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Article

Analyzing Expectation Dynamics and Public Discourse on the Metaverse Using X (Twitter) Data

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Abstract: This study examines how public expectations shaped the early diffusion of the metaverse by analyzing large-scale discourse on X (formerly Twitter) from January 2021 to May 2023. Drawing on innovation diffusion theory, the sociology of expectations, and the Hype Cycle framework, we combine BERTopic modeling with sentiment analysis to trace how public attention, themes, and affective orientations changed over time. A 10% daily random sample of 2,194,585 English-language posts was analyzed. BERTopic identified 218 topics, which were grouped into seven thematic categories, including excitement, successful projects, NFT and crypto, industry applications, games, culture, and ethics. The results show that metaverse discourse was highly event-sensitive. Public attention and positive sentiment rose sharply around Facebook's rebranding to Meta in October 2021, but declined thereafter as technical constraints, investment concerns, market uncertainty, and competing narratives became more visible. Although logical and pragmatic evaluations appeared in later discourse, they did not offset the broader decline in attention and enthusiasm. Rather than demonstrating a complete Hype Cycle trajectory, the evidence captures an early-stage process of escalation, peak attention, and subsequent disillusionment. We interpret sentiment as a proxy for affective orientation rather than as a validated measurement of emotional versus logical expectations. The study contributes by reframing metaverse-related social media discussion as a longitudinal process of collective anticipation rather than only as a topic or sentiment snapshot, and by showing how computational text analysis can help explain the role of public sentiment in emerging technology diffusion.

Keywords: Innovation diffusion; Hype Cycle; Emotional expectation; Logical expectation; Topic modeling; Sentiment analysis

1. Introduction

Since the 2000s, digital technologies such as social media platforms and cryptocurrencies have transcended traditional diffusion patterns, undergoing cycles of intense hype followed by periods of disillusionment. This progression highlights the transformative impact of digital technology on commerce and finance, as exemplified by platforms such as Airbnb, TikTok, as well as cryptocurrencies such as Bitcoin. These developments emphasize the dynamic and often unpredictable influence of digital technologies across various sectors. In particular, public enthusiasm can spike early in an innovation's life cycle due to lofty expectations, only to diminish when faced with practical realities – a pattern frequently described by the technology Hype Cycle model [1,2].

The metaverse – a virtual reality space where users interact through avatars – has recently garnered extraordinary public attention as a promising yet unproven innovation [3,4]. Major companies have invested heavily in metaverse technologies, with Facebook even rebranding itself as "Meta" to signal its commitment to this emerging digital frontier [5]. Gartner [6] predicted that by 2026, a quarter of the global population will spend at least an hour daily in the metaverse for work, education, shopping, or entertainment. This optimistic outlook gained considerable momentum amid the COVID-19 pandemic, as the widespread shift to remote work and online learning drove a surge in the use of virtual platforms and experiences. Several studies in the pandemic era explored digital adoption surges and the possibilities of metaverse applications in education and business, reflecting high hopes for this technology's transformative power [7-11].

At the same time, the metaverse faces substantial challenges and growing skepticism [12,13]. Critics highlight technical limitations in virtual reality (VR) and augmented reality (AR), as well as privacy and security risks, social concerns (such as addiction and isolation), and the uncertainty of regulatory oversight [14]. Interest in the metaverse also showed signs of waning in late 2022, especially with the advent of powerful alternatives like generative AI (for example, the launch of ChatGPT shifted public and media attention, with some declaring the "death" of the metaverse as a buzzword). This volatile trajectory of hype and doubt raises the question of how public expectations about the metaverse have evolved and what implications these shifting sentiments have for the diffusion of innovation.

Scholars have emphasized that collective expectations and narratives play a pivotal role in these early stages, influencing how stakeholders allocate resources and make strategic decisions [12,13]. Public expectations—ranging from emotionally charged optimism to sober, logical assessments—are known to significantly influence the adoption and development of emerging technologies. The sociology of expectations literature suggests that collective visions and discourses can create self-fulfilling prophecies, mobilizing resources and guiding innovation paths [12,15]. In the case of the metaverse, emotional expectations (e.g., excitement, fear) initially dominated public discourse. However, as the technology matures, logical expectations may emerge as discourse becomes more grounded in practical utility and evidence [1].

Understanding these potential shifts in expectation-related public discourse is important for analyzing early-stage innovation diffusion. The present study aims to investigate the evolution of public expectations in the diffusion of metaverse technologies. We specifically address how sentiment-driven expectations on social media have changed from the metaverse's initial surge of interest through its observed decline and whether these changes are consistent with early Hype Cycle dynamics, such as a peak of optimism followed by a downturn in enthusiasm.

To capture these dynamics, we focus on Twitter (now X) as our data source, given its prominence as a central platform for real-time public debate and sentiment expression concerning emerging technologies [16,17]. By analyzing a large dataset of Twitter posts, we examine how expectation-related public discourse surrounding the metaverse evolves over time, focusing on whether early discourse was characterized by positive sentiment—which we interpret as an indicator of emotional expectation—and how later discourse may reflect more pragmatic or evidence-based considerations. We also examine which themes dominated public discourse during pivotal turning points in the hype trajectory – for example, what topics and concerns trended when sentiment shifted from positive to negative.

We combine topic modeling with sentiment analysis to examine how the metaverse has been discussed on Twitter. By analyzing millions of tweets, we extract key discourse topics and track their associated sentiment trends, linking these patterns to real-world events and to the early escalation and disillusionment dynamics described by the Hype Cycle. This approach enables a data-driven evaluation of the metaverse's evolving expectations and offers insights into the broader dynamics of innovation diffusion in the digital age. Our analysis draws upon frameworks from innovation diffusion theory, Hype Cycle modeling, and public discourse analysis to interpret the findings.

Prior metaverse-focused social media studies have already used Twitter data and topic modeling to examine hype, sentiment, future expectations, and domain-specific discourse [18]. Building on this body of work, the present study contributes by interpreting longitudinal metaverse discourse through expectation dynamics, innovation diffusion theory, and early-stage Hype Cycle dynamics to examine how public attention and sentiment rise, peak, and decline over time.

2. Theoretical background and literature review

2.1. Diffusion of innovation and the S-curve model

The diffusion of innovations theory offers a foundational lens for understanding how new technologies spread throughout society. Rogers' seminal work (1962) described the diffusion process as an S-shaped curve, where adoption begins slowly among a few innovators, accelerates through early and majority adopters, and eventually levels off when the market becomes saturated. The S-curve model captures a typical progression of cumulative adoption that begins with initial exponential growth, gives way to linear growth at mid-adoption, and finally reaches an asymptotic plateau as the pool of potential new users is exhausted [19]. Subsequent research has expanded on Rogers' insights, identifying factors that influence different phases of the S-curve, such as social influence, communication channels, and perceived benefits of the innovation [20–22].

The S-curve remains an essential tool for businesses and policymakers to anticipate adoption rates and plan strategies (for example, tailoring interventions to encourage uptake during early phases or to address late-stage saturation) [22–24].

However, one limitation of the classical S-curve is that it focuses on actual adoption behavior and ex post measures of diffusion. It tends to neglect the role of pre-adoption expectations and public hype, which can significantly shape early adoption dynamics even before measurable uptake occurs [1]. For instance, an innovation that is excessively hyped may see a faster initial adoption (as early enthusiasts rush in) but might also face a sharper drop-off if disappointment sets in, deviating from a smooth S-curve. Recognizing this interplay sets the stage for incorporating the concept of Hype Cycles into our analysis.

2.2. Hype Cycle model

The Hype Cycle, introduced by Gartner in 1995, focuses explicitly on the ebbs and flows of public visibility and expectations for new technologies. Unlike the S-curve, which tracks adoption rates, the Hype Cycle traces collective expectations over time. It typically comprises five phases: (1) the Technology Trigger, an early breakthrough or launch that generates interest; (2) the Peak of Inflated Expectations, where excitement (often fueled by media and marketing) leads to unrealistic hopes and widespread buzz; (3) the Trough of Disillusionment, when technologies fail to meet the inflated expectations and interest wanes; (4) the Slope of Enlightenment, as understanding and practical improvements emerge gradually; and (5) the Plateau of Productivity, where the technology finds its practical niche and adoption stabilizes at more realistic levels [15]. **Figure 1** illustrates these five phases of the Hype Cycle.

Figure 1. The Hype Cycle curve [25].

