ECONSTOR Make Your Publications Visible.

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Yang, Kyongchyol; Jung, Jaemin

Conference Paper Analysis of the expectation dynamics and discourse on the metaverse using X(Twitter) data

24th Biennial Conference of the International Telecommunications Society (ITS): "New bottles for new wine: digital transformation demands new policies and strategies", Seoul, Korea, 23-26 June, 2024

Provided in Cooperation with:

International Telecommunications Society (ITS)

Suggested Citation: Yang, Kyongchyol; Jung, Jaemin (2024) : Analysis of the expectation dynamics and discourse on the metaverse using X(Twitter) data, 24th Biennial Conference of the International Telecommunications Society (ITS): "New bottles for new wine: digital transformation demands new policies and strategies", Seoul, Korea, 23-26 June, 2024, International Telecommunications Society (ITS), Calgary

This Version is available at: https://hdl.handle.net/10419/302496

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



WWW.ECONSTOR.EU

Analysis of the expectation dynamics and discourse on the metaverse using X(Twitter) data

Kyongchyol Yang¹, Jaemin Jung²

Abstract

This study aims to empirically investigate the role of expectations in innovation diffusion using metaverse discourse on social media. We also explore the dominant discourses that emerged during significant periods when expectations shifted. Expectations play a crucial role in the hype cycle and are involved in determining the direction of technological change and the speed of adopting innovations. We analyzed tweet data containing metaverse from January 2021, the year the metaverse first gained public attention, to May 2023, the latest available date. We performed topic modeling and extracted 218 topics. Results revealed that the peak number of tweets in the metaverse was concentrated in specific periods, but the timing of the decline in the number of tweets shows different patterns depending on the topic. After categorizing the extracted topics into themes, we conducted sentiment analysis to observe expectation changes. Expectations of metaverse technology changed over time: initially, positive emotional expectations were high, but after a certain point, they declined. From the discourse analysis, we found that the Metaverse was initially hyped and faced technical and practical limitations. The decline in expectations reflects these limitations. The combination of topic modeling and sentiment analysis provides a new approach to investigating public discourse and a comprehensive view of the collective flow around new technologies.

Keywords: Metaverse, Innovation diffusion, Innovation expectation, Hype cycle

¹ Doctoral Student, Moon Soul Graduate School of Future Strategy, KAIST, kcyang@kaist.ac.kr

² Professor, Moon Soul Graduate School of Future Strategy, KAIST

Introduction

Since the 2000s, digital technologies like social media platforms and cryptocurrencies have evolved beyond conventional diffusion patterns, experiencing cycles of hype and disillusionment. This evolution reflects the transformative impact of digital technology on commerce and finance, exemplified by platforms such as Airbnb, TikTok, and the rise of blockchain and cryptocurrencies like Bitcoin. These developments underscore digital technology's dynamic and often unpredictable influence across various sectors.

The COVID-19 has accelerated the adoption of digital platforms and virtual experiences for connecting with others (Adedoyin & Soykan, 2020; Koo, 2021; Kye et al., 2021). In fact, people around the world have been forced to adapt to new ways of learning and working remotely, which has increased the use of virtual collaboration tools and remote access to virtual environments. The metaverse, an emerging virtual reality space where users interact with each other and digital environments through avatars (Park & Kim, 2022), has been gaining significant attention in recent years (Damar, 2021). Leading companies are heavily investing in the development of metaverse technologies, shaping its future landscape. Facebook even changed its company name to Meta (Kraus et al., 2022). Forecasts predict that by 2026, a quarter of the population will spend at least an hour a day in the metaverse for work, shopping, education, social and entertainment (Gartner, 2022).

While there is a lot of excitement and optimism about the potential of the metaverse, there are also experts who have expressed negative thoughts about it (Anderson et al., 2022; Faraboschi et al., 2022). The metaverse faces a few challenges that need to be addressed for it to reach its full potential. Some of the key challenges facing the metaverse include: technical limitations of VR and AR core technologies, privacy and security concerns, social challenges

such as addiction and isolation, and lack of regulation (Zhang et al., 2022).

The metaverse is still in its infancy, both technically and industrially. But it has gained significant traction and public interest after Facebook rebranded itself as Meta. Over time, there was a trend of decreasing comments about the metaverse. After the announcement of ChatGPT by OpenAI in November 2022, the number of mentions of the metaverse in the news media and on social media, while the number of mentions of ChatGPT significantly increased. Even news articles and memes on social media say that the metaverse is dead because of ChatGPT.

In the early stages of adopting emerging technology, news coverage and public opinion can influence its later diffusion. Metaverse has received as much media attention as any other new technology and has generated public expectations. Whether these expectations are emotional or logical, they affect technology diffusion. Therefore, analyzing how public interest in the early stages of emerging technology affects the direction and speed of innovation diffusion is worth exploring.

This study aims to empirically investigate the role of expectations in early innovation diffusion by conducting sentiment analysis and topic modeling of early adopter-centric discourse about the metaverse on social media.

Theoretical background and literature review

S-curve model

After the publication of Rogers' seminal work on innovation diffusion in 1962, research in this area has significantly advanced, leading to the development of various diffusion models and the exploration of the S-curve phenomenon.

It has been observed that S-shaped curves effectively describe the diffusion processes of many innovations, and understanding the diffusion mechanism is essential for interpreting these

curves. The dynamics of firms and researchers play a crucial role in shaping the S-curve of technological evolution, with the curve typically consisting of slow initial growth, followed by rapid growth, and finally, a plateau as the market becomes saturated. The S-curve has been a valuable tool for businesses and policymakers to understand and manage the diffusion of innovations and technologies.

From an expectations perspective, the S-curve model fails to account for pre-adoption expectations, which can have a significant impact on the adoption process. The S-curve focuses primarily on actual adoption rates and does not consider the role of expectations in shaping the early stages of innovation diffusion. It lacks predictive power before adoption occurs, failing to capture the initial hype and excitement that can drive or hinder the adoption of an innovation (Shi & Herniman, 2023).



