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How did online misinformation impact stockouts in the e-commerce supply chain during COVID-19 – A mixed methods study

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A R T I C L E I N F O

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Electronic commerce
Buying behavior

A B S T R A C T

The proliferation of fake news across the internet has become a significant area of concern globally. The COVID-19 pandemic highlights that the propagation of fake news can jeopardize public health and heighten irrational behavior amongst consumers, like panic buying. However, the existing literature has not explored its impact on the supply chain. This study uses reactance and cognitive load theories to examine a model for fake news propagation causing supply chain disruption. Our research employed a computationally intensive big data-driven method across three studies to demonstrate misinformation's impact on supply chain disruption, identify the factors creating this impact, and validate an inferential analysis model to explain this phenomenon. Results highlight the relationship between unverified information sharing (UIS) and perceived threat, perceived scarcity, fear appeal, and information overload with panic buying. The paper dwells more profoundly on fake news disrupting the supply chain.

1. Introduction

The COVID-19 pandemic is one of the century's most challenging issues, causing global insecurity, instability, and fatalities. According to the WHO, the challenges are not limited to a worldwide pandemic but an "info-demic," underlining the grave concerns arising from the widespread dissemination of fake news and misleading news concerning COVID-19 (Laato et al., 2020b). Circumstances surrounding the COVID-19 pandemic have led to a significant amount of online information, including fake content or misinformation. Further, fake news jeopardizes public health, as news articles highlighted that consuming household disinfectants can cure COVID-19 (Times, 2020).

Fake news is a term for any purposeful false digital misinformation (false facts that mislead readers) and disinformation (incorrect information that confuses readers) (Shirish et al., 2021). It denotes false information that appears as the news but is generated without adhering to legitimate journalism processes and the requisite editorial checks (Lazer et al., 2018). Numerous studies have highlighted that fake news transmission is more rapid than genuine news (Dwivedi et al., 2018). One of those relevant examples from the recent past is the Russia-Ukraine conflict. Regrettably, spreading (intentional/unintentional) fake information and signs around the current status of the war has caused harm to the citizens of both countries. Globally, it led to multiple rounds of impulsive buying and selling of products ranging from commodities to even shares, causing losses or uneven gains to companies and individuals that can be indirectly tied to fake information circulated on the Russia-Ukraine conflict.

Figl et al. (2023) highlighted that fake news influences believability and user engagement. Several misinformation cases were observed, causing institutional tension and violence against minority communities. Allcott and Gentzkow (2017) outline fake news's role in influencing the 2016 U.S. presidential election and fueled hate crimes against Asian Americans after the COVID-19 pandemic (Kelley, 2020). In 2023, a Natural News article published a study stating, "European study

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reported long-term brain damage due to COVID vaccines." Later, the study's co-author claimed, "We have done zero experiments using the vaccine, and we have shown and claim zero side effects of the vaccine." Hence, POLITIFACT (The Poynter Institute) claimed it was false news.

The fake news encompassing COVID-19 (Dwivedi et al., 2020) triggered social panic, impacting consumer behavior(Aswani et al., 2019; Kar et al., 2022) and leading to the hoarding of products (Naeem, 2021). For example, Amazon claimed it removed millions of basic needs items due to misleading information and hiked prices (Lufkin, 2020). Furthermore, customers started overreacting and engaging in peculiar retail behavior, such as hoarding food, medicines, toilet paper, etc. (Hossain et al., 2023a; Naeem, 2021). These activities could impact manufacturers, wholesalers, and retailers and create challenges in order fulfilment (Hossain et al., 2023b). Therefore, the pandemic is perceived to have produced a ripple effect spreading across many industries, causing a bullwhip effect (Dolgui et al., 2020).