The Hype Cycle model has since become a subject of considerable academic scrutiny, with numerous studies seeking to validate, refine, and critique its framework. Konrad et al. [26] emphasized the importance of collective expectations (held by developers, users, media, etc.) in shaping strategic decisions during a technology's early stages. Their work suggests that public narratives and anticipation can heavily influence the trajectory of an innovation. While some researchers recognize the importance of collective expectations, others have questioned the empirical robustness of the Hype Cycle framework. For instance, Borup et al. [27] argued that real-world innovation pathways often exhibit more variability than the orderly sequence depicted in Hype Cycles due to unpredictable technological and social changes. In a systematic review of empirical cases, Dedehayir and Steinert [2] found that only 9 out of 23 studies conformed to the classic Hype Cycle pattern, indicating that many technologies do not neatly follow the model's curve. They recommended integrating hype dynamics into traditional technology life-cycle models (like the S-curve) to capture complexities better.

Researchers have attempted to quantify Hype Cycles through various methodological approaches to capture the dynamics of expectations. Van Lente et al. [15] developed a comprehensive framework combining quantitative media attention analysis with qualitative discourse analysis of expectation statements, examining three technologies (VoIP, gene therapy, and high-temperature superconductivity) across different levels of expectations—from project-specific to societal frames—using sources like the New York Times and technical journals. Khodayari and Aslani [28] employed patent citation data from Google Patents, alongside search trend analytics from Google Trends, to systematically position various energy storage technologies (compressed air storage, batteries, and superconductors) at different stages of the Hype Cycle, demonstrating how data-driven methods can assess technological maturity.

Despite its usefulness, the Hype Cycle model's predictive application remains challenging. Hype phases can be difficult to distinguish in real-time, and not all technologies undergo an obvious "trough" [2,29]. Moreover, external events can reset or amplify hype. In the context of the metaverse, for example, the hype was markedly amplified by Facebook's Meta announcement (a trigger event) and later tempered by the rise of AI as a competing focus of attention. These nuances underscore why careful empirical analysis of public discourse is needed to understand expectation dynamics rather than relying solely on generic models.

2.3. Public discourse analysis

Emerging technologies do not gain meaning or legitimacy in isolation – their significance is continually constructed, contested, and negotiated through public discourse. In Habermas's terms, the public sphere is an arena where individuals collectively debate and shape opinions on matters of common concern [30]. Through rational-critical discussion, public discourse helps confer legitimacy (or stigma) on innovations, influencing whether society deems a technology desirable, acceptable, or controversial.

Hajer's discourse theory further emphasizes that shared narratives (or "storylines") bind together discourse coalitions of actors who ascribe common meaning to innovation [31]. In other words, discourse is not just idle talk – it structures reality by framing how people understand a technology's purpose and potential [32]. Competing discourse coalitions may advance divergent storylines (for instance, utopian optimism vs. cautionary skepticism), thereby competing to define the dominant interpretation of nascent technology.

This dynamic was evident, for example, in early public debates on blockchain technology: proponents heralded it as a revolutionary infrastructure for a decentralized future, while critics pushed cautionary narratives of speculation and illicit activities [33,34]. Likewise, discourse around generative AI in 2023 oscillated between extreme hype (portraying AI as inevitable and transformative) and backlash (warning of AI's risks and overstatement) – often simultaneously [35]. Such cases demonstrate how public discourse becomes a site of sense-making where the very identity and future of an emerging technology are at stake.

Beyond merely reflecting meaning, public discourse often has a performative power in innovation – media narratives can actively shape how technologies develop by creating expectations that influence investors and policymakers [36]. Studies show that media coverage, social media trends, and public debate can amplify excitement or fear surrounding a new technology, which in turn influences real-world behavior, such as funding decisions, user adoption, and regulatory attention [37]. Moreover, the speed and global reach of modern communications (e.g., virality on Twitter) mean that hype and critique now diffuse faster than ever, potentially shortening the cycle between intense enthusiasm and rising skepticism [38]. As a result, innovation scholars argue that understanding how a new idea spreads today requires analyzing its narrative trajectory – how public discussions build up, peak, and shift over time – and they increasingly use public discourse analysis to trace these dynamics in diffusion processes [39].

2.4. The role of expectations in innovation evolution

Technological expectations are a critical driver of innovation diffusion, especially in the early stages of an emerging technology's development. Expectations can be articulated by various actors – entrepreneurs, industry analysts, media, government agencies, and the public – each of whom can influence the trajectory of development. High expectations can attract investment, guide research priorities, and encourage early adoption [40,41]. Conversely, negative expectations or widespread fears may induce hesitancy, invite regulatory scrutiny, or even lead to the abandonment of a nascent technology [29]. Prior studies have documented that expectations not only anticipate future adoption but also help shape innovation trajectories by generating momentum, pressure, caution, or resistance around technological change [12,26,42].

Within the sociology of expectations, scholars have categorized expectations along several dimensions. Alkemade and Suurs [13], for instance, distinguish expectations by their content (positive vs. negative), specificity (general visions vs. specific predictions), time horizon (short-term vs. long-term), and the type of actors expressing them (e.g., entrepreneurs, government agencies, or the public). More recently, Shi and Herniman [1] expanded this framework by proposing that expectations also vary fundamentally in their nature, falling into four basic types: positive emotional, negative emotional, positive logical, and negative logical. In the early stages of innovation, expectations often follow a pattern of sharp initial growth in positive expectations, which then either decline in positivity or give rise to growing negativity as reality sets in. This trajectory mirrors the Hype Cycle's rise and fall, but Shi and Herniman offer a nuanced lens by differentiating emotional versus logical expectations behind those swings.

Emotional expectations are those driven by collective sentiment, visceral excitement, and cultural narratives. They often appeal to basic human emotions, such as hope, fear, or the thrill of possibility. Emotional expectations can spread rapidly (especially via media and social networks) because they resonate widely on an affective level. However, they tend to be powerful but short-lived. Since they are less grounded in evidence, they may fade or flip to disappointment quickly if the technology does not immediately live up to the lofty vision. Logical expectations, in contrast, are based on a rational evaluation of an innovation's practical benefits, technical feasibility, and performance metrics. These fact-based expectations require time and evidence to develop, but they exert a more sustainable long-term influence once established. Logical expectations correspond to more concrete assessments of an innovation's efficiency, economic viability, or proven utility [1].

Crucially, as a novel technology matures, logical expectations may gradually replace emotional ones, reflecting more grounded assessments based on empirical evidence. Positive emotional expectations (e.g., hype-fueled optimism) often dominate the initial phase of adoption, propelling the innovation through its early hype-driven growth. However, over time, as real performance data accumulate and initial excitement fades, logical and often more critical expectations may gain prominence, focusing on measurable outcomes and return on investment [13]. This shift from emotion-driven optimism to pragmatic evaluation echoes the journey from the "Peak of Inflated Expectations" to the more sober "Plateau of Productivity" in Gartner's Hype Cycle model. Indeed, Shi and Herniman [1] suggest that the composite of emotional and logical expectation trends can produce a curve akin to the Hype Cycle – with emotional expectations creating the steep rise and fall and logical expectations underpinning the eventual stabilization.

Understanding the dynamics of expectations is essential for analyzing early-stage adoption of innovations. Early adopters are often swayed by visionary hype and affective appeal (emotional expectations), whereas later adopters demand evidence of value and reliability (logical expectations) before committing [2,15]. In diffusion theory terms, innovators and early adopters might embrace a technology due to excitement and bold promises. In contrast, the early majority and late majority require more tangible proof and practical justification – a correspondence that aligns with the emotional-to-logical shift in expectations over time. Thus, expectations provide a bridge between the Hype Cycle and the diffusion S-curve, linking the swings in collective sentiment to the decisions of individual adopters at each stage.

Empirical studies support this view of expectation dynamics. Analyzing hydrogen fuel-cell vehicles, for instance, Chung et al. [41] showed that early optimism eventually gave way to pragmatic assessments of technical efficiency and market readiness, highlighting the gap between initial innovation potential and subsequent commercial feasibility. Similarly, Sun et al. [18] employed a BERT-based topic modeling approach to analyze Korean Twitter discussions of the metaverse, categorizing public expectations into specific, generalized, and framed categories. Their study revealed that public sentiment on social media often reflects the expectations voiced by influential actors (such as tech CEOs or media outlets) rather than the technology's actual performance, emphasizing the complex interplay between social narratives and technological adoption. Building on such work, the present study differs by treating metaverse Twitter discourse as a temporal process of expectation formation and decline, rather than only as a set of topics, sentiments, or expectation categories. It connects large-scale topic and sentiment patterns to innovation diffusion and early Hype Cycle dynamics over time. These studies underscore the importance of understanding the dynamic role of expectations in shaping innovation diffusion and technological evolution. They also highlight the need to integrate sentiment analysis and predictive frameworks in research in order to better anticipate the challenges and opportunities associated with emerging technologies.

