Dating and Relationships under a Bluesky: An Educational Data Science Perspective on Informal Learning on BlueSky

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Abstract
Social media platforms increasingly play a central role in how individuals acquire knowledge, form expectations, and negotiate practices surrounding intimate relationships. Rather than relying primarily on formal education or interpersonal networks, adolescents and young adults often prefer digital sources when seeking advice and information about sex and relationships. Platforms such as X, Instagram, and BlueSky provide perceived advantages of anonymity, autonomy, and accessibility, enabling users to engage in the de-identified sharing of sensitive concerns. In doing so, they contribute to the ongoing transformation of "romantic media ideologies," understood as the taken-for-granted assumptions and discourses that shape how relationships are understood, evaluated, and experienced in contemporary societies. To date, much of the scholarship examining these dynamics has relied on qualitative methods such as interviews, ethnography, or discourse analysis. While such approaches offer valuable insights, they are limited in scope when considering the scale and complexity of digital interaction. Educational Data Science (EDS) offers a promising methodological framework to address this gap. By integrating Learning Analytics (LA) and Educational Data Mining (EDM), EDS provides robust tools for examining informal knowledge acquisition and meaning-making in online spaces. In this study, we apply three specific methods—social network analysis, natural language processing, and large language model annotation/classification—to analyze dating and relationship discourse on BlueSky, thereby extending EDS into a largely unexplored domain. Another dimension concerns the role of social media influencers as emerging "new experts" in the domain of dating and relationships. These figures act as knowledge brokers: they are perceived as credible and authentic, often combining entertainment with didactic or advisory content. At the same time, their interventions are not unproblematic, as advice can be contradictory, selective, and shaped by platform-specific logics of visibility, brand-building, and monetization. Our analyses identify three archetypal user groups—Knowledge-based Authority, Commercial Positioning, and Experiential Discourse. Each group demonstrates distinct communication styles, with varying degrees of formalized expertise and credibility claims. While all engage in advice-giving, their thematic emphases diverge, ranging from wellness and self-care to promotional strategies and lived relational experiences. By mapping these dynamics, the study contributes to scholarly debates on the evolution of romantic media ideologies and the social construction of expertise in digital discourse.

Keywords
Informal learning, dating advice, social media, educational data science, social network analysis, natural language processing, large language models

Objectives & Purpose

Social media platforms have increasingly become central to shaping individuals' understanding, aspirations, behaviors, and expectations surrounding intimate relationships (Barker et al., 2018). As Jänkälä (2017) notes, individuals are now more likely to seek information about sex and relationships from media sources rather than formal education or personal networks. Kim et al. (2017) further highlight that adolescents often turn to online peers for support with romantic challenges, appreciating the anonymity and autonomy these digital spaces provide over traditional avenues such as adult guidance or formal instruction. Platforms like X, Instagram, and BlueSky enable this kind of peer-to-peer support through anonymous sharing of sensitive personal experiences. Similarly, Belotti et al. (2022) assert that communication practices on these platforms are reshaping "romantic media ideologies" (p. 47).

Much of this research relies on qualitative methodologies. However, Educational Data Science (EDS) presents a valuable set of tools to explore these phenomena from a quantitative perspective. EDS encompasses two closely related fields—Learning Analytics (LA) and Educational Data Mining (EDM) (Piety et al., 2014). Since the early 2000s, both have grown in prominence and have recently seen renewed interest (Cerezo et al., 2024). LA and EDM offer complementary insights, especially when analyzing digital artifacts and user-generated content, thereby contributing to a deeper understanding of how individuals acquire knowledge informally online (Lang et al., 2017; Romero & Ventura, 2020). In this study, we utilize social network analysis, natural language processing, and large language model-based annotation and classification as our primary methodological approaches. Despite their growing relevance, these methods have been rarely applied to the context of dating and relationship discussions on social media. By analyzing data from BlueSky, this study seeks to address that gap.