Figure 1. Innovation manifesting Through adoption: S-curve (Shi & Herniman, 2023).

Hype Cycle model

Introduced by Gartner in 1995, the hype cycle describes the dynamics of the early stages of a technology and has gained popularity among innovation management practitioners (Shi & Herniman, 2023). The application of this model focuses primarily on the dynamics of expectations of a technological innovation leading up to its initial adoption to understand the state of development in a technology field and to advise strategic investment decisions (Steinert & Leifer, 2010; Van Lente et al., 2013).



Figure 2. The hype cycle curve (Linden & Fenn, 2003).

The hype cycle provides a framework (Linden & Fenn, 2003) for understanding the maturity, adoption, and social application of technologies, depicting their progression through five phases: technology trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and plateau of productivity (Van Lente et al., 2013). This model is significant for technology forecasting and strategic decision-making, as it highlights the phases of hype and disillusionment that technologies may go through before reaching productivity. Konrad et al. (2012) studied how a new technology's hype and subsequent disappointment affect the strategic responses of various stakeholders, including firms, investors, and policymakers. They emphasized the importance of collective expectations in the strategic decision-making process during the early stages of development for the innovation of new technologies.

On the other hand, there are also critical views of the hype cycle. Borup et al. (2006) criticized it for being too general in providing more room for the kinds of variation and unpredictability that characterize the place of expectations in technological, and social change.

Dedehayir & Steinert (2016) pointed out inconsistencies between the hype cycle model's predictions and the actual technological developments as recorded in Gartner's databases. They found that only 9 out of 23 empirical studies could explain the hype cycle pattern. From their findings, they noted that although the hype cycle model is a popular conceptual tool among practitioners, its predictive power may be overestimated. Therefore, they recommended that future research should explore incorporating the concept of hype dynamics into existing technology life cycle models to better capture the complex nature of technological advancement.

While the S-curve highlights the adoption and diffusion patterns of an innovation, the hype cycle provides an important complementary perspective by focusing on the visibility and changing expectations surrounding a particular technology over time. Together, these two models can provide a more holistic view of an innovation's journey from concept to widespread use, capturing both the tangible progress of market adoption and the intangible fluctuations in public expectations and sentiment (Shi & Herniman, 2023).

The role of expectation in innovation evolution

While expectations in their general form can be defined as the state of looking forward, technological expectations can more specifically be described as real-time representations of future technological situations and capabilities (Borup et al., 2006).

Expectations play a crucial role in the hype cycle. They serve as a driving force behind the development and adoption of emerging technologies or innovations. They are involved in determining the direction of technological change and the speed of adopting innovations (Berkhout, 2006; Borup et al., 2006). Expectations help focus research efforts, attract funding and resources, and generate public interest and support (Rusconi & Mitchener-Nissen, 2014). Expectations can shape the innovation trajectory and influence decision-making in business and

technology planning (Khodayari & Aslani, 2018).

An expectation pattern is the temporal pattern of expressed expectations about a technology. Alkemade & Suurs (2012) distinguished types of expectation patterns to analyze the dynamics of technological innovation systems, particularly in the exploratory phase of sustainable mobility technologies within the Netherlands. Firstly, expectations were categorized by their content as either positive or negative, indicating whether they express a favorable or unfavorable future performance of the technology. Secondly, the content was also classified as general or specific, with general expectations relating to the technology's contribution to societal issues and specific expectations addressing the technology's performance. Thirdly, the timeframe of the expectations was considered, distinguishing between short-term (less than ten years) and long-term expectations. Additionally, the type of actor expressing the expectation was noted, such as entrepreneurs, government, knowledge institutes, NGOs, etc.

Building on the characteristics of expectations suggested in the Alkemade & Suurs (2012), Shi & Herniman (2023) further proposed four basic types of innovation expectation: positive emotional, negative emotional, positive logical, and negative logical.

Generally, the pattern of expectations over time tends to be a sharp increase in positive expectations followed by a decrease in positive or an increase in negative expectations (Alkemade & Suurs, 2012).

Shi & Herniman (2023) defined emotional and logical expectations as follows. Emotional expectations are based on the expectation that an innovation or idea will evoke a significant emotional response from the public based on collective sentiment and cultural narratives. Emotional expectations are formed quickly by appealing to basic human emotions such as excitement, fear, and greed, leading to powerful but temporary social behaviors.

In contrast, logical expectations are based on beliefs about the efficiency and effectiveness of an innovation or idea. It results from a more careful and systematic assessment of the practical merits of an innovation, appealing to systematic reasoning and careful evaluation of means and ends. Logical expectations rely on rational analysis and specific information about the innovation's performance and technical capabilities. Establishing these expectations takes considerable effort and time, reflecting an institutionalization process that creates a homogenous model-based understanding. Although slow to gain social acceptance, the persuasive power of logical expectations persists over time, gradually replacing emotional expectations as more empirical evidence and information becomes available.

This methodological approach is driven by rhetorical justification. Rhetoric helps to better understand the diffusion process by examining the interaction between different actors, their framing strategies, and the discourses that shape it (Huang et al., 2011).

As an important influence on expectation patterns, emotions affect interpersonal relationships and emotional expectation provides social information that produces interpersonal effects by triggering affective reactions and inferential processes. The interpersonal function of emotion is evident across various domains of social influence such as negotiation, leadership, attitude change, compliance, and conformity in groups (Van Kleef, 2009). The key to understanding the hype cycle and early-stage adoption of an innovation is the dominance of positive emotional expectations and the decline and homogenization of logical expectations.

Shi & Herniman (2023) formalized the role of expectations in innovation evolution by developing a conceptual framework of expectation types that reflects the characteristics of innovation diffusion and models. To simplify their conceptual framework development and presentation in the context of early-stage innovations, they limited their scope of discussion to

emotional and logical justifications. Logical expectations increase as more factual information and evidence about the innovation become available. This typically happens after the initial phase, where emotional expectations dominate due to the innovation's novelty and excitement. As the innovation progresses and more data is gathered, such as user experiences, performance metrics, and market analysis, logical expectations start to form and increase.

