Methodological Review of Approaches to Studying Digital Communication[1]

Mayiana Mitevska, Prof. D.Sc.
Plovdiv University "Paisii Hilendarski", Faculty of Pedagogy, Department of Psychology, Bulgaria, Plovdiv

Ivanka Davcheva
Plovdiv University "Paisii Hilendarski", Faculty of Pedagogy, Department of Psychology, Bulgaria, Plovdiv

Abstract: This review systematizes some of the main existing methods, emphasizing their importance for understanding the complex mechanisms of digital communication and its impact on society. The overview of approaches to studying digital communication highlights the necessity of combining traditional and technology-oriented methods to achieve a comprehensive understanding of the socio-psychological processes in online communication and to develop effective strategies for promoting digital literacy and mental health.

Keywords: digital communication, social networks, mental health, quantitative and qualitative methods, machine learning

Introduction

Digital communication is an integral part of modern social life, significantly influencing personal development, social relationships, mental health, and societal processes. It changes the way people interact, build connections, and express themselves, while simultaneously creating new challenges and risks. Danah Boyd (2014) describes digital media as a space that "creates a number of new social spheres for young people" (Boyd, 2014), aiming to understand their collective impact and the functions of individual media.

As Vodennicharski (2020) reminds us, "the field of public communication has a long and venerable history" (p. 8), and many of today's digital strategies of influence can be traced back to mechanisms that civilizations have used for centuries. Similarly, "dramatised events as effective tools of propaganda and public relations also originate from Antiquity" (Vodennicharski, 2020, p. 16), showing that digital media practices echo ancient communicative techniques of attention management.

To unravel the complex mechanisms governing digital communication, scholars employ diverse methods encompassing both quantitative and qualitative approaches. Quantitative methods include surveys, social network analysis, and big data analytics, which allow insights into behavioral patterns and trends. For instance, a systematic review by Keles, McCrae, and Grealish (2019, 2020) found that all analyzed aspects of social media use—time, activity, investment, and addiction—were interconnected with depression, anxiety, and psychological stress in adolescents.

Qualitative approaches, such as interviews, focus groups, and thematic analysis, provide deeper insights into personal experiences, motivations, and emotional responses related to digital communication. A global review of holistic studies by Keles and colleagues emphasized the importance of additional qualitative research to uncover mechanisms affecting mental health in relation to social media use (Keles, McCrae, & Grealish, 2020).

Beyond traditional approaches, researchers are increasingly integrating innovative technologies such as machine learning and physiological measurements to analyze digital interactions more precisely. As Vodennicharski (2020) notes, "strategic public communications manifest themselves in different civilizational models—from the campaigns of Alexander the Great and the Roman Empire to today's global attempts at the 'export of democracy'" (p. 7). In this light, the evolution of digital media can be viewed as a continuation of long-standing communication traditions, adapted to the technological affordances of the 21st century.

I. Quantitative Methods: Standardized Questionnaires and Scales

These tools collect large volumes of data on behavioral and psychological aspects of digital communication.

Internet Addiction Test (IAT) – Young, 1998

The Internet Addiction Test (IAT; Young, 1998) was developed to measure the presence and severity of Internet and technology dependence among adults. As an emerging cultural and clinical phenomenon, internet addiction is regarded as a new clinical disorder requiring assessment and treatment. The IAT was the first validated instrument in this area. It can be applied to assess symptoms of internet addiction across various testing settings. The term "Internet" refers to all contacts individuals have with web-based services, including websites, online games, social media, and digital entertainment accessed via different devices—computers, screens, mobile phones, portable devices, and other technologies. The IAT is widely used in clinical practice and scientific research.

Widyanto & McMurran (2004) conducted a psychometric validation of the IAT in the United Kingdom, confirming its reliability. Faraci et al. (2013) adapted the IAT for Italian participants, demonstrating good internal consistency. A recent Israeli study (Israeli et al., 2021) confirmed the two-factor structure of the scale among more than 4,000 individuals.

Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2016)

The BSMAS measures addiction to social networks through a brief questionnaire designed to identify signs of social media dependency and provide a quick, reliable assessment. It is suitable for adults and adolescents over 13, as it addresses behaviors typical of both youth and adult social media users. The scale has been applied in studies of youth in Germany to investigate the link between social media addiction and mental health (Kuss et al., 2017).

The BSMAS is grounded in theoretical models of addiction and behavioral disorders. It offers a fast and easy method for identifying and validating social media dependency, making it useful for early detection of problematic usage and for developing prevention and intervention strategies. An Iranian study confirmed good validity and reliability among adults (Cronbach's $\alpha \approx .80$), with positive correlations between BSMAS scores, the IAT, and symptoms of depression, anxiety, and stress (Sadeghi, Shalani, Firouzabadi, et al., 2025). In Denmark, a longitudinal analysis showed that higher BSMAS scores predicted increased risk of depression, social isolation, and reduced mental well-being (Santini, Thygesen, Andersen, et al., 2025).

Cyberbullying Victimization Scale (Hinduja & Patchin, 2010)

This instrument measures the frequency and severity of experiences of online harassment, providing valuable insights into vulnerability and the risk of psychological consequences. The test consists of items addressing various forms of online abuse, such as cyberbullying, threats, and the posting of humiliating material.

It is used in:

research on digital safety and mental health,
educational programs for online harassment prevention,
clinical and youth counseling practice,
the development of school and platform safety policies.

The tool is particularly suitable for students and adolescents aged 11–18, the group most active online and most

vulnerable to cyberbullying. It provides a reliable and valid measure of online victimization, a phenomenon of increasing relevance in today's digital world (Hinduja & Patchin, 2010).

Online Social Support Scale (OSSS; Cohen & Wills, 1985)

The OSSS was designed to measure the level of social support that individuals receive through digital platforms and online communication. It assesses emotional, informational, and practical support provided via the Internet and social media. Items address aspects such as stress coping, a sense of belonging, and mutual assistance.

Applications include:

research on the role of digital support in mental health,
programs to improve online communication and social integration,
clinical and counseling practices, particularly for individuals who rely on the Internet as a primary source of support.

It is suitable for adults and adolescents over 16 who actively use digital platforms for social connection. The OSSS highlights the importance of online social support as a factor in psychological well-being, particularly in the modern digital era (Cohen & Wills, 1985).

II. Qualitative Methods

Interviews and Focus Groups

This approach allows in-depth exploration of participants' experiences, attitudes, and motivations. It uncovers subjective perceptions and emotional responses to the digital environment. For example, studies of cyberbullying victims using interviews have revealed their psychological reactions and coping strategies (Livingstone et al., 2009). According to Livingstone et al. (2009), "interviews provide opportunities to understand inner dynamics and personal narratives often hidden in quantitative data."

Thematic Analysis

This method involves analyzing the content of online posts and discussions to identify key themes, patterns, and trends (Moreno, Binger, Zhao, & Eickhoff, 2020). For instance, research on Reddit discussions about mental health highlighted core concerns, supportive interactions, and social attitudes among users (Huang & Ki, 2025). Thematic analysis is a valuable tool for understanding complex social and psychological processes manifested in online communication.

Projective Techniques

These techniques are used to study internal attitudes and emotional reactions to the digital environment that participants may not express directly. Projective methods provide a unique window into the subconscious aspects of digital communication and personal interpretation of online situations. For example, Zubova (2023) demonstrated their effectiveness as a way of "evoking significance and transforming concrete experiences into visual discourse" (Porr et al., 2011).

III. Social Network Analysis (SNA)

SNA maps and measures relationships and interactions between different entities, which may include individuals, groups, or digital elements such as computers or URLs. In SNA, entities are represented as nodes, while the ties between them illustrate flows of information, resources, or relationships. Analyses may be sociocentric (focused on entire networks) or egocentric (focused on personal networks and their consequences, e.g., in healthcare or social behavior).