Perspective(s)

The rise of social media has led to a panoply of online communication spaces or sites, such as Facebook, YouTube and BlueSky, wherein individuals can engage into informal communication and informal learning trajectories (Rehm et al., 2021, 2022). Consequently, there has been a growing amount of research that investigated the potential of such spaces for informal learning (Goodyear & Armour, 2021; Kumar & Nanda, 2024; Temban et al., 2021). These platforms essentially provide informal learning spaces that can initiate professional development processes (Spanhel, 2010). However, just by entering these spaces, learning cannot be guaranteed. Instead, they provide an opportunity to communicate and engage into discussions with a wide variety of other individuals (Tynjälä, 2012) and by stimulating them to critically reflect on their actions (Kolb, 1983). We therefore argue that social networking sites constitute social opportunity spaces, which provide the meta-context wherein knowledge creation is fostered and learning processes are stimulated by the complex interplay of various underlying relations and factors (Rehm et al., 2021, 2022).

More specifically, in the context of this study, social media platforms have been found to serve a pivotal role in circulating and reinforcing images, narratives, and discourses surrounding dating and relationships, which gradually become normalized as “taken-for-granted” understandings within everyday life (Barker et al., 2018; Jänkälä, 2017). Large and Mulvihill (2025) argue that influencers on platforms such as Instagram are increasingly being positioned as “new experts,” offering dating and relationship advice that blends entertainment with educational intent, often framed around raising awareness of gender inequality. These influencers are often perceived as more relatable and trustworthy than traditional celebrities, especially among young adults, due to their perceived authenticity. However, the advice they offer can at times be inconsistent, which may contribute to confusion or social anxiety. Furthermore, a portion of their content may be shaped by the platform’s inherent “logic of brand-building and income generation” (Large & Mulvihill, 2025, p. 8).

In this context, these influencers or “new experts” can be conceptualized as knowledge brokers—key actors in the informal dissemination of information within digital communication networks (Rycroft-Smith, 2022). The literature attributes a diverse range of roles and qualities to knowledge brokers that emphasize their significance in informal networks (Dobbins et al., 2009). For example, they may help cultivate shared understandings of goals and cultural norms (Kitson et al., 1998), facilitate the discovery, access, and contextualization of new information (Van Kammen et al., 2006), and possess deep insights into the communities they bridge (Monod-Ansaldi et al., 2019). Additionally, they can foster new connections across domains and link otherwise disconnected users (Kwon et al., 2020). Gaining a deeper understanding of the roles and positions of such knowledge brokers—particularly these emerging “new experts”—can shed light on foundational aspects of social interaction and broader societal dynamics, especially within the realm of dating and relationships. Drawing on these considerations and using Educational Data Science, we propose the following research questions:

RQ1. What types of knowledge brokers can we identify in dating and relationship chats on BlueSky?
RQ2. Can we identify distinct discourse patterns and communication styles?
RQ3. What types of topics are being covered in the observed chats on dating and relationships?

Data & Methods

Data

Accessing the BlueSky API, relevant posts were identified using a set of keywords related to dating and relationship advice. The keywords are identified through a qualitative driven process, whereby we started off with very broad and generic terms and hashtags that suggested relevant content and then iteratively zoomed in to ensure a comprehensive capture of relevant posts. Eventually, we used the following hashtags and keywords: "advice", "dating tips", "relationship", "attract men", "attract women", "#datingadvice", "#datingtips”. Overall, we then collected 554,016 posts from 236,858 unique users from 1 Jan 2023 until 1 June 2025. At this stage, we would like to acknowledge that the collection of data from social media has raised questions of ethical concern among the research community (Koene et al., 2015). In this context, we follow the work by Moreno and colleagues (2013), who define a human subject as “*a living individual about whom an investigator obtains data through interaction with the individual or identifiable private information*” (p. 709). Based on this definition, BlueSky qualifies as an exemption from strict ethical guidelines and considerations, as users publicly disseminate their thoughts, ideas and experiences. Consequently, as in our case, if researchers only collect publicly available data from social media, which requires no password to obtain, concerns about confidentiality and trust can be relaxed.

Social Network Analysis (SNA)

Social network theory is concerned with the patterns of social relationships that exists between people in a social network (Scott, 2017). A social network perspective extends the primary focus on individuals to understanding the interaction with the larger social infrastructure in which they reside (Cross et al., 2001). It has been increasingly employed to analyze and visualize communication processes within social networking sites (Buccafurri et al., 2015; Steinfield et al., 2008; Yoon, 2014), and provides insights into the social structures of underlying communication processes (Daly et al., 2010). In applying this method to the BlueSky, we first collected data and then build a directed unweighted 1-mode network. Secondly, we computed the in-, out-, and overall degree centrality metrics of all users (nodes) taking part in the applicable discussions.