The expectations for Hydrogen Production Technology (HPT) are relatively high due to its potential to reduce greenhouse gas emissions and provide a stable energy supply. A recent study analyzed the life cycle and commercialization readiness of hydrogen production technology (HPT), highlighting its maturity and competitive strength but noting the need for cost reductions to achieve large-scale commercialization, especially for electrolysis methods (Chung et al., 2023). Chung et al. (2023) analyzed the technology life cycle using the expectations framework proposed by Shi & Herniman (2023).



Figure 3. Evolving expectation, rhetoric and connotation (Shi & Herniman, 2023).

Sun et al. (2023) analyzed Korean Twitter user data to explore the hype surrounding the metaverse. They collected and analyzed tweets using BERT-based topic modeling and classified

the extracted topics into three expectation frameworks: specific expectations, generalized expectations, and frames. They also found that the public responds to the expectations of other actors about the technology rather than expecting the technology itself (Sun et al., 2023).

Research questions

The objective of this research is to analyze and understand the dynamics of expectations surrounding metaverse technologies and how these expectations evolve over time. To accomplish the objectives of this study, we explore the following research questions.

RQ1. How do expectations of the metaverse technologies change over time?

Based on prior research, early-stage positive emotional expectations are high, but they gradually decrease after a certain point. We examine whether the metaverse that have received considerable public attention exhibit changes in expectations consistent with hype cycles. It also explores an increase of overall positive expectations of an innovation during its early stage is associated with multitudes of emotional expectations and a higher proportion of emotional expectations. We additionally examine whether a decrease in overall positive expectations and an increase in overall negative expectations for the metaverse technologies are associated with a decrease in emotional expectations and an increase in logical expectations. This explores the transition from emotion-driven optimism to a more logical and pragmatic view of the metaverse as the technology matures.

RQ2. What was the metaverse discourse being discussed on Twitter at significant times when expectations changed?

Through discourse analysis, we can infer the causes of shifts in expectations. By analyzing how the discourse of a highly anticipated metaverse changes over time, we explore the public's response to technological change.

Data and Method

Data collection

Early adopters are essential in innovation diffusion research because they are crucial in adopting and spreading innovations. They are the first individuals or organizations to embrace and implement an innovation, serving as influential models for others in the adoption process. Early adopters are often seen as opinion leaders and are more likely to take risks and try new technologies or ideas(Dedehayir et al., 2017; Raman et al., 2023).

Please note that Twitter, as referenced in this study, was rebranded as X in July 2023, and we will continue to refer to it as "Twitter". We collected Twitter data to study the role of technological expectations in the early stages of metaverse innovation diffusion. Twitter is suitable for innovation diffusion research on emerging technologies. It is an important social platform that people use to consume, share, and discuss information, including politics, entertainment, sports, and more (Pelletier et al., 2020). Consequently, It serves as an invaluable data source for understanding human behavior, communication patterns, and public opinion and trends (Kim et al., 2013). It has also become a popular media for experts and the public to exchange information on scientific innovations and emerging technologies (Kohl et al., 2018; López-Goñi & Sánchez-Angulo, 2018). Because of these features, Twitter has been used to study the diffusion of innovation (Bolici et al., 2020). Twitter has also been used to measure inflation expectation(Angelico et al., 2022) and analyze expectations for upcoming information systems(Banerjee et al., 2021), and studies have analyzed technological expectations in the metaverse(Sun et al., 2023).

When Facebook changed its name to Meta in 2021, public interest in the metaverse increased. Other studies have shown a significant increase in research papers (Sun et al., 2023)

and tweets after 2021 (777 in 2020 and 141,016 in 2021) (Cano-Marin et al., 2023). We also used the Twitter API to retrieve the daily tweet count by metaverse search terms from January 2021 to May 2023 and plotted it as shown in (Figure 4) to confirm the scope of the collection.



Figure 4. Metaverse Tweet count from January 2021 to May 2023

To achieve the primary goal, we collected tweet data from January 2021, the year the Metaverse first gained public attention, to May 2023, the latest available date. We were able to collect data up to May 2023 because Twitter stopped using the Academic API in June 2023. We collected tweet data that contained the English word "metaverse." Using the Twitter developer Academic API2.0 and the Python programming language. To exclude retweet data from a collection, Twitter collection options were used. We tested Twitter's API and found it was limited in speed and volume, so we collected data monthly and saved it as a CSV file. In the end, we collected 21,949,301 tweet data.

Sampling

We had to analyze over 20 million pieces of data. For the data analysis, we leveraged GPUs within the Google Colab environment to enhance computational efficiency and accuracy.

Considering the large data, direct analysis of 20 million cases for topic modeling is impossible due to computational constraints, even with GPU resources. Therefore, we adopt a sampling strategy to manage large-scale data while ensuring the integrity and reliability of the analysis.

The main reason for sampling comes from computational limitations. Processing tens of millions of tweets is resource-intensive, requiring significant computing power and time. Sampling can significantly reduce computational time, making the task more manageable and efficient. This approach aligns with the principle of prioritizing quality over quantity of data. A small, well-curated data set will yield more meaningful and actionable findings than a large, cumbersome one.

We selected a random sample of 10% of the collected Tweets for this study. We also randomly selected 10% per day to cover 2021 to 2023. A 10% sample size is large enough to capture the diversity and range of discourse in Twitter's metaverse conversations yet manageable from a computational perspective. In the end, 2,194,585 data were sampled.

Preprocessing data

The tweet data collected for this study is unstructured data and was preprocessed to improve the data quality and the analysis's accuracy during data analysis. The data preprocessing process used the Python programming language. After checking the collected data, we found duplicate data in the datasets. Since duplicate data distorts the analysis results, we identified and removed duplicate data.