The ripple effect depicts the downstream spread of reduced demand fulfillment due to disruptions in the supply chain (SC). On the other hand, the bullwhip effect refers to small changes in consumer demand, which amplifies operational deviations in the upstream direction (Dolgui et al., 2020). Several manufacturing plants and companies have halted operations due to government protection measures (Goodman, 2021). Distribution challenges, a rise in online orders, and staffing problems at warehouses and distribution centers were the obstacles experienced by the delivery and distribution (Margherita and Heikkilä, 2021).

Existing literature has suggested that the COVID-19 pandemic has produced considerable uncertainty in demand and affected customer choices (Choi et al., 2020). The effect of the pandemic has been relatively stable and predictable for e-commerce platforms (Shen and Sun, 2023). Spreading false news has severe consequences, including mistakes in understanding the situation, the downplaying of the facts, and the spread of chaos and speculations, ultimately impacting the effectiveness of the containment measures (Coleman, 2020). Spreading false news during COVID-19 increases psychological stress and heightens customer behavioral responses such as panic buying (Bermes, 2021), leading to unexpected stockouts (Khan and DePaoli, 2023). Knowing the impact of COVID-19 social media platforms (SMP) fake news posts on the supply chain (SC) could be crucial for stakeholders such as suppliers, distributors, retailers, consumers, and regulators. Therefore, the study seeks to highlight and identify how fake news during the pandemic leads to panic in buying products for future consumption.

Furthermore, the panic buying behavior of the customers leads to a surge in demand variation but limited supply, causing SC disruption. This study used three consecutive studies to address these research gaps. It employed an inductive research methodology based on big data to model SC disruption due to online news articles surrounding the pandemic. The news articles were collected from multiple online news sources, typically called grey literature (Adams et al., 2017). Then, we used computationally intensive big data-driven methods for theory building, as highlighted in the editorial directions (Berente et al., 2019; Kar and Dwivedi, 2020), to generate theoretical insights from trace data media news articles and user-generated content in e-commerce websites.

In totality, three research questions are addressed in this study through an inductive research methodology (Kar et al., 2023) across three studies that combine collective intelligence from perceived domain experts and experiences from different customers on e-commerce platforms to generate an integrative perspective.

RQ1. Does misinformation impact panic buying and e-commerce product availability for customers?

RQ2. Which factors determine how online misinformation impacts supply chain disruption?

RQ3. How do these factors cause supply chain disruption because of online news sharing?

In doing so, we present a model for Misinformation Induced Supply Chain Disruption (MISCD) by integrating Reactance Theory (RT) and Cognitive Load Theory (CLT). The online news articles were collected from multiple sources using web scraping and natural language processing approaches to identify the variables (Rathore et al., 2017). First, using the triangulation method (Smelser and Baltes, 2015), factors and theories related to online news articles surrounding COVID-19 causing SC disruption were chosen from the literature. Second, user-generated content about the products mentioned in the online news articles was collected from various sources. Last, the MISCD model was developed and validated using multiple regression analysis.

The following is the structure of the paper: Section 2 presents the literature review, followed by the research design in Section 3. Section 4 is the exploratory study, and Section 5 outlines confirmatory analysis. In Section 6, we present a discussion. Section 7 outlines the conclusions of the study.

2. Literature review

The literature review is divided into two subsections: fake news propagation during COVID-19 and a theoretical lens for model development.

2.1. COVID-19 impacts on information management

In the contemporary context of dwindling trust in traditional news sources, fake news has found a broad audience among people who use social media (SM) as their primary source of news (Shearer, 2018). The prevalence and intensity of fake news are a worldwide issue. Researchers have claimed that fake news can spread faster than trustworthy news through SM (Vishwanath, 2015). During COVID-19, the most detrimental fake news propagation was witnessed (Pennycook et al., 2020). Literature and news articles globally exhibited a surge in fake news about COVID-19 (Dwivedi et al., 2020) on SMP, such as instructing people to consume salty or warm water and bleach to cure the fatal virus (Lampos et al., 2021).