Natural Language Processing (NLP)

NLP refers to “*the computational examination of texts’ linguistic properties*” (Crossley et al., 2016, p. 7) that can handle large amounts of text data that are being produced, among others, within social networking sites e.g. BlueSky. In terms of specific methodological approaches and types of analyses, for the purpose of this study, we will focus on Part-of-Speech tagging (POS) (Chiche & Yitagesu, 2022). The main idea of POS is to assign each word of a text to its proper syntactic tag in the context of its appearance (Chiche & Yitagesu, 2022). This is also referred to as grammatical tagging (Khan et al., 2019) and includes verbs, adjectives, adverbs, and nouns. By implementing POS, we are also able to determine key phrases and n-grams (Ojo et al., 2021; Sidorov, 2019). This enables us to get a more nuanced view on the content and topics of the underlying data.

Large Language Model Classification (LLM)

We conducted two rounds of LLM text annotation (Alizadeh et al., 2025; Ni et al., 2024). This type of approach has experienced rapid growth in recent months, as the “*ease-of-use, high accuracy, and relatively low costs*” (Törnberg, 2024, p. 2) enabled a sophisticated, quantitative classification of large scale textual data sets (Gilardi et al., 2023). Using Claude 3.5 Sonnet, we targeted 5,000 posts per round. Our annotation schema measured professional positioning (rated from 1-5 from personal to strong commercial/expert positioning) and authority markers (credentialing, commercial intent, expertise claims) to identify aspects of how users claim dating expertise, credibility (Breeze, 2021) and authority (Battersby, 2019; Weismueller et al., 2022), as well as seven non-mutually exclusive discourse types and five communication styles to identity communicative purposes and differences in style as distinguishing aspects of the posts viewed as communicative genres (Lomborg, 2011). A multilayer RoBERTa (Liu et al., 2019) classifier achieved strong performance: professional positioning RMSE of 0.596, discourse types macro F1 of 0.635, and communication style F1 of 0.776. Finally, we conducted topic modeling using BERTopic (Grootendorst, 2022) implemented for the posts written by members in each group, revealing interesting trends in the variability and types of topics being engaged in by knowledge authorities, for commercial purposes and users preoccupied with the sharing of dating experiences.

Results

Social Network Analysis

In the context of our SNA, we discovered that only 7,087 users actually engaged into bilateral communication. The vast majority of users (77,693; 91,64%) rather just shared information without specifically addressing particular users or replying to their contributions. Moreover, as Figure 1 (below) shows, the overall network is very sparsely connected. Instead, BlueSky seemingly was sued by a wide variety of smaller n-tuples that engaged into iterative exchange of information and supposedly advice.

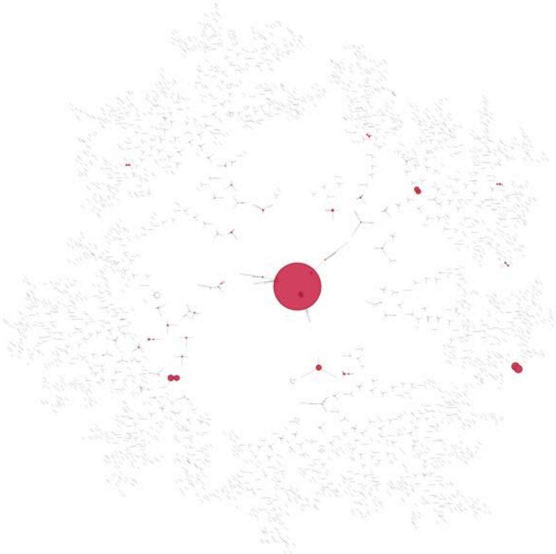

Figure 1. Whole Network Visualization of captured BlueSky Communication
(Note: Size of Nodes = Overall Degree)

NLP

The main findings of our NLP are summarized in Table 1 below. As can be seen, a wide variety of types of relationships were communicated about. The most commonly discussed phrase was "parasocial relationships", which describe one-sided relationships that individuals develop with celebrities, influencers, or fictional characters, where one party (e.g. a fan) feels a strong emotional connection, while the other party (e.g. celebrity) is unaware of the individual's existence. There are also signs of discussions around the impact of the COVID-19 pandemic on dating and relationships, as well as long distance relationships and different types of harmful relationships (e.g. toxic and abusive).