Due to the nature of social media, Twitter data contains URLs and hashtags and should be removed according to the purpose of the study. In this study, we removed URLs, hashtags, and words starting with hashtags. It is essential to analyze the type of expectation in the sentences rhetorically. Therefore, we removed the words after the hashtag representing simple

word occurrences. We found that some of the data collected had an abnormal creation time. For the analysis of data over time, the abnormal data was deleted.

Text mining

Expectations of technology are expressed in rhetorical expressions. Therefore, we utilize text mining techniques to analyze texts. Specifically, this study conducted topic modeling among text mining methods on Twitter data and further conducted sentiment analysis on significant topics to analyze the types of expectations of the metaverse in which discourse on various metaverse fields occurs.

In contrast to previous studies on new technology innovation diffusion, which primarily focused on retrospective analysis using data sources like patents and research papers, this study aims to project the future of innovation diffusion. We employ topic modeling and sentiment analysis on contemporary social media data, providing a forward-looking perspective in the context of current innovation diffusion.

Topic modeling

Topic modeling is a form of statistical modeling used in machine learning and natural language processing to identify hidden topic patterns within a collection of text (Guo et al., 2017). A topic is a set of words with a high probability of co-occurring.

BERTopic is a method that has high versatility and stability in various domains and has the advantages of automatically finding the number of topics, supporting hierarchical topic reduction, and enabling various visualizations (Egger & Yu, 2022). For these reasons, BERTopic was selected in this study to analyze large amounts of Twitter data effectively.

Reducing topics

The selection of the optimal number of topics in topic modeling is essential to ensure the

model's interpretability, coherence, and the meaningful representation of underlying themes within the data. An excessive number of topics can lead to an overly complex model, making interpretation and subjective validation challenging (Zhao et al., 2015). On the other hand, more topics may need to be more concise in representing the underlying themes within the data, leading to the loss of critical semantic nuances (Gan & Qi, 2021).

Despite various attempts (Egger & Yu, 2022; El-Assady et al., 2018; Sbalchiero & Eder, 2020; Weston et al., 2023), there is no standardized way to find the optimal number of topics. the researcher's objectives and subjectivity determine the number of topics.

We performed topic modeling on 2,125,076 of the sampled data after removing duplicates. BERTopic used in this study utilizes cosine similarity to calculate the number of topics automatically, which automatically generated 7,205 topics. BERTopic assigns topic numbers based on their frequency of occurrence; topic number 0 would represent the most frequently occurring topic, followed by the next most frequent topic, number 1. This method arranges topic numbers sequentially, where each number reflects that topic's relative frequency of occurrence.



Figure 5. Topic modeling frequency distribution with the automatically determined number of topics.

Rounds	Total number of topics	Median count	Topic number of Median
1	7,205	51	3,585~3,658
2	3,584	59	1,779~1,801
3	1,778	103	883~893
4	882	181	440
5	439	242	230~231
6	218	390	108

 Table 1. Topic modeling frequency distribution

After analyzing 2 million data, many topics were generated. As shown in (Figure 5), most of the topics have insufficient topic-specific data to perform further sentiment analysis. Therefore, we had to reduce the number of topics manually, and we chose the median as the criterion for reduction. The median is chosen as the criterion to maintain consistency so that the frequency distribution is uniform. We repeated the topic modeling by specifying the number of topics so that topics with lower frequencies were merged into topics with higher frequencies. We performed a total of six rounds of topic modeling, and the criteria for reducing the number of topics and the content of the topic reduction are shown in (Table 1).

Sentiment analysis

Sentiment analysis is a method that automatically determines the sentiment in text data. Sentiment analysis extracts positive and negative words from text (Taboada, 2016), categorizing text into predefined sentiment categories such as neutral, negative, and positive. We applied the "cardiffnlp/twitter-roberta-base-sentiment" model to perform sentiment analysis in this study. This is a pre-trained BERT model based on a large Twitter dataset and highly understands Twitter data. These characteristics are essential for accurately identifying the sentiment of the Twitter data analyzed in this study. BERT is a deep learning model based on Transformer, which has been utilized in various studies due to its robust performance in natural language processing (NLP) (Zoughi & Homayounpour, 2019).

Results

Using BERTopic topic modeling, we extracted a total of 218 topics. Figure 6 is a bar chart showing the top 20 topics out of 218 topics. This chart outputs five high-frequency words (terms) for each topic. In Topic 0, 'game,' 'metaverse,' 'round,' 'nfts,' and 'nft' are the most frequent words. We performed the analysis at the sentence level rather than the morpheme level to reflect the nature of the data in English and social media. Hence, the method recognized nft and nfts as separate words. The numbers below the bar are the relative c-TF-IDF scores between words in the topic. BERTopic provides users with each topic's primary keyword information through its algorithm.



Figure 6. Top 20 topics out of 218 topics from the final topic modeling

Theme	Topic Label (by ChatGPT API)	Topic Words(Terms)	Topic 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	Topic 1 : Successful Diverse Scene Creation	'project', 'good', 'nice', 'successfully', 'scenes', 'diverse', 'congratulations', 'held', 'projector', 'hopefully'	60,410
Project	Topic 15 : Nice Job Congrats	'nice', 'good', 'awesome', 'job', 'love', 'great', 'amazing', 'thank', 'dlr', 'congrats'	7,141
Defi, NFT & Cypto	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	Topic 8 : Adidas Free Metaverse Hoodie	'adidas', 'fashion', 'hoodie', 'hoodies', 'shirt', 'free', 'claiming', 'wear', 'party', 'originals'	15,327
Game	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'	
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

Table 2. Categori	es of topics	and Number of t	weets for each topic
-------------------	--------------	-----------------	----------------------

It also offers automatic label information for each topic through a ChatGPT API

connection. Using this information, seven themes were selected, requiring further analysis to observe hype cycles and expectations (Table 2). To select the themes, we analyzed the "topic count" (number of documents assigned to a particular topic) and "Topic Words" of the 218 topics. For each theme, we mapped representative topics. Table 2 shows each topic's label, topic words, and topic count.