3. Research questions

This research aims to analyze the dynamics of expectations surrounding metaverse technologies and their evolution over time. To achieve this objective, the study addresses the following research questions:

RQ1: How do expectations regarding metaverse technologies evolve over time?

Building on prior research, early-stage expectations for emerging technologies are often characterized by high levels of positive emotional sentiment. These expectations typically decline as the technology matures. This study examines whether the metaverse, which has garnered significant public attention, follows a pattern consistent with the Hype Cycle. Specifically, we examine whether the initial surge in positive sentiment—which we interpret as emotional expectation—declines over time, and how later-stage discourse may reflect more pragmatically framed perspectives, as observed through qualitative analysis of representative tweets. This analysis explores how discourse evolves from emotion-driven optimism toward more pragmatic framings as the metaverse progresses.

RQ2: What are the key themes in Twitter discourse during notable shifts in metaverse expectations?

By analyzing Twitter discourse, this study seeks to identify and interpret key topics discussed during critical moments of expectation shifts. Through discourse analysis, the research aims to uncover the causes of these changes and gain insights into how the public responds to the evolution of metaverse technologies and their perceived potential.

These research questions provide a framework for understanding the relationship between public expectations and the diffusion of metaverse technologies.

4. Methods

4.1. Data collection

This study collected Twitter data to analyze the role of technological expectations in the early stages of metaverse innovation diffusion. Twitter, a widely used platform for sharing and discussing emerging technologies, provides a valuable data source for studying innovation diffusion due to its diverse user base and real-time information exchange [16, 17, 43-47]. The platform has been utilized in prior research to study technological expectations, including information systems [48] and the metaverse [18].

To achieve the study's objectives, tweets containing the English keyword "metaverse" were retrieved using Twitter's Academic API 2.0. Data collection spanned from January 2021, when the metaverse began receiving public attention, through May 2023, the final month for which data could be retrieved using Twitter's Academic API. This period includes key events such as Facebook's rebranding to Meta in October 2021, which coincided with an observed increase in public discourse on the metaverse. The API's speed and volume limitations required a monthly data retrieval process, and retweets were excluded to focus on original user-generated content.

The raw corpus contained 21,949,301 tweets matching the keyword "metaverse" during this period. It served as the sampling frame for the analytic sample used in the subsequent topic-modeling and sentiment analyses.

4.2. Sampling

Given the resource-intensive nature of processing over 20 million tweets, this study employed a sampling strategy to ensure computational feasibility while maintaining the integrity and diversity of the data. A random sample comprising 10% of the total tweets collected from January 2021 to May 2023 was selected. To account for temporal variations, 10% of tweets were sampled daily across the entire study period, resulting in an analytic sample of 2,194,585 tweets.

4.3. Data preprocessing

The unstructured Twitter data underwent preprocessing to improve analytical accuracy. Duplicate entries were removed to prevent distortion of results. For computational preprocessing, non-essential elements such as URLs, hashtags, and words beginning with hashtags were eliminated before topic modeling and sentiment analysis to focus on the rhetorical content of the tweets. Additionally, tweets with abnormal timestamps were excluded to ensure temporal consistency in the analysis.

The data were retrieved using Twitter's Academic API 2.0 in accordance with the platform's API access conditions, and only publicly available posts were collected; no protected accounts or private content were accessed. To reduce privacy and re-identification risks, user identifiers were hashed during analysis, and user handles in the example tweets quoted in Tables 2–6 were replaced with "@[anonymized]". Quantitative analyses are presented only in aggregate. Because the study analyzed only public, secondary social-media data and did not involve interaction with human participants, no formal institutional review board (IRB) review or exemption was sought.

4.4. Text mining

To analyze the expectations surrounding the metaverse, text mining techniques were applied. Specifically, topic modeling and sentiment analysis were employed to identify dominant themes and classify sentiments as positive, negative, or neutral. Unlike retrospective studies relying on patents or research papers, this approach provides a forward-looking perspective using contemporary social media discourse.

4.5. Topic modeling, topic reduction, and topic labeling

BERTopic was used to identify latent thematic patterns in the analytic sample. The topic modeling was implemented in Python in a Google Colab Pro GPU environment. After preprocessing and duplicate removal, topic modeling was performed on 2,125,076 tweets. Sentence embeddings were generated using the sentence-transformers/all-MiniLM-L6-v2 model and were precomputed before topic modeling to improve computational efficiency.

The BERTopic pipeline used GPU-accelerated cuML UMAP for dimensionality reduction with n_neighbors = 50, n_components = 5, metric = "cosine", and random_state = 42. Clustering was conducted using the cuML HDBSCAN implementation with min_cluster_size = 20, min_samples = 20, gen_min_span_tree = True, and prediction_data = False. To reduce memory usage, a fixed vocabulary was constructed using CountVectorizer by retaining terms that appeared at least 15 times in the corpus; this yielded 45,366 terms, with English stop-word removal applied.

An initial BERTopic model generated 7,205 topics. Because this initial result was too fragmented for interpretation and many low-frequency topics contained too few tweets for subsequent sentiment analysis, we applied an iterative topic-reduction procedure using the median topic frequency as the reduction criterion. In each round, the topic-frequency distribution was inspected and a reduced target number of topics was specified so that low-frequency topics below the median were merged into higher-frequency or semantically similar topics. Across six successive rounds, the total number of topics was reduced from 7,205 to 3,584, 1,778, 882, 439, and finally 218 topics, with corresponding median frequencies of 51, 59, 103, 181, 242, and 390. The final set of 218 topics was used for theme categorization and subsequent sentiment analysis.

Topic labels were then generated for these 218 topics using the OpenAI representation model implemented in BERTopic. The ChatGPT API model used for labeling was gpt-3.5-turbo. For each topic, the prompt provided representative topic documents and topic keywords and asked the model to generate a concise descriptive label of no more than five words in the format “topic: <topic label>.” The generated labels were used as descriptive aids for interpreting the topics. Final theme interpretation was based on the ChatGPT-assisted labels together with the c-TF-IDF terms, topic counts, and, where necessary, representative topic documents.

4.6. Sentiment analysis

Sentiment analysis was conducted using the "cardiffnlp/twitter-roberta-base-sentiment" model, a pre-trained BERT model optimized for Twitter data. This model effectively classifies text into sentiment categories (positive, negative, neutral) with high accuracy, leveraging deep learning techniques based on the Transformer architecture. This step provided sentiment polarity (positive, negative, or neutral) for each tweet. We note that the classifier captures three-way sentiment polarity rather than directly distinguishing emotional and logical expectations as separate measurable constructs. Accordingly, we use the sentiment results to examine sentiment dynamics and complement them with qualitative interpretation of representative tweets in Section 5.3, rather than treating the results as a validated measurement of emotional versus logical expectations.

By integrating sampling, preprocessing, topic modeling, and sentiment analysis, this methodology effectively captures and interprets public expectations about the metaverse, offering valuable insights into innovation diffusion patterns.

5. Results

Using BERTopic, a total of 218 topics were extracted from the analytic sample. **Figure 2** highlights the top 20 topics, with five high-frequency terms associated with each. For example, Topic 0 includes terms such as 'game,' 'metaverse,' and 'NFTs,' reflecting the prominent themes within the discourse. The analysis was performed at the sentence level to account for the linguistic characteristics of English social media posts, and the relative importance of terms was measured using c-TF-IDF scores.