Table 1. Top Phrases (ngrams) from BlueSky Network

Phrases	N
parasocial relationships	3,429
family relationships	3,132
romantic relationships	2,897
long term	2,262
positive impact	2,118
impact family	2,094
latest survey	2,092
pandemic positivity	2,091
healthy relationships	1,682
personal relationships	1,675
abusive relationships	1,625
interpersonal relationships	1,392
building relationships	1,350
good relationships	1,164
toxic relationships	1,157
long distance	1,108

Large Language Model Classification

Three archetypical groups of users

Three distinct knowledge archetypes were identified through algorithmic classification based on users' aggregated SNA positioning patterns. User assignment employed mutually exclusive selection criteria based model on predictions: 1) The *Knowledge-based Authority Group* (n = 2,627) defined as users with an authority score ≥ 2.5 OR Expertise claims ≥ 3.0, AND Professional positioning ≥ 2.0, 2), the *Commercial Positioning Group* (n = 608) defined as user with commercial intent ≥ 2.5, and 3), and the *Experiential Discourse Group* (n = 1,116) defined as experiential sharing ≥ 50% of posts, AND professional positioning < 2.5, AND Commercial intent < 2.0. Figure 2 shows the differences in professional positioning across five dimensions with authority score being a composite measure combining credentialing and expertise claims. Additionally, Figure 3 plots the relationship between commercial intent and authority scores for members of the three groups showing three behavior clusters. As can be seen, all archetypical groups of users only use low amounts of credentialing. Moreover, in the case of the *experiential discourse group*, the applicable users also exhibit low scores for expertise claims, indicating that these members of this group are sharing their own stories, while clearly indicating that those are subjective perceptions and experiences.

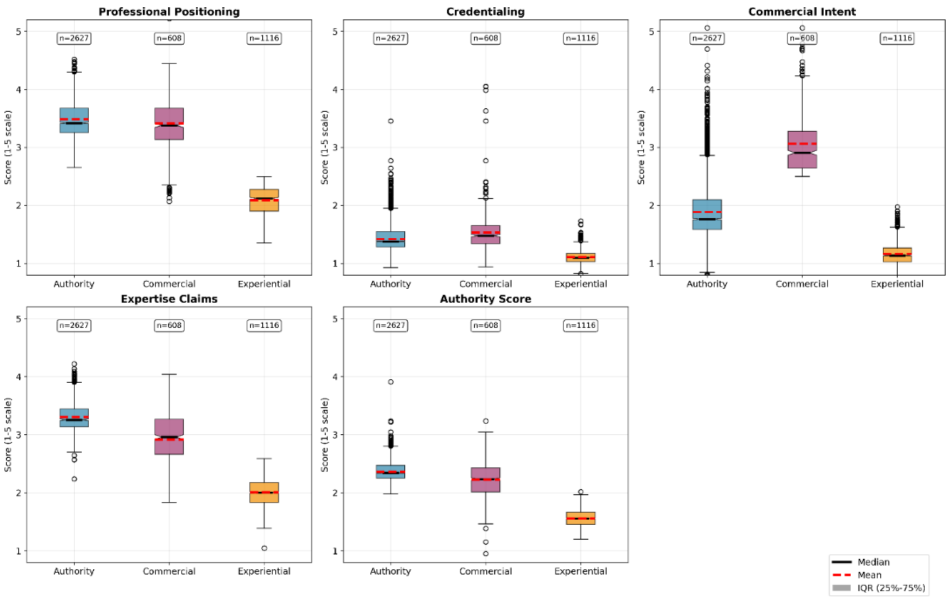

Figure 2: Distribution of professional positioning dimensions across knowledge archetypes.