Figure 7. Topic Tweet monthly count from January 2021 to May 2023

We examined the monthly tweet count for representative topics per category (Figure 7). While the relative number of tweets varies, we found that the graph shape of each topic is different. The peak in discourse for each topic coincided with when Facebook renamed it Meta. We also found that the shape of the decline in the hype cycle for each topic was different.

We focused on the role of expectations in this study and conducted a sentiment analysis to identify positive and negative expectations in each topic to examine our first research question. We categorized them as negative, neutral, and positive to reflect neutral opinions. Through topic modeling, we observed a wide range of discourse on Twitter about the technologies and interests that comprise the metaverse. Therefore, we compared the change in sentiment for the entire sample data with the change in sentiment for the main topics.



Figure 8. Tweet by sentiment monthly count from January 2021 to May 2023

Figure 8 shows the monthly change in sentiment in all sample tweets. Analyzing these changes confirms our proposition that initial expectations are positive but tend to decline over time. In Figure 9, Topic 0, "Exciting Metaverse," has an apparent initial peak of positive sentiment followed by a decline. Similarly, topics 2 and 8 show a pattern of high initial positive

expectations declining over time, and topic 31, while having fewer data points, is consistent with this trend. However, there is an exception. Topic 62 is about ethics, and as such, a relatively large number of negative tweets about ethics were posted during high public attention.



Figure 9. Topic Tweet by sentiment monthly count from January 2021 to May 2023

Topic 1 is about Defi; the number of positive sentiments significantly exceeds the other sentiment types. However, the number of tweets on the topic decreased sharply over time, indicating that the initial public interest in Defi quickly faded. In addition, topic 18 is about games with NFTs, which showed a decreased pattern similar to topic 1.

We identified positive sentiment tweets (Table 3). In October 2021, tweets expressing excitement (excited, hope) about the news that Facebook had changed its name to Meta were posted. In March 2022, a tweet was posted predicting the market value of the metaverse in 2028. Some tweets expressed hope that ChatGPT, released in November 2022, will be applied to the metaverse. In May 2023, a tweet was posted expressing expectations that the metaverse could be used in sports as a virtual stadium for the inclusion of all abilities, ages, and backgrounds.

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
Jan 31, 2023	ChatGPT is making waves worldwide. This AI tech can be applied to numerous fields & amp; is already being utilized. Among them, @Highstreet 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.

Table 3. Positive sentiment tweets text for Topic 0: Exciting Metaverse

We observed skepticism and concern about the metaverse when we analyzed negative

sentiment tweets (Table 4). In June 2021, one user humorously noted that they didn't understand the metaverse concept, suggesting a disconnect with the new technology. In October 2021, after Facebook rebranded itself as Meta, critical voices pointed out the attempt to shift to a metaverse amid ongoing scrutiny of the platform's impact on the real world.

In September 2022, tweets included concerns that using lifelike avatars in the metaverse could exacerbate body image issues. In January 2023, a tweet was posted expressing his disappointment with the metaverse project in a rather drastic way. In May 2023, a tweet was posted declaring the end of the metaverse, attributing its downfall to the rise of ChatGPT. This tweet indicates a shift in public interest and trust in the technology's viability.

Table 4. Negative sentiment tweets text 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 Obession, Is Officially Dead. ChatGPT Killed It.

Finally, we identified neutral sentiment tweets (Table 5). Compared to positive and negative sentiment tweets, neutral sentiment was expressed in the form of curiosity, speculation,

and factual reporting about the metaverse. In June 2021, tweets were posted about the nature of non-fungible tokens (NFT), which coincided with a surge of interest in the digital asset space at the time. In October 2021, a discussion of the ethical considerations of centralized versus decentralized metaverses was posted. In February 2023, a tweet was posted by Japanese tech and financial giants about trends in the metaverse industry. In March 2023, a tweet describing a media report that Disney had decided to close its metaverse division as part of widespread layoffs was posted, with no positive or negative judgment.

Table 5. Neutral sentiment tweets text for Topic 0: Exciting Metaverse

Date	Tweet Text
Jun 16, 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

Additionally, we identified logical expectations (Table 6). We examined the negative sentiment content of Topic 0. Logical expectations are based on specific, verifiable information about the innovation's performance and technical capabilities. In October and December 2021, news of Facebook's investment in the Metaverse and the issuance of NFTs were posted. This was a time of high public interest in the metaverse, but because it was still in its infancy, there were fewer logical expectations. In April and August 2022, there were tweets about declining prices of metaverse-related stocks and real estate traded on the metaverse. In October 2022, a

controversial P2E gaming project in South Korea caught the public's attention.

In 2023, we found an increase in logical expectations, which includes results and outcomes for the metaverse-related projects started in the second half of 2021 and beyond. In January 2023, a negative post was published about the EU Commission's investment in metaverse events, and in April, a post was registered about the decline in sales of VR headsets. In May, a post was posted describing the problematic current situation of the NFT-based gaming market.

Table 6. Logical Expectations tweets text 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.
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

We analyzed the discourse to investigate our second research question, which examines how

public expectations about the metaverse have changed over time and the reasons behind those changes.

