaction of emotions through the digital ecosystem (Manikanda et al., 2018).

The current literature shows a high skewness towards text-based analysis while non-verbal indicators of emotions, such as emojis, symbols, or pictures, are less explored. The real-time emotional cues were found to be relatively less explored, which limits the dynamic affective shifts in digital interactions. Bridging this gap would enhance the clinical utility and interpretability. Current systematic review synthesises the methodological sequences and theoretical insights based on emotions represented through the social media ecosystem. A strong convergence was found towards data-driven, text-centric approaches. The incorporation in the advancement in machine learning and deep learning. Reviewed studies indicated the beginning of large-

scale data acquisition through APIs and web scraping tools such as Scrapy. Data acquisition at the preliminary stage in collecting data from social media platforms through Application Programming Interface (API), that allows structured access to social media platforms and using Web Scrapping tools, extracts data from public webpages where APIs are limited. This is further followed by data pre-processing, including noise removal, normalisation, tokenisation, and lemmatisation, to improve model robustness (Manikonda et al., 2018; Singla et al., 2024). The third step of data augmentation was facilitated using techniques such as word swapping or back translation, which were highly adopted for data sparsity. Social media raw data cannot be processed by machine learning models, hence, the traditional Bag- of- Words or advanced Word2Vec, Glove or BERT, converts words into dense vector representations capturing semantic meaning, contextual similarity or Emotional nuance. (Kour & Gupta, 2022). The deep learning frameworks were predominantly used for the classification of emotions and sentiment of the data using CNNs and LSTMs, often in hybrid or parallel sequences (Pliseki & Sobieszek, 2024). Topic modelling techniques of Latent Dirichlet Allocation were used to synthesise the thematic structures within emotional discourse (Correia et al., 2024). The interpretability is further enhanced using approaches including difference in differences approaches. Further, the performance of the model was evaluated using standard matrices based on accuracy, precision, recall and F1 score (Baghdadi et al., 2022). The findings indicates that social media acts as both an emotional outlet and a diagnostic mirror as an emotional ecosystem.

Social media was found to act as an emotional outlet and a diagnostic mirror, as verified from this review. Social media platforms provide and facilitate affective expression, and it simultaneously expose users to heightened emotional distress. Hence, the integration of social media platforms for emotional recognition and health must balance between empathetic responsiveness and ethical responsibility. Future research could focus more into building cross-platform emotional models capable of recognising and tracking emotional injuries.

Conclusion

This systematic review shows evidence for the transformative potential of social media platforms in decoding emotional patterns and expressions through digital media. The findings show the potential of the human-centred computational algorithms that not only recognise emotions, but also modify based on the emotional pattern and preference of the users. It can further help in the early recognition of mental health and emotional conditions and to improve digital empathy with the development of emotionally intelligent algorithms. By maintaining the technical advancement and ethical boundaries, the digital emotional space not only limits in providing a space for emotional expression, but to a compassionate and empathetic technological understanding.

Declarations

Author Contribution

Sarath CJ wrote the first draft of the manuscript. Both authors reviewed and edited the manuscript.