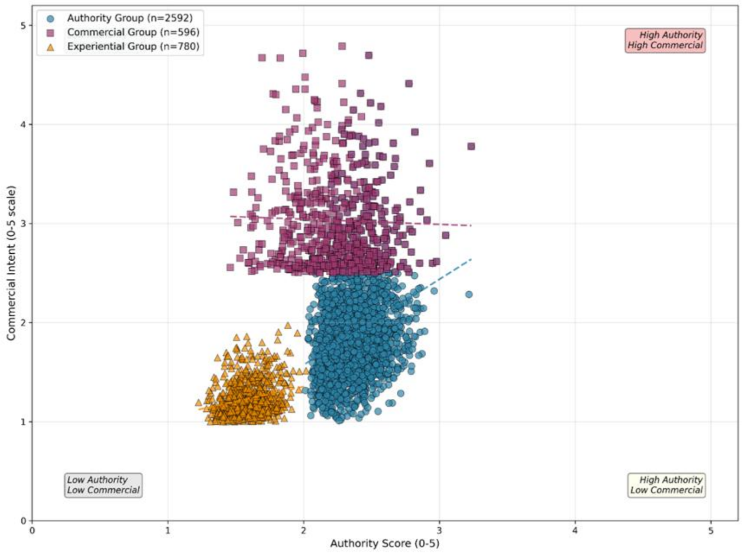

Figure 3: Authority score vs. commercial intent according to knowledge archetypes.

Discourse patterns and communication styles across identified archetypical groups of users
Following up on these first insights and findings, we used the multilayered Roberta-based classifier's predictions on posts from members of the three groups. This allowed us to identify discourse and style patterns that distinguish the groups as shown in Figure 4.

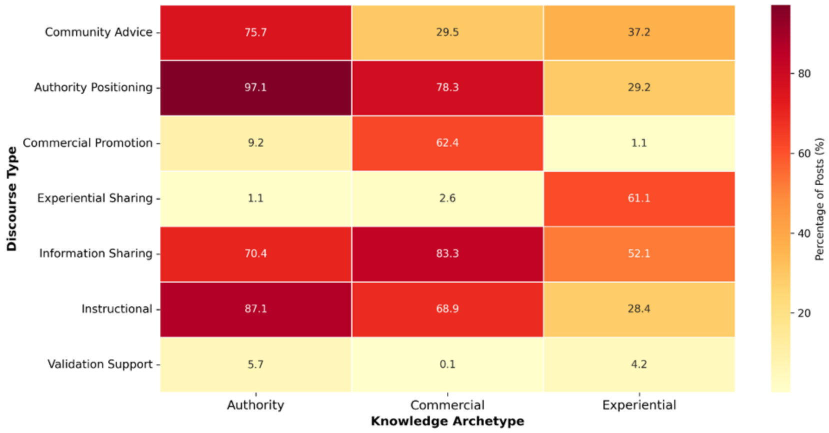

Figure 4: Discourse type usage patterns. Values show the percentage of posts containing each discourse type.

When comparing the distributions, some notable patterns emerge with the *Knowledge-based Authority Group* being more prone to providing community advice and a higher amount of authority positioning and instructional discourse than *Commercial Positioning Group* members, who score higher than the other groups on information sharing. The *Experiential Discourse Group is* characterized by relatively low scores, except for experiential sharing where they score highest. Their discourse patterns also show contributions to information sharing, community advice, and to some extent instructional and authority positioning. The classifier's predictions for communication style of the posts by the members in each group can be seen in Figure 5.

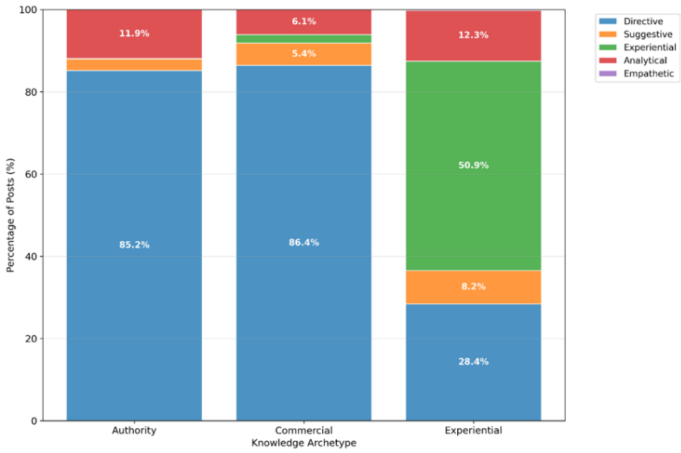

Figure 5: Communication style distribution across knowledge archetypes.

The model predicts that *Knowledge-based Authority Group* and *Commercial Positioning Group* posts are characterized by similar communication styles with a prevalence of a directive style and to a lesser extent an analytical style, for the authority group more so than the commercial group who also use an instructional style to some extent. The communication style pattern for the *Experiential Discourse Group* is more varied with the experiential and directive style most frequently represented. The overall high frequency of directive and analytical styles throughout is likely related to the necessity for brevity imposed by the 300 character-limit on Bluesky combined with possibilities for hyperlinking and use of hashtags which are noted by Zappavigna and Ross (2022) as contributing to a regulative metadiscourse on social media. Presumably, this, as well as the fact that users display very limited networking behavior, may also explain the lack of empathetic communication.