During COVID-19, public participation in various SMs was a leading cause of information propagation (ITU, 2021). Fake news sharing amplified the crisis's magnitude and endangered public lives. Information sharing on SM triggered panic buying behavior driven by the SM photos (Islam et al., 2021). The availability of information on SMP does not highlight the increased knowledge of the customers but rather the high quantity of data (Bermes, 2021). Significant information overload increases the likelihood of fake news due to more significant psychological strain on consumers (AON, 2020). Conversations on SMP exacerbated the situation, leading to an echo chamber where a particular set of beliefs is magnified without encountering any competing perspective, leading to confirmation bias (Kar et al., 2022).

2.2. Supply chain disruption

The dissemination of fake news on SMP about COVID-19 (Zheng et al., 2021) substantially influences global SC, mainly due to an unexpected surge in demand (Ho, 2020). Past research has highlighted SM discussions on consumer panic buying experiences, impacting SC disruption due to echo chamber effects (Kar et al., 2022). During the pandemic, the global supply chain network faced production and logistics disruption (Ivanov et al., 2015; Chowdhury et al., 2021). These disruptions can distort organizations' plans, leading to goods shortages and unmet customer demand (Paul et al., 2016). The pandemic disrupted the supply chain, resulting in an unprecedented stockout of health-related products like sanitizers, masks, soaps, and everyday consumer products like toilet paper, food, etc. (Khan and DePaoli, 2023).

Global SC activities, particularly medical space and food supplies, have been extensively disrupted due to COVID-19 (Chopra et al., 2021).

Nagurney (2021) highlighted that on the supply side, implications of COVID-19 include a decrease in labor availability, higher risk, and a surge in prices of the products in all sectors. Consumers shifted to internet shopping, hoarding, and excessively purchasing essential products (Kar et al., 2022), producing a significant supply shock in many SCs. After consumers emptied the shelves, the retailers were forced to ration after consumers emptied shelves to ensure just distribution during panic buying (Kogan and Herbon, 2022). Further, movement restrictions imposed by the government caused labor shortages, limited production capacity, and transportation interrupted the flow of products, information, and funds (Chopra et al., 2021), intensifying the SC disruption. The pandemic has emphasized the need for strengthening and restructuring the global SC network.

2.3. Theoretical lens

In the study, the model for the analysis is developed based on two theories: RT (Brehm and Brehm, 1981) and CLT (Sweller, 2011). As per these theories, consumers' fear of severe consequences causes individuals to panic about buying bulk products, causing SC disruption. The study has focused on integrating two theories, i.e., RT and CLT, to propose the model for MISCD.

2.3.1. Cognitive load theory

According to CLT, individuals can be overloaded with excessive information due to their limited capacity, implying that it is difficult for the human brain to process a large amount of information (Sweller, 2011). Sweller (2011) has suggested using CLT in instructional science to understand the human ability to learn in a given setting. However, much information on SMP results in cognitive load on the human brain (Islam et al., 2020). Samson and Kostyszyn (2015) outline that information overload reduces social trust among people due to the incapacity to comprehend the information leading to irrational decision-making. During COVID-19, exposure to SMP increased, leading to information strain and the probability of sharing fake news (Bermes, 2021). Improved technologies like SMP have changed information consumption patterns. Factors like social influence are at play (Laato et al., 2020a); information overload is a source of stress in a crisis in the internet age. SM influences support the development of socially influenced panic buying practices (Naeem and Ozuem, 2021). When consumers are overwhelmed with excessive information, it undermines their motivation to make sense, and they withdraw from putting in extra effort to verify it (Hausman, 2000). Consumers under the strain of information are likely to spread fake information. Empirical evidence exists on the spread of fake news via SM during the ongoing COVID-19 outbreak.