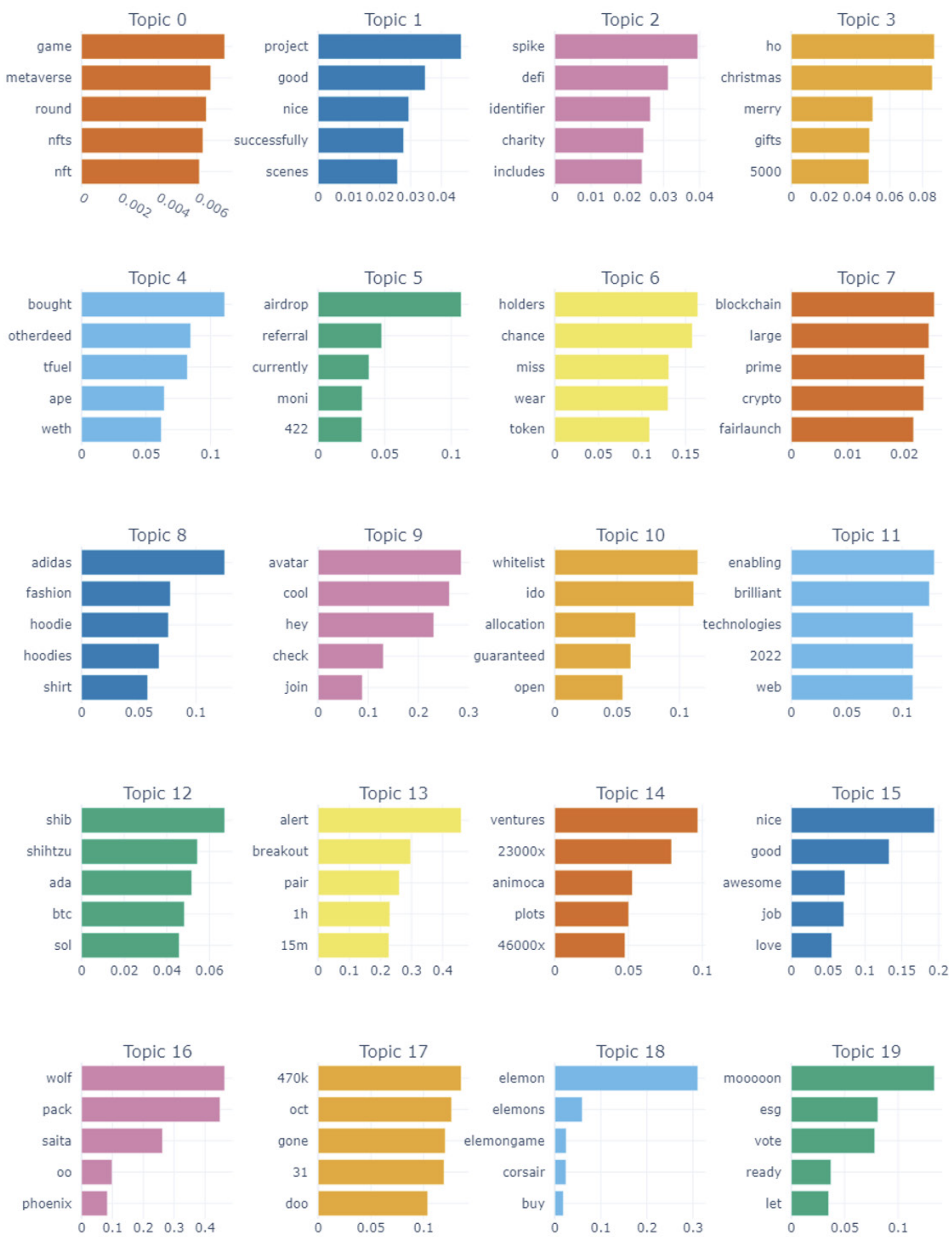

Figure 2. Top 20 topics out of 218 topics from the final topic modeling

5.1. Topic categorization and sentiment trends

The extracted topics were categorized into seven overarching themes, including Exciting Metaverse, Successful Metaverse Projects, NFT & Crypto, Industry Applications, Games, Culture, and Ethics (**Table 1**). We emphasize that this categorization is based on the authors' qualitative interpretation rather than on automated classification. To enhance interpretive consistency, the authors reviewed the topic keywords, representative tweets, and temporal patterns, and any ambiguous cases were resolved through discussion and consensus. Therefore, the theme labels should be understood as interpretive summaries of model-derived topics rather than as mutually exclusive categories produced by a supervised classifier. The categorization provided a structured way to analyze discourse and expectations within the metaverse domain. For each theme, the monthly volume of tweets was examined, revealing distinct temporal trends. The rebranding of Facebook to Meta in October 2021 coincided with an observed peak in discourse across several representative topics. However, the subsequent decline in tweet volumes and the unique decline patterns observed for different topics were notable (**Figure 3**, which shows the four high-frequency representative topics (Topics 0, 1, 2, and 8); the corresponding trends for Topics 18, 31, and 62 are provided in Supplementary **Figure S1**).

Table 1. Topic categories and tweet counts for selected representative topics

Theme	Topic Label(ChatGPT-assisted)	Topic Words (Terms)	Tweet Count
Exciting Metaverse	Topic 0: Exciting NFT Game Round	'game', 'metaverse', 'round', 'nfts', 'nft', '1st', 'limited', 'ends', 'cmc', 'audit'	266,375
Successful and nice Metaverse Project	Topic 1: Successful Diverse Scene Creation	'project', 'good', 'nice', 'successfully', 'scenes', 'diverse', 'congratulations', 'held', 'projector', 'hopefully'	60,410
	Topic 15: Nice Job Congrats	'nice', 'good', 'awesome', 'job', 'love', 'great', 'amazing', 'thank', 'dlr', 'congrats'	7,141
DeFi, NFT & Crypto	Topic 2: Spike Cross-Chain Defi	'spike', 'defi', 'identifier', 'charity', 'includes', 'focused', 'naka', 'cross', 'wallet', 'marketplace'	50,598
	Topic 3: Christmas gifts giveaway	'ho', 'christmas', 'merry', 'gifts', '5000', 'heroes', 'contest', 'waiting', 'bring', 'pool'	43,082
Industry Applications	Topic 8: Adidas Free Metaverse Hoodie	'adidas', 'fashion', 'hoodie', 'hoodies', 'shirt', 'free', 'claiming', 'wear', 'party', 'originals'	15,327
Games	Topic 18: elemon game	'elemon', 'elemons', 'elemongame', 'corsair', 'buy', 'strategic', 'hold', 'love', 'game', 'summoning'	5,612
	Topic 32: Growing Ecosystem	'evergrowing', 'number', 'grow', 'does', 'ecosystem', 'look', 'main', '40', '17', 'locked'	2,955
Culture	Topic 31: Avant-Garde Art Sensibility	'art', 'sensibility', 'avant', 'garde', 'gallery', 'sharpened', 'uploaded', 'thankyou', 'feel', 'wonderful'	3,131
	Topic 64: Snoop Dogg's Crypto Metaverse Collab	'snoop', 'dogg', 'collab', 'notorious', 'music', 'video', 'son', 'tp', 'row', 'usm'	1,127
Ethics	Topic 62: Virtual Metaverse Sexual Assault	'raped', 'sexual', 'woman', 'whistleblower', 'sexually', 'virtually', 'assaulted', 'researcher', 'rape', 'assault'	1,153

Note: The table presents selected representative topics from the final set of 218 topics rather than a complete list of all topics.