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Figures

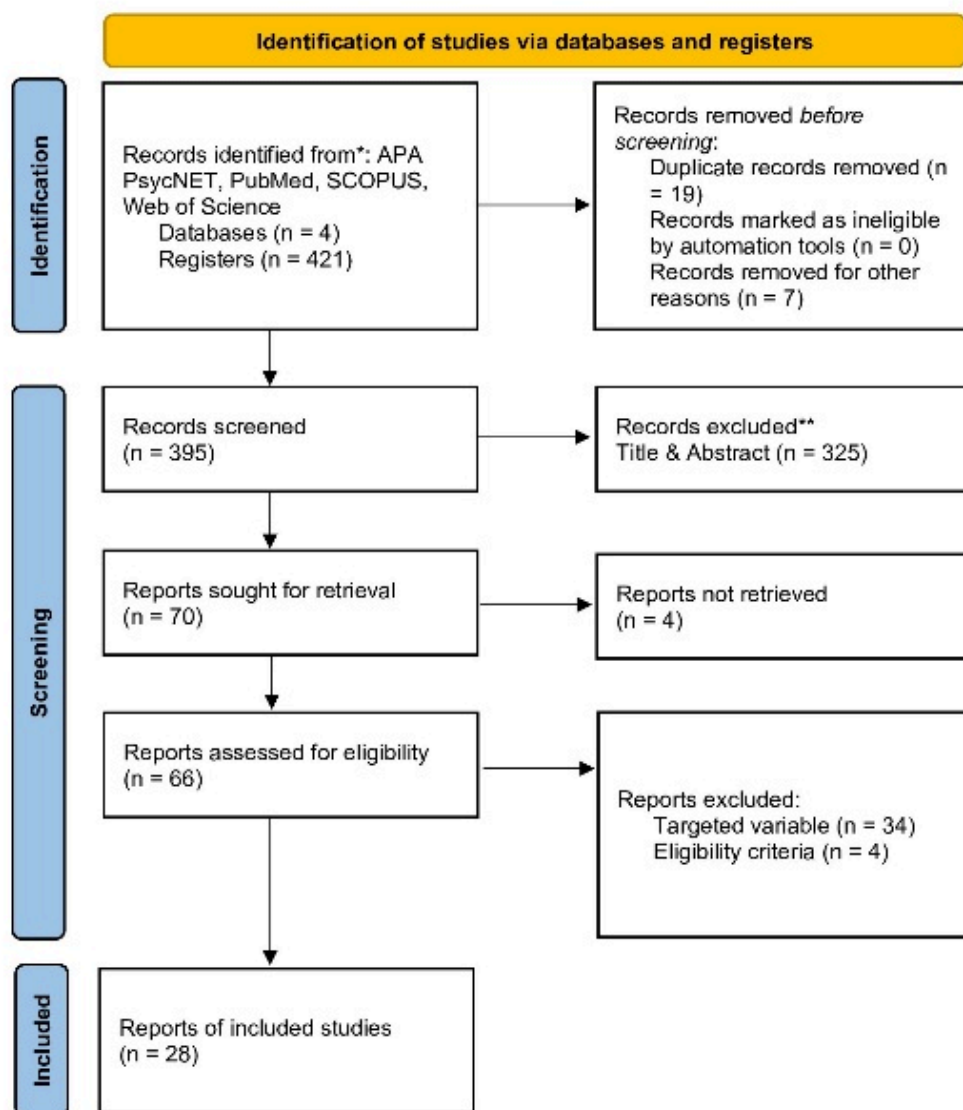


Figure 1

Fig 1.1: PRISMA Flow chart

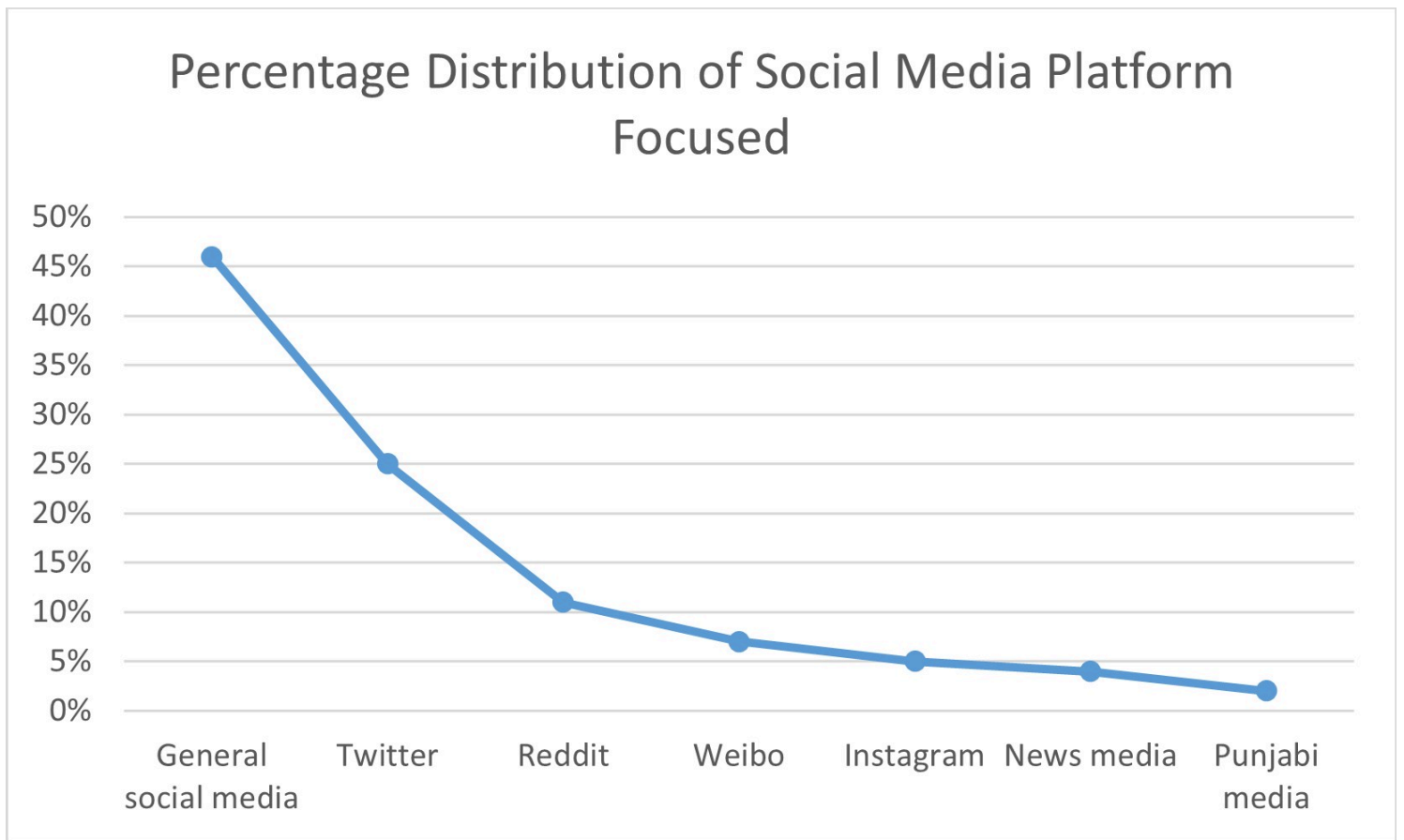