Table 7. Examples of Top Retweeted Tweet Texts

-

Date	Tweet Text	Retweet count
Jan 30, 2023	The largest free mint ever from Japan! Your adorable #metaverse pet XANA:#PENPENZ x #CryptoNinja will launch on 25th Feb! Don't miss to get #AL! Follow @rio_noborderz Join https://t.co/Npdg0hRTjB Like & amp; RT	169,091
Aug 30, 2022	Thank you @MTV for the Best Metaverse Performance award!BLINKs, we are so honored and grateful for the overwhelming support and love we always receive from you #VMAs ♥ ♥ https://t.co/H2EkCOV4Dz	37,767
Oct 29, 2021	Hot take: Everyone is wrong about the Metaverse. here's my 3 part theory	11,060
May 23, 2023	Metaverse is one of the biggest funniest scams of all time. \$40 billion from investors to get a Wii port of Second Life. <u>https://t.co/Kjo1q4mLwV</u>	6,268
May 23, 2022	How I'm going to be entering metaverse Walmart <u>https://t.co/UdgnT8p3Tu</u>	3,472
Oct 28, 2021	The metaverse is the next evolution of social connection. It's a collective project that will be created by people all over the world, and open to everyone. You'll be able to socialize, learn, collaborate and play in ways that go beyond what's possible today. https://t.co/655yFRm8yZ	1,661

First, we selected top retweeted data as one of the public interest indicators. The types of tweets that received an overwhelming number of retweets were related to digital assets such as NFTs, cryptocurrencies, and virtual real estate. This suggests public expectations for the metaverse regarding digital assets were exceptionally high. However, it is essential to exercise caution when generalizing these findings to reflect public expectations for the metaverse. The next most frequently retweeted type of tweet was related to celebrities' activities in the metaverse. The retweet frequency of this type was relatively higher than tweets about the metaverse's concepts, views, and phenomena (Table 7). We analyzed the discourse considering the characteristics of the retweet patterns in this metaverse tweet data.

To answer the second research question, we conducted a discourse analysis on Topic0(Exciting Metaverse), which encompasses general content about the metaverse, as identified through topic modeling. Specifically, we analyzed tweets around time points when the volume of metaverse-related tweets changed significantly.

 Table 8. Twitter Discourse on the metaverse

Date	Tweet Text
Jan 02, 2021	The "Metaverse" is comingAny better option than 2nd life?#virtualworlds 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 & amp; training is emerging as one of the areas of the metaverse with the most interest for investors." "Engaging storylines & amp; gameplay-like missions are the key to keeping students engaged" #StateOfXRhttps://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 @ChanceHMiller
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 <u>https://t.co/bFqMFIIXjo</u>
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

Through discourse analysis, we could see the evolution of the Metaverse discourse on Twitter (Table 8). On January 2, 2021, a tweet was posted announcing a column on the metaverse written by Roblox CEO, "Metaverse is coming." The tweet was an expression of expectation for the metaverse. After that, expectations for the metaverse increased significantly. Eventually, on October 29, 2021, when Facebook announced its rebranding to Meta, expectations for the metaverse reached their peak. As expectations for the metaverse continue, a tweet was posted on April 4, 2022, about investments in the metaverse educational applications, showing that efforts to implement the metaverse come from various areas.

However, in the second half of 2022, positive expectations for the metaverse began to erode rapidly. On September 30, a tweet was published about Apple CEO Tim Cook's hostile interview about the metaverse, suggesting that skepticism about the metaverse was growing. On October 1, a tweet was published criticizing Mark Zuckerberg's investment decisions and highlighting the meta's massive financial losses. Since then, public interest in the metaverse has declined, and major companies have not made a tangible return on investment. Microsoft's announcement on February 9, 2023, that it was disbanding its Metaverse-related team and laying off employees could be interpreted as a bleak outlook for the metaverse's future.

In conclusion, the discourse around the metaverse has experienced initial over-expectation and gradually confronted technical and realistic limitations and challenges. This is similar to the pattern that social acceptance of new technologies typically experiences, suggesting that the metaverse will need to evolve in a more realistic and pragmatic direction to live up to public expectations.

Conclusion and discussion

Implications of research

We analyzed the Twitter data to investigate the role of expectations in the early diffusion of metaverse technologies. Furthermore, we examined the metaverse discourse on Twitter at significant times when expectations shifted, allowing us to infer the causes of these changes and

explore the public's response to technological change in the metaverse. We applied topic modeling and sentiment analysis to an extensive Twitter dataset to understand the evolving public expectations of metaverses from January 2021 to May 2023.

Our analysis found that after pivotal events such as Facebook's rebranding to Meta, public interest and expectations for the metaverse increased significantly, coinciding with the peak phase of the hype cycle. However, these initial expectations faded over time, demonstrating the transitory nature of public interest according to the hype cycle model: a peak of inflated expectations followed by disillusionment before the technology stabilizes for productive use.

Sentiment analysis uncovered a trajectory of subsiding excitement from high positive expectations. This decline in positive emotional expectations highlights the complex interplay between public sentiment and technological progress. The findings support the hypothesis that initial expectations of emerging technologies are primarily positive and emotional but tend to become negative and pragmatic as the innovation progresses. This supports the pivotal role of expectations in the life cycle of technology hype, especially in the context of the metaverse.

Regarding the hypothesis that logical expectations would increase following a decrease in emotional expectations, we observed discourse expressing logical expectations. However, there was no significant increase in logical expectations, and metaverse discourse continued to trend downward. These findings suggest that emotional and logical expectations have decreased since the initial hype.

This study contributes to the body of knowledge on innovation diffusion, particularly the application of the hype cycle to understand social media narratives. The combination of topic modeling and sentiment analysis offers a new approach to investigating public discourse and provides a comprehensive view of the collective flow around a new technology.

Our findings suggest that practitioners respond to initial enthusiasm with cautious optimism. Tracking the transition from emotional to logical expectations as the technology evolves allows for more accurate predictions of its trajectory. By incorporating such analysis into their strategic plans, companies can better navigate the turbulence of innovation hype and consider adjusting their investments and efforts accordingly.

The study also highlights the importance of managing public expectations through transparent communication and realistic previews of technology capabilities to mitigate the potential disillusionment trap. Policymakers can use these insights to create a regulatory environment supporting sustainable innovation while protecting consumer interests.

In conclusion, while the metaverse is still a new phenomenon, the patterns observed in this study can inform future explorations of the life cycle of similar technologies, providing a template for anticipating and responding to public sentiment that can make or break a technology venture.