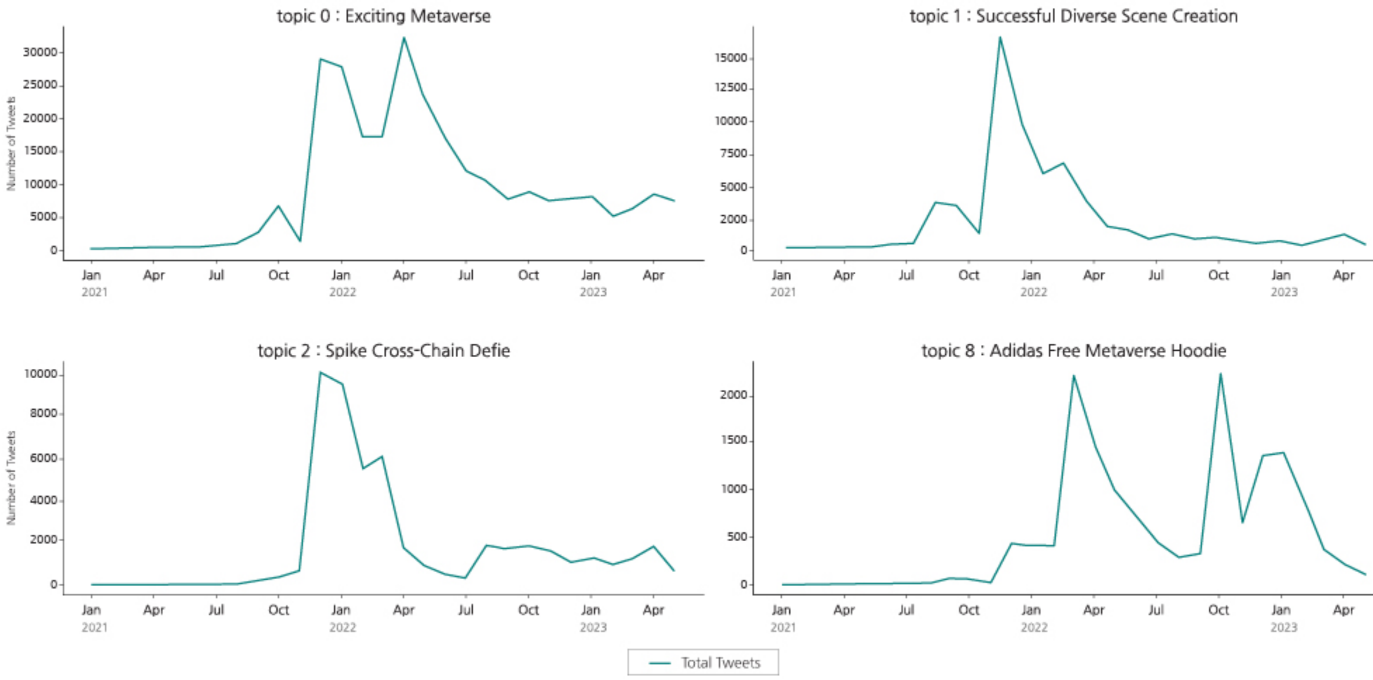

Figure 3. Monthly tweet counts (raw counts) for four representative topics (Topics 0, 1, 2, and 8), January 2021 to May 2023. The corresponding monthly trends for Topics 18, 31, and 62 are provided in Supplementary Figure S1

5.2. Sentiment analysis of metaverse discourse

To address the first research question, sentiment analysis was conducted on all sampled tweets, categorizing them as positive, neutral, or negative. The sentiment classification results, visualized in **Figure 4**, indicate an initial dominance of positive sentiment, which gradually declined over time. We interpret this positive-sentiment trajectory as broadly consistent with the rise and fall of emotional expectations described in prior literature, while acknowledging that sentiment polarity alone does not directly operationalize emotional and logical expectations as separate measurable constructs. For example, Topic 0 (Exciting Metaverse) showed a clear pattern of high early positivity, which diminished as public excitement waned. Similarly, topics related to NFTs and Industry Applications followed this trend, whereas topics addressing Ethics displayed a higher proportion of negative sentiment throughout the study period (see Supplementary **Figure S2** for the corresponding sentiment trends of Topics 18, 31, and 62). **Table 2**, **Table 3**, and **Table 4** provide illustrative examples of positive, negative, and neutral sentiment tweets for Topic 0, respectively.

Table 2. Positive sentiment tweet examples for Topic 0: Exciting Metaverse

Date	Tweet Text
Oct 30, 2021	Have you watched Facebook's announcement of the Metaverse? Personally I'm super excited XD I hope Twitter moves as fast towards this as Facebook is
Mar 19, 2022	One fact that boosts our confidence in the possibilities of the new digital world order is that the Metaverse market is expected to reach an estimated $828.95 billion by the year 2028.
Oct 23, 2022	Apple CEO Tim Cook loves AR in the Metaverse, and here's why

Continuation Table:

Date	Tweet Text
Jan 31, 2023	ChatGPT is making waves worldwide. This AI tech can be applied to numerous fields & is already being utilized. Among them, @[anonymized] deserves attention after they announced introduction of ChatGPT. Other metaverse projects also have the potential to link ChatGPT to games.
May 11, 2023	The metaverse is fostering inclusivity in sports, with accessible virtual stadiums that can be enjoyed by fans of all abilities, ages, and backgrounds.

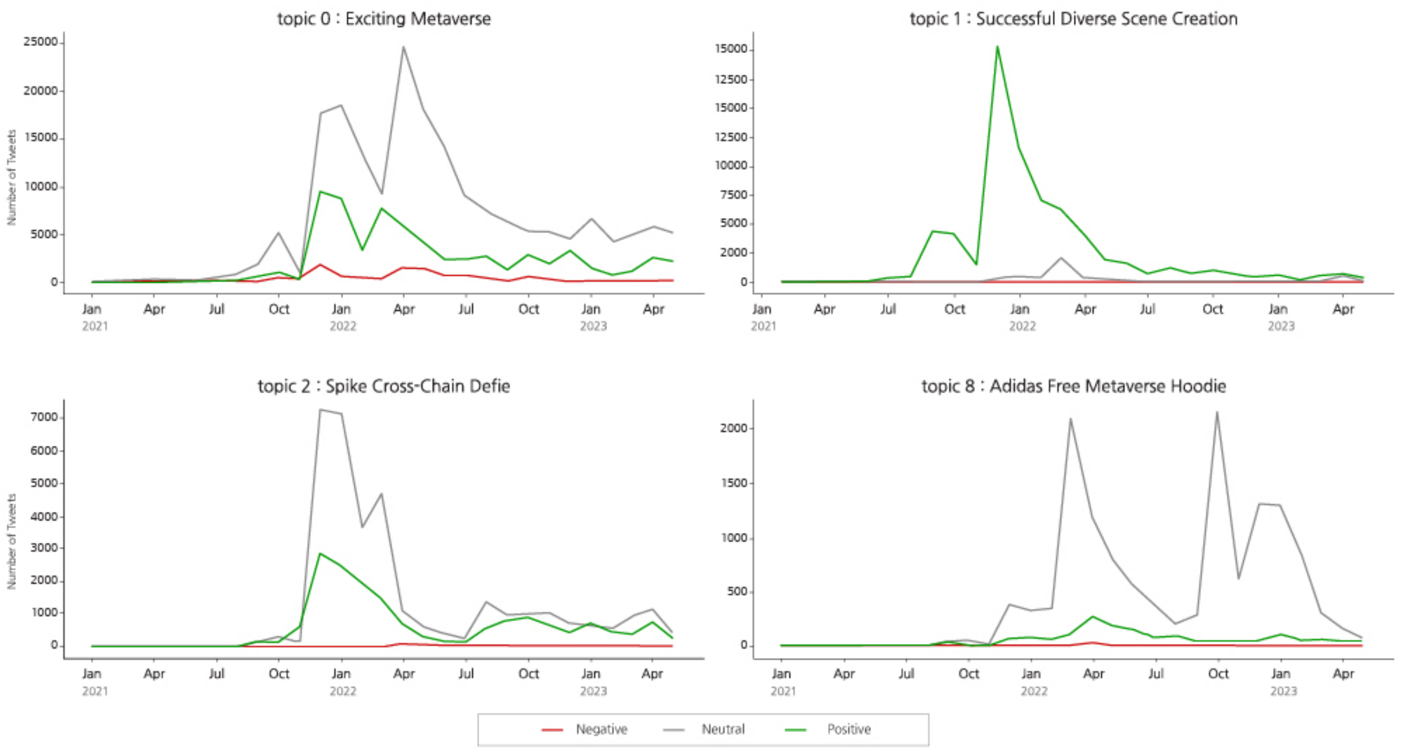

Figure 4. Monthly tweet counts by sentiment (raw counts) for four representative topics (Topics 0, 1, 2, and 8), January 2021 to May 2023. The corresponding sentiment trends for Topics 18, 31, and 62 are provided in Supplementary Figure S2

Table 3. Negative sentiment tweet examples for Topic 0: Exciting Metaverse

Date	Tweet Text
Jun 26, 2021	am I the only one who doesn't get metaverse thingy hahaha like I understand how it works but I cannot consume it hahahahah maybe I'm just getting old hahahaha
Oct 31, 2021	Facebook is changing its corporate name to Meta as it shifts its focus to the "metaverse" and confronts wide-ranging scrutiny of the real-world harms from its various platforms after a whistleblower leaked hundreds of internal documents.
Sep 30, 2022	Some people are excited to see realistic avatars that look like them in the metaverse. Others worry it might make body image issues even worse.
Jan 31, 2023	Don't expect hope from Ziliga, the only thing it produces is lie projects, Web 3 game console, Metaverse, none of them came true in the promised time and does not inspire confidence.
May 15, 2023	The Metaverse, Zuckerberg's Tech Obsession, Is Officially Dead. ChatGPT Killed It.

Table 4. Neutral sentiment tweet examples for Topic 0: Exciting Metaverse

Date	Tweet Text
Jun 26, 2021	what is nft define as nonfungible token it can be anything like art pictures drawing music etc in digital is it safe
Oct 31, 2021	a centralised v decentalised metaverse life is at stake the ethics of the metaverse
Mar 31, 2022	my next metaverse im buying land in will be on lfg
Feb 28, 2023	Japanese Tech and Finance Giants Launch Japan Metaverse Economic Zone
Mar 31, 2023	Disney Eliminates Its Metaverse Division as Part of Company's Layoffs Plan - WSJ - The Wall Street Journal

5.3. Sentiment dynamics and qualitative illustration of expectation types

The study also examined sentiment dynamics and qualitatively interpreted how expectation-related discourse changed over time. Early discourse was characterized by positive emotional sentiment, including excitement and aspirational visions of the metaverse. For instance, tweets highlighted the transformative potential of virtual worlds for gaming, entertainment, and even social interactions.