Figure 2

Fig 1.2: Social media platform focused on the study distribution

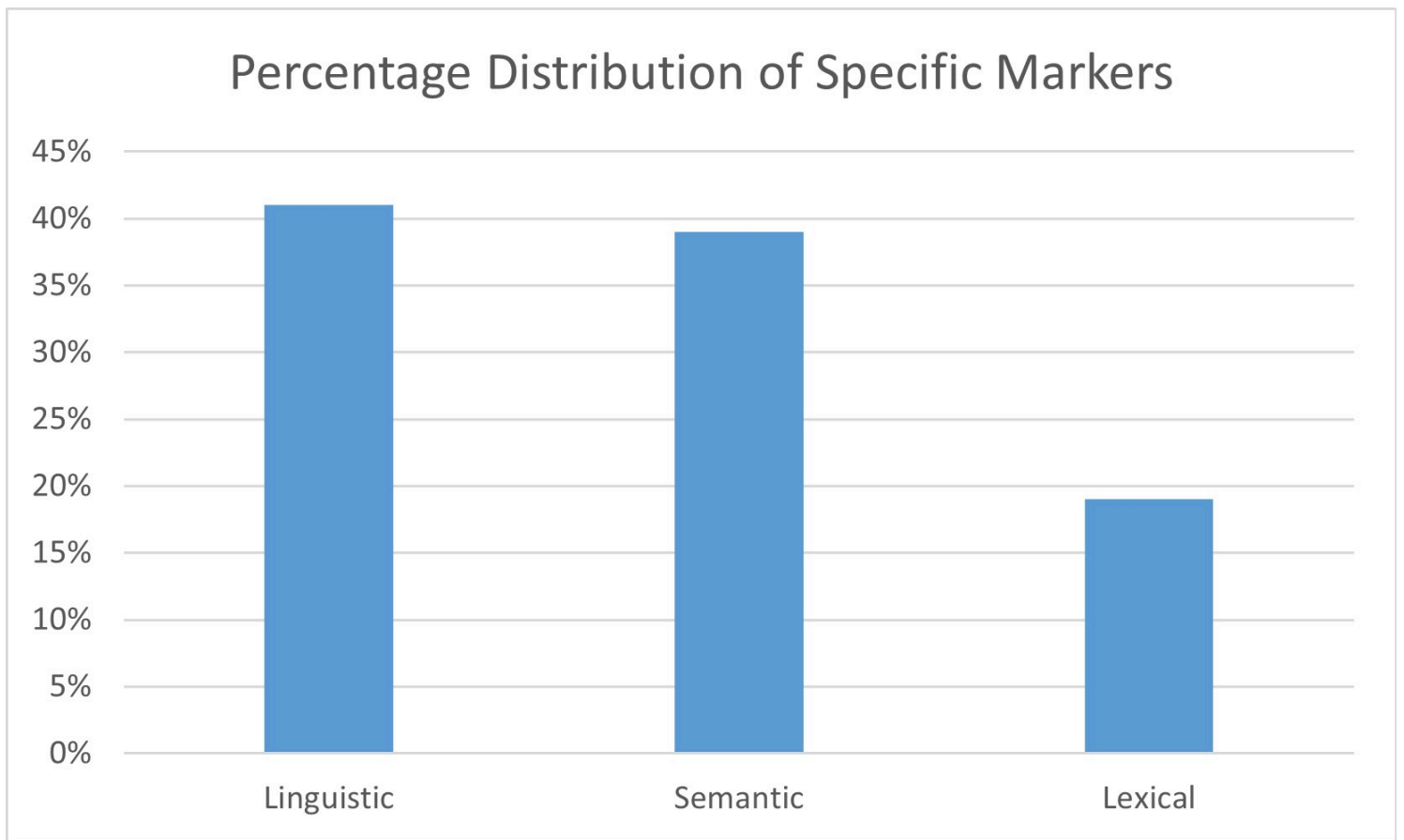


Figure 3