Visualization and Analysis

Tools such as Gephi and NodeXL allow researchers to analyze user connections in relation to the spread of information or disinformation. This method enables detailed examination of network structures and the identification of key players. For example, Bovet & Makse (2019) investigated misinformation on Twitter during U.S. elections, concluding that "network patterns play a crucial role in the speed and scope of false news dissemination." Similarly, Pierri, Piccardi, & Ceri (2020) analyzed Twitter diffusion networks, showing systematic structural differences between reliable and misleading news. Another application is identifying influencers and network structures that facilitate the spread of misinformation.

Impact Analysis

SNA reveals communication patterns and central nodes that influence the entire network. For instance, Bovet & Makse (2019) demonstrated how certain Twitter nodes had disproportionate influence in spreading disinformation, emphasizing the role of "internal central nodes acting as primary disseminators" (p. 118).

IV. Psychophysiological Measurements

Brain and Physiological Responses

These techniques allow objective assessment of emotional and cognitive reactions to digital content.

fMRI studies: Research linking aggressive behavior and social rejection in adolescents showed that amygdala activity in response to emotional faces correlated with aggression tendencies (Swartz, Carranza, & Knodt, 2019).

EEG analyses: A 2023 meta-review found that online social exclusion led to increased N2 and P3 amplitudes, more negative frontal LSW, and elevated frontal theta activity—indicators of heightened attention and emotional regulation (Mills et al., 2024).

Skin conductance and heart rate: These measure stress and emotional reactivity to digital stimuli.

Other physiological responses: Studies of adolescents found elevated amygdala activation when perceiving social aggression, particularly in response to negative online comments (Swartz et al., 2019).

V. Experimental Approaches

Controlled Experiments

These designs allow evaluation of causal relationships between digital communication and psychological responses. Examples include:

the effects of online anonymity on aggression (Suler, 2004), experiments on the effects of positive reinforcement in social networks on mood (Reece et al., 2017).

VI. Big Data Analytics and Machine Learning

Automated Classification and Prediction

Large-scale data processing is applied to uncover patterns.

Toxic comment classification: Transformer-based models such as BERT have been developed to detect toxic online content, showing high success in identifying linguistic patterns (Wang et al., 2018).

Emotion prediction: Machine learning models analyze mobile data to predict mood and risk of digital dependence (Reece et al., 2017), contributing to the understanding of digital impacts on mental health.

VII. Natural Language Processing (NLP)

Emotional Content Analysis

NLP is used for automatic classification of sentiment and identification of disinformation. For example:

Twitter (X) data analysis for detecting negativity and cyberbullying (Davidson et al., 2019).

Fake news detection: machine learning models analyze the spread of true and false information on Twitter, revealing that false news spreads faster and more widely than true news (Vosoughi et al., 2018).

Conclusion

Digital communication has established itself as both an enriching and challenging phenomenon that transforms social connections, personal development, and mental health. Research shows that it creates new spaces for self-expression and belonging (Boyd, 2014), but also increases risks of negative outcomes such as anxiety, depression, and online aggression (Keles et al., 2020).

The multilayered nature of digital interactions requires a combination of research approaches. Quantitative methods such as SNA and big data analytics identify patterns of information diffusion and influence structures in social networks. Qualitative approaches, through interviews and projective techniques, reveal deep personal and emotional dimensions of online interactions.

Innovative techniques such as psychophysiological measurements (fMRI, EEG, skin conductance) and experimental designs add objective perspectives, while machine learning and NLP provide scalable tools for early detection of mental health conditions and content analysis.

By integrating traditional social science methods with new technologies, research on digital communication uncovers its ambivalence: it is simultaneously a resource for social support and innovation, and a factor of vulnerability. This complexity calls for an interdisciplinary approach that can support strategies for improving digital literacy, reducing misinformation risks, and strengthening mental health in today's digital society.

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