Tweets that we interpret as reflecting more logical or evidence-based reasoning appeared less frequently during the initial phases. As the technology matured and concrete outcomes emerged, such tweets—referencing verifiable information and pragmatic assessments—appeared more prominent in discussions of financial performance, adoption challenges, and technological limitations. Consistent with the interpretive approach used for topic categorization, these examples are presented as illustrative cases rather than as exhaustive or mutually exclusive classification. For example, later-stage tweets frequently referenced declining VR headset sales, unmet revenue projections, and critiques of the practicality of fully immersive virtual environments (**Table 5**). This pattern may be interpreted as indicative of a movement from initial optimism toward more critical and pragmatic evaluations of the metaverse.

Table 5. Logical Expectations tweet examples for Topic 0: Exciting Metaverse

Date	Tweet Text
Oct 30, 2021	Facebook invests billions in metaverse efforts as ad business suffers By Reuters
Dec 17, 2021	World's biggest douchebag releases NFT collection
Jan 30, 2022	The inventor of the PlayStation says the metaverse is pointless
Apr 30, 2022	Metaverse play Unity Software has fallen 62% from its high. Is it time to buy? . Despite beating expectations with its latest earnings, Unity Software (U) slipped to a 52-week low in March, a victim of the general downdraft in...
Aug 9, 2022	The metaverse housing market has crashed 85% since its peak earlier this year. Would you still buy land in the metaverse?
Oct 31, 2022	Metaverse Project WeMade Put on 'Caution' List in South Korea After Releasing Inaccurate Token Data
Jan 5, 2023	The EU commission did spend US$410,000 on a 'metaverse gala event' that was supposed to explain the GG concept to 18-35-year-olds. The event flopped and was lambasted as a social media debacle.

Continuation Table:

Date	Tweet Text
Apr 15, 2023	VR headsets sales slumped in 22. But supposedly $120 billion invested in the Metaverse. Which is set to be a trillion dollar industry. Supposedly. Something doesn't add up does it? Presumably Metaverse is no longer a VR thing.
May 9, 2023	most nfts games currently suffer low player base due to expensive initial cost for a new player to take part in the game how does axes metaverse is attracting large group of players can you talk some of its features which make it different from other

5.4. Evolution of emotional and logical expectations

To address the second research question, discourse analysis was conducted on selected tweets surrounding pivotal moments, such as Facebook's rebranding to Meta and public critiques in late 2022. The analysis showed that early tweets predominantly emphasized the potential and promise of the metaverse, whereas later tweets increasingly reflected skepticism and criticism, particularly regarding investment returns. These patterns are consistent with the early escalation and subsequent disillusionment phases of the Hype Cycle.

For a more detailed exploration, the discourse of Topic 0 (Exciting Metaverse), which encompasses general content about the metaverse, was analyzed. Specifically, tweets from periods of notable changes in metaverse-related tweet volume were examined. This analysis highlighted the evolution of metaverse discourse on Twitter (**Table 6**). For instance, on January 2, 2021, a tweet by the CEO of Roblox referred to a column titled "Metaverse is coming," expressing optimism and anticipation for the metaverse. This sentiment corresponded to an observed rise in expectation-related discourse.

Table 6. Twitter discourse examples on the metaverse

Date	Tweet Text
Jan 02, 2021	The "Metaverse" is coming...Any better option than 2nd life? https://t.co/6XyTnVMXye
Oct 29, 2021	Facebook is changing its corporate name to Meta as it shifts its focus to the "metaverse" and confronts wide-ranging scrutiny of the real-world harms from its various platforms after a whistleblower leaked hundreds of internal documents. https://t.co/eeC6kvGts4 https://t.co/hjfk8ai1Oi
Apr 04, 2022	Metaverse hype is driving investments in edu: "VR learning & training is emerging as one of the areas of the metaverse with the most interest for investors." "Engaging storylines & gameplay-like missions are the key to keeping students engaged" https://t.co/iFqS26GuT3
Sep 30, 2022	Tim Cook in new interview: 'I'm really not sure the average person can tell you what the metaverse is' https://t.co/ceAy18R5gV by @[anonymized]
Oct 01, 2022	Zuckerberg Lost More Money This Year Than Any Other American, After Censoring President Trump and Making Dumb, Childish Bets on the Metaverse https://t.co/bFqMFIlXjo
Feb 09, 2023	Microsoft has killed a team formed in October to help customers use the metaverse in industrial settings and laid off its roughly 100 employees. https://t.co/7jqGmcbm8c

The peak of public enthusiasm occurred on October 29, 2021, when Facebook announced its rebranding to Meta. Following this, tweets such as one posted on April 4, 2022, about investments in metaverse educational applications, showcased diverse efforts to implement the metaverse across different domains.

However, in the latter half of 2022, positive sentiment in the discourse began to decline rapidly. On September 30, 2022, Apple CEO Tim Cook gave a critical interview about the metaverse, signaling growing skepticism. The next day, a tweet criticized Mark Zuckerberg's investment decisions, highlighting Meta's substantial financial losses. By early 2023, metaverse-related tweet volume had declined substantially in the observed data. Microsoft's February 9, 2023, announcement of the dissolution of its metaverse team and subsequent layoffs provided another contextual example of discourse associated with a declining outlook for the metaverse.

This discourse trajectory illustrates the initial wave of over-expectation, followed by a confrontation with technical and practical limitations.

Overall, the findings suggest a temporal pattern in public sentiment regarding the metaverse. Early discourse was characterized by positive emotional sentiment, fueled by excitement over its transformative potential. Over time, the discourse appeared to include more pragmatic and evaluative narratives, particularly around feasibility and practicality.

6. Discussion

6.1. Implications of research

The findings have several implications for understanding public expectations around emerging technologies. First, metaverse discourse on Twitter was highly event-sensitive: major corporate and media events amplified public attention and concentrated discourse around selected topics, suggesting that social-media attention can intensify technology hype rapidly, especially when an innovation is framed through high-profile corporate narratives.

Second, our analysis suggests that pivotal events, such as Facebook's rebranding to Meta, were associated with a marked increase in public interest and expectation-related discourse about the metaverse, a pattern broadly consistent with the Peak of Inflated Expectations described in the Hype Cycle [15]. Over time, these heightened expectations diminished. Thus, the evidence supports a narrower interpretation: the observed Twitter discourse captures hype escalation, a Peak of Inflated Expectations, and subsequent disillusionment, but it does not demonstrate later Hype Cycle phases such as the Slope of Enlightenment or Plateau of Productivity.

Sentiment analysis showed a decline in positive sentiment over time, which we interpret as broadly consistent with a decline in emotional expectations. This is suggestive rather than definitive, given that the sentiment classifier does not directly distinguish emotional from logical content. These findings are consistent with prior literature suggesting that early-stage discourse around emerging technologies is often positive and emotionally charged, while later discourse may become more skeptical and pragmatic over time. Interestingly, while logical expectations were observed in the discourse, their presence did not offset the decline in emotional expectations, and overall discourse about the metaverse continued to decline. This suggests that both emotional and logical expectations tapered off after the initial hype.

Compared with prior metaverse-focused Twitter analyses, this study contributes by explicitly integrating large-scale social media discourse with expectation dynamics, innovation diffusion theory, and early-stage Hype Cycle interpretation over time. This framing helps reposition metaverse Twitter discourse as evidence of how public expectations are formed, amplified, and weakened during early innovation diffusion.

This study contributes to innovation diffusion research, particularly in applying the Hype Cycle to analyze social media narratives. By integrating topic modeling and sentiment analysis, we provide a novel approach to examining public discourse, delivering a holistic view of the collective sentiment dynamics around new technologies. Our findings show how social media platforms serve as arenas for technological sense-making, where competing narratives accelerate both the rise and fall of technological hype compared to traditional media channels [31,38].

The findings have practical implications for industry practitioners and policymakers. Practitioners should approach the initial enthusiasm surrounding emerging technologies with cautious optimism, recognizing that emotional expectations are inherently unstable and prone to rapid deflation [12]. Monitoring the transition from emotional to logical expectations provides an opportunity to predict a technology's trajectory more accurately. By leveraging such analyses, companies can better manage the turbulence of innovation hype, enabling them to refine strategic investments and operational efforts.