Topic modeling across identified archetypical groups of users

Topic modeling using BERTopic (Grootendorst, 2022) implemented for the posts written by members in each group reveals interesting trends in the variability and types of topics being engaged in by knowledge authorities, for commercial purposes and users preoccupied with the sharing of dating experiences. Overall, the BERTopic topic clustering technique identifies one very large topic cluster for the experiential and the authority group respectively, whereas there is more variability and a higher outlier rate for the commercial group which may suggest that dating discourse is used for a variety of commercial purposes. Although all three clusters revolve around or include "advice" as a keyword, some notable differences can be identified. Separate keywords characterizing the authority group include highlighting wellbeing, "health" and "boundary" setting, for the commercial group application and practical aspects are particularly salient ("howto…", "..tips") as well as identifying a target group ("…for men"), and for the experience-based group social, interpersonal, and experience-based aspects are prevalent ("relationships", "life", "partner"), including identifying a potential dating context ("online") and problems related to dating ("misogyny").

Conclusions

This study advances the understanding of how online chats and communication can potentially contribute to informal learning on the topics of dating and realtionships. Individuals can move across authority-based, commercial, and experiential discourses, each offering differing inputs for ther informal learning trajectories. This can be interpreted as supporting the notion of social opportunity spaces (Rehm et al., 2021, 2022), where individuals can compare perspectives, reflect on their own circumstances, and navigate among diverse communicative styles, types of advice, and experiential narratives. By engaging with these social opportunity spaces, individuals gain an opportunity to communicate and engage into discussions with a wide variety of other individuals (Tynjälä, 2012), fostering a process of critical reflection on their own actions (Kolb, 1983).

Here, by employing LLM text annotations and classifications, we are able to identify three archetypical user groups—*Knowledge-based Authority*, *Commercial Positioning*, and *Experiential Discourse* (RQ1). Through a combination of a Roberta-based classifier, and BERTopic modeling, we are also able to provide nuanced insights into the typology of user discourse patterns and communicatin styles (RQ2). Our key findings demonstrate that authority and expertise are only weakly credentialed across all groups, with the experiential group particularly refraining from formalized knowledge claims, instead highlighting personal experiences and subjective observations. Moreover, the authority group prioritizes instructional and advisory content with analytical and directive tones, while the commercial group focuses on practical, promotional discourse. The experiential group contributes most to subjective storytelling and interpersonal reflection, aligning with a more varied communication style. Finally, our topic modeling reveals that while all groups engage with "advice"-oriented content, the thematic focus diverges significantly—ranging from wellness and boundaries to marketing strategies and lived relational experiences (RQ 3). Overall, this study not only contributes to a better understanding the emerging "new experts" in online dating and relationship communication, but also sheds light on how evolving "*romantic media ideologies*" are shaped and discussed.

Complementing these discourse-centred analyses, our SNA shows that only 7,087 users actively engaged in bilateral communication, while the vast majority (77,693; 91.64%) primarily shared information without addressing or replying to others. The resulting network is highly sparse, with BlueSky being used predominantly by a wide variety of smaller n-tuples that exchanged information and advice in iterative but fragmented ways. This structural perspective underlines that, despite shared thematic interests, interaction is scattered and rarely consolidated into larger, densely connected communities. Our NLP-based analysis further broadens the picture by demonstrating the wide range of relational types and dynamics being discussed (Table 1). The most prominent phrase, "parasocial relationships," highlights users' concern with one-sided attachments to celebrities, influencers, or fictional figures. Additionally, discussions touched on the effects of the COVID-19 pandemic on dating and relationships, long-distance relationships, and harmful dynamics such as toxic or abusive partnerships.

Overall, while a more elaborate analyses are required, our preliminary findings highlight the potential for these types of mixed-methods that allow for a meaningful inclusion of more qualitative methods to analyse big data. Moreover, this study not only contributes to a better understanding of the emerging "new experts" in online dating and relationship communication (Large & Mulvihill, 2025), but also sheds light on how evolving "romantic media ideologies" (Belotti et al., 2022, p. 47) are shaped, shared, and networked across fragmented but thematically rich online exchanges.

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