Fig 1.3: Number of studies using Specific Markers

Percentage Distribution of Identified Themes

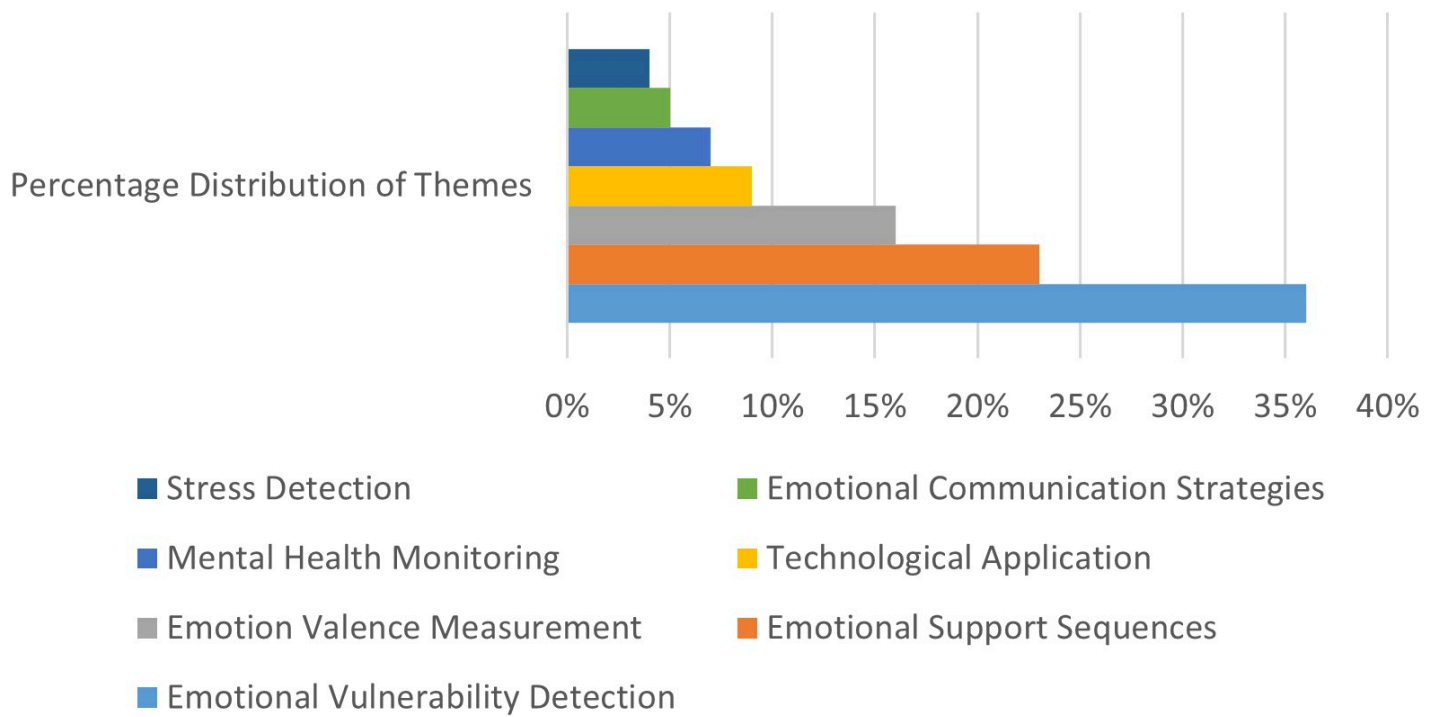


Figure 4

Fig 1.4: Major themes distribution