Limitation and suggestions

This study endeavors to explore expectations surrounding the metaverse through the application of topic modeling and sentiment analysis methods. Utilizing an extensive dataset, our empirical findings indicate a gradual decrease in the initial hype of positive emotional expectations over time.

For this research, we utilized Twitter data. However, there are doubts about whether Twitter is the optimal social media platform for reflecting public opinion, especially considering the decline in the number of Twitter users. Additionally, due to policy changes at Twitter, we were unable to collect data after June 2023, which limited the analysis period. We expect that future research, analyzing public expectations about new technologies across various social

media platforms, will be more convincing.

Second, we did not collect retweet data due to its size and the possibility that popular minority opinions may be overrepresented. However, if multiple users retweet the same tweet, this can be considered data that may reflect public opinion. In future research, we propose to apply a weighting scheme that leverages the retweet frequency of individual tweets to reflect the importance of opinions, which may lead to more sophisticated and representative topic modeling results.

Third, this study manually analyzed the content of specific topics to identify logical expectations. However, it was only practical to check some of the data. Further research is needed to clarify the rhetorical criteria that can distinguish between logical and emotional expectations so that machine learning models can be applied to classify them automatically. For this purpose, we can first manually categorize both types of data and then use this data to train a classifier.

Fourth, this study investigated different types of expectations expressed on social media, where the public shares their opinions. To gain insights into the media elite's perspective on the metaverse, it's essential to analyze metaverse-related discourse in news media. Furthermore, a comparison of expectation types found in social media with those in news media could offer a deeper understanding of the metaverse's development.

References

- Adedoyin, O. B., & Soykan, E. (2020). Covid-19 pandemic and online learning: the challenges and opportunities. *Interactive Learning Environments*, 0(0), 1–13. https://doi.org/10.1080/10494820.2020.1813180
- Alkemade, F., & Suurs, R. A. A. (2012). Patterns of expectations for emerging sustainable technologies. *Technological Forecasting and Social Change*, 79(3), 448–456. https://doi.org/10.1016/j.techfore.2011.08.014
- Angelico, C., Marcucci, J., Miccoli, M., & Quarta, F. (2022). Can we measure inflation expectations using Twitter? *Journal of Econometrics*, 228(2), 259–277. https://doi.org/10.1016/j.jeconom.2021.12.008
- Banerjee, S., Singh, J. P., Dwivedi, Y. K., & Rana, N. P. (2021). Social media analytics for end-users' expectation management in information systems development projects. *Information Technology and People*, 34(6), 1600–1614. https://doi.org/10.1108/ITP-10-2020-0706
- Berkhout, F. (2006). Normative expectations in systems innovation. *Technology Analysis and Strategic Management*, 18(3–4), 299–311. https://doi.org/10.1080/09537320600777010
- Bolici, F., Acciarini, C., Marchegiani, L., & Pirolo, L. (2020). Innovation diffusion in tourism: how information about blockchain is exchanged and characterized on twitter. *TQM Journal*. https://doi.org/10.1108/TQM-01-2020-0016
- Borup, M., Brown, N., Konrad, K., & Van Lente, H. (2006). The sociology of expectations in science and technology. *Technology Analysis and Strategic Management*, 18(3–4), 285–298. https://doi.org/10.1080/09537320600777002
- Cano-Marin, E., Blanco-Gonzalez-Tejero, C., Ribeiro-Soriano, D., & Arya, V. (2023). The metaverse through the lens of public big data analytics: a social perspective. *Journal of Ambient Intelligence* and Humanized Computing, 0123456789. https://doi.org/10.1007/s12652-023-04723-5

- Chung, D., Kwon, Y., & Kim, Z. (2023). Technology life cycle and commercialization readiness of hydrogen production technology using patent analysis. *International Journal of Hydrogen Energy*, 48(33), 12139–12154. https://doi.org/10.1016/j.ijhydene.2022.12.186
- Damar, M. (2021). *Metaverse Shape of Your Life for Future: A bibliometric snapshot*. 1–8. http://arxiv.org/abs/2112.12068
- Dedehayir, O., Ortt, R. J., Riverola, C., & Miralles, F. (2017). Innovators and early adopters in the diffusion of innovations: A literature review. *International Journal of Innovation Management*, 21(8). https://doi.org/10.1142/S1363919617400102
- Dedehayir, O., & Steinert, M. (2016). The hype cycle model: A review and future directions. *Technological Forecasting and Social Change*, 108, 28–41. https://doi.org/10.1016/j.techfore.2016.04.005
- Egger, R., & Yu, J. (2022). A Topic Modeling Comparison Between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts. *Frontiers in Sociology*, 7(May), 1–16. https://doi.org/10.3389/fsoc.2022.886498
- El-Assady, M., Sevastjanova, R., Sperrle, F., Keim, D., & Collins, C. (2018). Progressive Learning of Topic Modeling Parameters: A Visual Analytics Framework. *IEEE Transactions on Visualization* and Computer Graphics, 24(1), 382–391. https://doi.org/10.1109/TVCG.2017.2745080
- Gan, J., & Qi, Y. (2021). Selection of the optimal number of topics for LDA topic model—Taking patent policy analysis as an example. *Entropy*, *23*(10). https://doi.org/10.3390/e23101301
- Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism Management*, 59, 467–483. https://doi.org/10.1016/j.tourman.2016.09.009
- Huang, J., Hsu, C., Galliers, R. D., Lin, Y. T., & Newell, S. (2011). The rhetorics of system adoption and diffusion in the Taiwan mutual fund industry. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2004, 1–10. https://doi.org/10.1109/HICSS.2011.427