Policymakers can benefit from these insights by creating a regulatory environment that supports sustainable innovation while safeguarding consumer interests. Transparent communication and realistic presentations of technological capabilities are crucial in managing public expectations and avoiding the disillusionment trap that often accompanies emerging technologies.

Methodologically, the main strengths of this study lie in its use of a large-scale longitudinal dataset to track technology hype in real time and its integration of computational methodologies (BERTopic, sentiment analysis) with existing innovation theory. This enabled us to trace sentiment dynamics over time and to qualitatively interpret selected narratives in relation to early-stage Hype Cycle dynamics.

6.2. Limitations

Although the results of this study provide valuable insights, the study has several limitations that should be addressed in future research.

First, this study relied exclusively on Twitter data to examine public expectations. However, the suitability of Twitter as a platform for capturing public opinion is debatable, particularly given the recent decline in its user base and changes in its policies. The inability to collect data beyond May 2023 further constrained the analysis period, limiting the temporal scope of our findings. This temporal constraint may have prevented us from observing potential recovery phases or longer-term sentiment shifts that could occur beyond our observation window.

Second, retweet data were excluded due to the large dataset size and the risk of overrepresenting minority opinions that gain popularity. However, retweets may also serve as an indicator of opinions that resonate with a broader audience, making them a valuable measure of public sentiment. This exclusion potentially underestimates the reach and impact of widely shared viewpoints in our analysis.

Third, this study did not formally operationalize emotional and logical expectations as separate measurable constructs. The sentiment model classified tweets into positive, negative, and neutral categories, while discourse reflecting more pragmatic or evidence-based reasoning was interpreted qualitatively from representative tweets and discourse characteristics. Given the large volume of data, it was impractical to hand-code all relevant content or train a dedicated classifier within the scope of this study. Therefore, the findings should be interpreted as sentiment dynamics complemented by qualitative illustration rather than as a validated measurement of emotional versus logical expectations. This approach may introduce subjectivity and limit consistency in distinguishing between emotional and logical content types.

Fourth, a further limitation concerns the composition of our corpus. Public Twitter discourse on emerging technologies may include promotional, giveaway, spam-like, and campaign-driven content, particularly within NFT-, crypto-, and gaming-related themes. Several of the highest-frequency topics in our analysis (e.g., "Exciting NFT Game Round," "Christmas gifts giveaway," and "Adidas Free Metaverse Hoodie") appear consistent with this possibility. Beyond the general preprocessing steps described above, we did not perform dedicated bot detection, spam filtering, coordinated-campaign detection, or commercial-content exclusion, nor did we conduct a sensitivity analysis comparing promotional and non-promotional subsets. Therefore, these topics should be interpreted with caution, as such content may affect topic prevalence and the interpretation of the corpus as representing organic public expectations. Future research should apply dedicated bot- and campaign-detection methods, commercial-content classification, and sensitivity analyses comparing promotional and non-promotional subsets to better distinguish organic public discourse from promotional or campaign-driven content.

In addition, although this study reports the main BERTopic configuration and ChatGPT-assisted labeling procedure to improve methodological transparency, it did not conduct formal topic-coherence or topic-stability tests across repeated model runs. Future research should assess the robustness of topic solutions using coherence metrics, repeated runs with alternative random seeds, or comparisons across alternative topic-modeling configurations.

This study was designed as a descriptive longitudinal analysis of topic and sentiment dynamics rather than as a formal statistical test of event effects. Future research could complement this descriptive and qualitative interpretation of sentiment dynamics with quantitative longitudinal analysis.

6.3. Future research agenda

This study analyzed Twitter data to explore the role of expectations in the early diffusion of metaverse technologies. To overcome the limitations of this study and deepen our understanding of expectation dynamics, we propose the following future research directions. Future research should extend beyond text-based, single-platform analysis. By integrating multimodal data, such as visual rhetoric analysis of YouTube videos on the metaverse concept, or multi-platform data comparing Twitter and other social media with legacy media discourse, such integration could provide a more comprehensive perspective. A more sophisticated methodology is needed to distinguish between emotional and logical expectations more rigorously. For example, future studies could develop hand-coded validation sets with clear annotation guidelines, assess intercoder agreement, or train dedicated classifiers to distinguish affective-hype rhetoric from evidence-based pragmatic evaluation. Dynamic topic models could also be used to track the semantic evolution of key concepts such as the metaverse. Additionally, future research should analyze retweet chain reactions to uncover key opinion leaders and the underlying influence networks that fuel hype. Furthermore, comparative case studies applying this study’s methodology to other hyped technologies, such as generative AI or blockchain, will contribute to building a more generalizable theory of expectation dynamics in the digital age.

7. Conclusion

While the metaverse remains a nascent phenomenon, the patterns observed in this study offer valuable lessons for understanding the life cycle of similar emerging technologies. Rather than demonstrating a complete Hype Cycle trajectory, the evidence captures an early-stage process in which metaverse-related discourse surged with positive, aspirational sentiment and later shifted toward more skeptical and pragmatic evaluation when confronted with technical reality and competing narratives. These findings provide a framework for anticipating and managing future technology Hype Cycles: By tracking sentiment and discourse, stakeholders can identify when expectations are becoming inflated and take steps to communicate limitations, avoid overpromising, and support more realistic evaluation. For the metaverse, specifically, our research highlights the need for transparent communication about progress and limitations and for strategic alignment among developers, investors, and communicators to set realistic expectations that can be met over time. Taken together, the study contributes to the literature by reframing metaverse Twitter discourse as a longitudinal expectation-dynamics process rather than only as a topic or sentiment snapshot. More broadly, the integration of sentiment analysis with diffusion theory and Hype Cycle modeling in this study contributes a novel approach to examining innovation ecosystems. It underscores that managing the narrative around technology is an integral part of managing the innovation itself. By acknowledging the power of expectations to both drive and derail technological diffusion, researchers and practitioners can better navigate the challenges of bringing transformative ideas to fruition in society.

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References

1. Shi Y, Herniman J. The role of expectation in innovation evolution: Exploring Hype Cycles. Technovation. 2023, 119:102459. https://doi.org/10.1016/j.technovation.2022.102459.
2. Dedehayir O, Steinert M. The Hype Cycle model: A review and future directions. Technological Forecasting and Social Change. 2016, 108:28–41. https://doi.org/10.1016/j.techfore.2016.04.005.
3. Park SM, Kim YG. A Metaverse: Taxonomy, Components, Applications, and Open Challenges. IEEE Access. 2022, 10:4209–4251. https://doi.org/10.1109/ACCESS.2021.3140175.
4. Damar M. Metaverse Shape of Your Life for Future: A bibliometric snapshot. Journal of Metaverse. 2021, 1(1):1–8.
5. Kraus S, Kanbach DK, Krysta PM, et al. Facebook and the creation of the metaverse: radical business model innovation or incremental transformation? International Journal of Entrepreneurial Behavior and Research. 2022, 28(9):52–77. https://doi.org/10.1108/IJEBR-12-2021-0984.
6. Gartner Predicts 25% of People Will Spend At Least One Hour Per Day in the Metaverse by 2026. Available online: https://www.gartner.com/en/newsroom/press-releases/2022-02-07-gartner-predicts-25-percent-of-people-will-spend-at-least-one-hour-per-day-in-the-metaverse-by-2026 (accessed on 06 May 2025). GARTNER is a trademark of Gartner, Inc. and/or its affiliates.
7. Adedoyin OB, Soykan E. Covid-19 pandemic and online learning: the challenges and opportunities. Interactive Learning Environments. 2020, 31(2):863–875. https://doi.org/10.1080/10494820.2020.1813180.