- Khodayari, M., & Aslani, A. (2018). Analysis of the energy storage technology using Hype Cycle approach. Sustainable Energy Technologies and Assessments, 25(November 2017), 60–74. https://doi.org/10.1016/j.seta.2017.12.002
- Kim, A. E., Hansen, H. M., Murphy, J., Richards, A. K., Duke, J., & Allen, J. A. (2013). Methodological considerations in analyzing twitter data. *Journal of the National Cancer Institute - Monographs*, 47, 140–146. https://doi.org/10.1093/jncimonographs/lgt026
- Kohl, C., Knigge, M., Baader, G., Böhm, M., & Krcmar, H. (2018). Anticipating acceptance of emerging technologies using twitter: the case of self-driving cars. *Journal of Business Economics*, 88(5), 617–642. https://doi.org/10.1007/s11573-018-0897-5
- Konrad, K., Markard, J., Ruef, A., & Truffer, B. (2012). Strategic responses to fuel cell hype and disappointment. *Technological Forecasting and Social Change*, 79(6), 1084–1098. https://doi.org/10.1016/j.techfore.2011.09.008
- Koo, H. (2021). 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*, 18, 1–4. https://doi.org/10.3352/JEEHP.2021.18.33
- Kraus, S., Kanbach, D. K., Krysta, P. M., Steinhoff, M. M., & Tomini, N. (2022). Facebook and the creation of the metaverse: radical business model innovation or incremental transformation? *International Journal of Entrepreneurial Behaviour and Research*, 28(9), 52–77.
 https://doi.org/10.1108/IJEBR-12-2021-0984
- Kye, B., Han, N., Kim, E., Park, Y., & Jo, S. (2021). Educational applications of metaverse: Possibilities and limitations. *Journal of Educational Evaluation for Health Professions*, 18, 1–13. https://doi.org/10.3352/jeehp.2021.18.32
- Linden, A., & Fenn, J. (2003). Understanding Gartner's hype cycles. *Strategic Analysis Report Nº R-20-*1971. Gartner Research, May, 12. http://www.ask-force.org/web/Discourse/Linden-HypeCycle-2003.pdf

- López-Goñi, I., & Sánchez-Angulo, M. (2018). Social networks as a tool for science communication and public engagement: Focus on Twitter. *FEMS Microbiology Letters*, 365(2). https://doi.org/10.1093/femsle/fnx246
- Park, S. M., & Kim, Y. G. (2022). A Metaverse: Taxonomy, Components, Applications, and Open Challenges. *IEEE Access*, 10, 4209–4251. https://doi.org/10.1109/ACCESS.2021.3140175
- Pelletier, M. J., Krallman, A., Adams, F. G., & Hancock, T. (2020). One size doesn't fit all: a uses and gratifications analysis of social media platforms. *Journal of Research in Interactive Marketing*, 14(2), 269–284. https://doi.org/10.1108/JRIM-10-2019-0159
- Raman, R., Mandal, S., Das, P., Kaur, T., JP, S., & Nedungadi, P. (2023). University students as early adopters of ChatGPT: Innovation Diffusion Study. *Research Square*, 1–32. https://doi.org/10.21203/rs.3.rs-2734142/v1
- Rusconi, E., & Mitchener-Nissen, T. (2014). The role of expectations, hype and ethics in neuroimaging and neuromodulation futures. *Frontiers in Systems Neuroscience*, 8(October), 1–7. https://doi.org/10.3389/fnsys.2014.00214
- Sbalchiero, S., & Eder, M. (2020). Topic modeling, long texts and the best number of topics. Some Problems and solutions. *Quality and Quantity*, 54(4), 1095–1108. https://doi.org/10.1007/s11135-020-00976-w
- Shi, Y., & Herniman, J. (2023). The role of expectation in innovation evolution: Exploring hype cycles. *Technovation*, 119(January 2022), 102459. https://doi.org/10.1016/j.technovation.2022.102459
- Steinert, M., & Leifer, L. (2010). Scrutinizing gartner's hype cycle approach. PICMET '10 Portland International Center for Management of Engineering and Technology, Proceedings - Technology Management for Global Economic Growth, 254–266.
- Sun, S., Kim, J. H., Jung, H. S., Kim, M., Zhao, X., & Kamphuis, P. (2023). Exploring Hype in Metaverse: Topic Modeling Analysis of Korean Twitter User Data. *Systems*, 11(3). https://doi.org/10.3390/systems11030164

- Taboada, M. (2016). Sentiment Analysis: An Overview from Linguistics. *Annual Review of Linguistics*, 2, 325–347. https://doi.org/10.1146/annurev-linguistics-011415-040518
- Van Kleef, G. A. (2009). How Emotions Regulate Social Life. *Current Directions in Psychological Science*, *18*(3), 184–188. https://doi.org/10.1111/j.1467-8721.2009.01633.x
- Van Lente, H., Spitters, C., & Peine, A. (2013). Comparing technological hype cycles: Towards a theory. *Technological Forecasting and Social Change*, 80(8), 1615–1628. https://doi.org/10.1016/j.techfore.2012.12.004
- Weston, S. J., Shryock, I., Light, R., & Fisher, P. A. (2023). Selecting the Number and Labels of Topics in Topic Modeling: A Tutorial. Advances in Methods and Practices in Psychological Science, 6(2). https://doi.org/10.1177/25152459231160105
- Zhang, X., Chen, Y., Hu, L., & Wang, Y. (2022). The metaverse in education: Definition, framework, features, potential applications, challenges, and future research topics. *Frontiers in Psychology*, *13*(October), 1–18. https://doi.org/10.3389/fpsyg.2022.1016300
- Zhao, W., Chen, J. J., Perkins, R., Liu, Z., Ge, W., Ding, Y., & Zou, W. (2015). A heuristic approach to determine an appropriate number of topics in topic modeling. *BMC Bioinformatics*, 16(13), S8. https://doi.org/10.1186/1471-2105-16-S13-S8
- Zoughi, T., & Homayounpour, M. M. (2019). DBMiP: A pre-training method for information propagation over deep networks. *Computer Speech and Language*, 55, 82–100. https://doi.org/10.1016/j.csl.2018.10.001