8. Koo H. Training in lung cancer surgery through the metaverse, including extended reality, in the smart operating room of Seoul National University Bundang Hospital, Korea. Journal of Educational Evaluation for Health Professions. 2021, 18:1–4. https://doi.org/10.3352/jeehp.2021.18.33.
9. Kye B, Han N, Kim E, et al. Educational applications of metaverse: Possibilities and limitations. Journal of Educational Evaluation for Health Professions. 2021, 18:1–13. https://doi.org/10.3352/jeehp.2021.18.32.
10. Mirza R, Lytras MD, Alzamzami O, et al. Clustering potential metaverse users with the use of a value-based framework: Exploiting perceptions and attitudes on the use and adoption of metaverse for bold propositions. Telematics and Informatics. 2024, 87:102074. https://doi.org/10.1016/j.tele.2023.102074.
11. Sanz-Labrador I, Cuerdo-Mir M, Doncel-Pedrera LM. The Use of Digital Educational Resources in Times of COVID-19. Social Media + Society. 2021, 7(3):20563051211049246. https://doi.org/10.1177/20563051211049246.
12. Heupel K, Fonseca JA, Rutherford M, et al. Feeding the Hype Cycle: Entrepreneurial swagger, passion, and inflated expectations. Journal of Business Venturing. 2024, 39(6):106432. https://doi.org/10.1016/j.jbusvent.2024.106432.
13. Alkemade F, Suurs RAA. Patterns of expectations for emerging sustainable technologies. Technological Forecasting and Social Change. 2012, 79(3):448–456. https://doi.org/10.1016/j.techfore.2011.08.014.
14. Zhang X, Chen Y, Hu L, et al. The Metaverse in Education: Definition, Framework, Features, Potential Applications, Challenges, and Future Research Topics. Frontiers in Psychology. 2022, 13:1–18. https://doi.org/10.3389/fpsyg.2022.1016300.
15. Van Lente H, Spitters C, Peine A. Comparing technological Hype Cycles: Towards a theory. Technological Forecasting and Social Change. 2013, 80(8):1615–1628. https://doi.org/10.1016/j.techfore.2012.12.004.
16. Bolici F, Acciarini C, Marchegiani L, et al. Innovation diffusion in tourism: how information about blockchain is exchanged and characterized on twitter. The TQM Journal. 2020, 36(9):255–279. https://doi.org/10.1108/TQM-01-2020-0016.
17. Kohl C, Knigge M, Baader G, et al. Anticipating acceptance of emerging technologies using twitter: the case of self-driving cars. Journal of Business Economics. 2018, 88(5):617–642. https://doi.org/10.1007/s11573-018-0897-5.
18. Sun S, Kim JH, Jung HS, et al. Exploring Hype in Metaverse: Topic Modeling Analysis of Korean Twitter User Data. Systems. 2023, 11(3):164. https://doi.org/10.3390/systems11030164.
19. Christensen CM. Exploring the limits of the technology S-curve. Part I: component technologies. Production and Operations Management. 1992, 1(4):334–357. https://doi.org/10.1111/j.1937-5956.1992.tb00001.x.
20. Adner R, Kapoor R. Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. Strategic Management Journal. 2016, 37(4):625–648. https://doi.org/10.1002/smj.2363.
21. Overall J, Wise S. An S-Curve Model of the Start-Up Life Cycle Through the Lens of Customer Development. The Journal of Private Equity. 2015, 18(2):23–34. https://doi.org/10.3905/jpe.2015.18.2.023.
22. Kucharavy D, De Guio R. Application of S-shaped curves. Procedia Engineering. 2011, 9:559–572. https://doi.org/10.1016/j.proeng.2011.03.142.
23. Sossa JWZ, Marro FP, Alzate BA, et al. S-Curve analysis and technology life cycle. Application in series of data of articles and patents. Revista ESPACIOS. 2016, 37(7).
24. Nunes PF, Breene T. Jumping the S-Curve: How to Beat the Growth Cycle, Get on Top, and Stay There. Harvard Business Review Press. 2011.
25. Linden A, Fenn J. Understanding Gartner's Hype Cycles. Strategic Analysis Report No R-20-1971. Gartner. 2003, (May):12. HYPE CYCLE is a trademark of Gartner, Inc. and/or its affiliates. This Gartner content is archived and is included for historical context only.
26. Konrad K, Markard J, Ruef A, et al. Strategic responses to fuel cell hype and disappointment. Technological Forecasting and Social Change. 2012, 79(6):1084–1098. https://doi.org/10.1016/j.techfore.2011.09.008.
27. Borup M, Brown N, Konrad K, et al. The sociology of expectations in science and technology. Technology Analysis and Strategic Management. 2006, 18(3–4):285–298. https://doi.org/10.1080/09537320600777002.
28. Khodayari M, Aslani A. Analysis of the energy storage technology using Hype Cycle approach. Sustainable Energy Technologies and Assessments. 2018, 25:60–74. https://doi.org/10.1016/j.seta.2017.12.002.
29. White GRT, Samuel A. Programmatic Advertising: Forewarning and avoiding hype-cycle failure. Technological Forecasting and Social Change. 2019, 144:157–168. https://doi.org/10.1016/j.techfore.2019.03.020.
30. Habermas J. The Structural Transformation of the Public Sphere: An Inquiry into a Category of Bourgeois Society. MIT

Press. 1991.
31. Hajer MA. The Politics of Environmental Discourse: Ecological Modernization and the Policy Process. Clarendon Press. 1995.
32. Gommeh E, Dijstelbloem H, Metze T. Visual discourse coalitions: visualization and discourse formation in controversies over shale gas development. Journal of Environmental Policy & Planning. 2021, 23(3):363–380. https://doi.org/10.1080/1523908X.2020.1823208.
33. Atzori M. Blockchain technology and decentralized governance: Is the state still necessary? Journal of Governance and Regulation. 2017, 6(1):45–62. https://doi.org/10.22495/jgr_v6_i1_p5.
34. Clifton J, Pal LA. The policy dilemmas of blockchain. Policy and Society. 2022, 41(3):321–327. https://doi.org/10.1093/polsoc/puac025.
35. Watching the Generative AI Hype Bubble Deflate. Available online: https://ash.harvard.edu/resources/watching-the-generative-ai-hype-bubble-deflate/ (accessed on 20 June 2025).
36. Bareis J, Katzenbach C. Talking AI into Being: The Narratives and Imaginaries of National AI Strategies and Their Performative Politics. Science, Technology, & Human Values. 2022, 47(5):855–881. https://doi.org/10.1177/01622439211030007.
37. Zhao X, Li X, Zhao Z, et al. Media attention and electric vehicle adoption: Evidence from 275 cities in China. Transportation Research Part A: Policy and Practice. 2024, 190:104269. https://doi.org/10.1016/j.tra.2024.104269.
38. Brannon W, Roy D. The speed of news in Twitter (X) versus radio. Scientific Reports. 2024, 14(1):11939. https://doi.org/10.1038/s41598-024-61921-7.
39. Kriechbaum M, Posch A, Hauswiesner A. Hype Cycles during socio-technical transitions: The dynamics of collective expectations about renewable energy in Germany. Research Policy. 2021, 50(9):104262. https://doi.org/10.1016/j.respol.2021.104262.
40. Rusconi E, Mitchener-Nissen T. The role of expectations, hype and ethics in neuroimaging and neuromodulation futures. Frontiers in Systems Neuroscience. 2014, 8:1–7. https://doi.org/10.3389/fnsys.2014.00214.
41. Chung D, Kwon Y, Kim Z. Technology life cycle and commercialization readiness of hydrogen production technology using patent analysis. International Journal of Hydrogen Energy. 2023, 48(33):12139–12154. https://doi.org/10.1016/j.ijhydene.2022.12.186.
42. Berkhout F. Normative expectations in systems innovation. Technology Analysis and Strategic Management. 2006, 18(3–4):299–311. https://doi.org/10.1080/09537320600777010.
43. Guerrero-Solé F. Interactive Behavior in Political Discussions on Twitter: Politicians, Media, and Citizens' Patterns of Interaction in the 2015 and 2016 Electoral Campaigns in Spain. Social Media + Society. 2018, 4(4):2056305118808776. https://doi.org/10.1177/2056305118808776.
44. Kim AE, Hansen HM, Murphy J, et al. Methodological Considerations in Analyzing Twitter Data. JNCI Monographs. 2013, 2013(47):140–146. https://doi.org/10.1093/jncimonographs/lgt026.
45. Komorowski M, Huu TD, Deligiannis N. Twitter data analysis for studying communities of practice in the media industry. Telematics and Informatics. 2018, 35(1):195–212. https://doi.org/10.1016/j.tele.2017.11.001.
46. López-Goñi I, Sánchez-Angulo M. Social networks as a tool for science communication and public engagement: focus on Twitter. FEMS Microbiology Letters. 2018, 365(2). https://doi.org/10.1093/femsle/fnx246.
47. Pelletier MJ, Krallman A, Adams FG, et al. One size doesn't fit all: a uses and gratifications analysis of social media platforms. Journal of Research in Interactive Marketing. 2020, 14(2):269–284. https://doi.org/10.1108/JRIM-10-2019-0159.
48. Banerjee S, Singh JP, Dwivedi YK, et al. Social media analytics for end-users' expectation management in information systems development projects. Information Technology & People. 2021, 34(6):1600–1614. https://doi.org/10.1108/ITP-10-2020-0706.