2.3.2. Reactance theory

The RT seeks to explain how individuals react when threatened with losing their freedom (Brehm and Brehm, 1981). It outlines that when an individual's freedom is threatened, they enter a motivated state targeted towards regaining that freedom and averting the loss of all others (Brehm, 1966) due to COVID-19 government and health authorities imposed unprecedented restrictions on personal liberty. Social and economic norms were disrupted due to a desperate measure to contain the spread of the virus, and citizens were encouraged to adopt protective behavior such as hygiene practices, social distancing, and quarantines (Kleitman et al., 2021). In the context of COVID-19, reactance theory is suitable for explaining customer reactions.

This theory has been applied to numerous domains (Fitzsimons, 2000; Murray and Häubl, 2011) that explore how customers react to out-of-stock situations in a retail setting, outlining that reactance to restrictions on customers' freedom of choice can affect customer satisfaction adversely. Hoarding behavior and a sense of urgency to purchase can be caused by psychological reactance comparable to panic buying. For this study, we have employed perceived scarcity, perceived threat, and fear appeal for the research model. Past studies have highlighted that perceived scarcity (Yuen et al., 2022) and perceived threat (Ross, 2023) increase the likelihood of engaging in panic buying. An individual is more likely to panic buy when perceiving an item as scarce or limited (Yuen et al., 2022). Horowitz and Gumenik (1970) highlighted that fear appeal is a source of reactance by eliminating more freedom and inducing specific actions, leading to attitude change. Uncertainties caused by government lockdown caused stockout situations (Argouslidis et al., 2018) led consumers to perceive it as a threat to their prior freedom of choice, hence the role of reactance in the situations of product unavailability as theoretically and managerially important.

3. Research design

This study intends to examine the impact of fake online news on consumer behavior during the rising COVID cases around the globe, which led to the government reinstating stronger regulations to combat the increasing cases. This research's framework has been outlined in Fig. 1, which is based on computationally intensive big data-driven methods. A three-stage strategy is used in the framework: event study, exploratory study, and confirmatory analysis. In the event study, we intended to explore customers' perspectives by analyzing user reviews. In the exploratory study, we developed the MISCD model by analyzing the social sharing of news articles. We undertook an inferential analysis to validate the MISCD model in the confirmatory study. The procedure and results are explained in the next section.

3.1. Research methods

The research framework is developed based on computationally intensive big data-driven methods, as highlighted in editorial directions (Berente et al., 2019; Kar and Dwivedi, 2020; Miranda et al., 2022). It has highlighted a four-step process including (i) sampling and data collection, (ii) synchronic analysis, (iii) lexical framing, and (iv) Diachronic analysis. In our study, the data collected are news articles from multiple sources for sampling and data collection. Second, we merged synchronic analysis and lexical framing, a part of our exploratory study for categorization, identifying the raw association of concepts and developing lexical frameworks to analyze data used to understand the raw association between constructs. Lexical farming influences what patterns we identify and how we express and interpret them. We used LSTM-based topic modeling, which is widely used to extract hidden topics in large documents for linguistic framing (Kushwaha et al., 2021). Lastly, diachronic analysis is a part of the confirmatory study. It includes developing the inductive model for the research and statistically analyzing and validating the hypothesis.

3.2. Data collection

We downloaded the news articles using a scraping tool developed in Python. The articles collected are from the United States of America, Europe, and India. European countries include Belgium, Bosnia and Herzegovina, Croatia, Czech Republic, Denmark, Finland, France, Georgia, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Netherlands, North Macedonia, Poland, Portugal, Serbia, Spain, Sweden, Ukraine, and the United Kingdom. We ensured that the data collected were in English from various sources: India Today articles, NDTV, Reuters U.K., The Hindu, The New York Times, etc. Few official news websites allow access to historical news articles using public API (application programming interface). We utilized these APIs as well to build our sample. The data collection exercise was done from February '21 to May '21. Panic buying is a human behavior that triggers the thought process; hence, we considered a few keywords to understand this behavior during the pandemic. The keywords used for the data collection are 'COVID-19′, 'Pandemic,' 'Wave2', 'Coronavirus,' 'Social Distance,' 'Self-quarantine,' 'Shortage,' 'Availability,' 'Ventilators,'

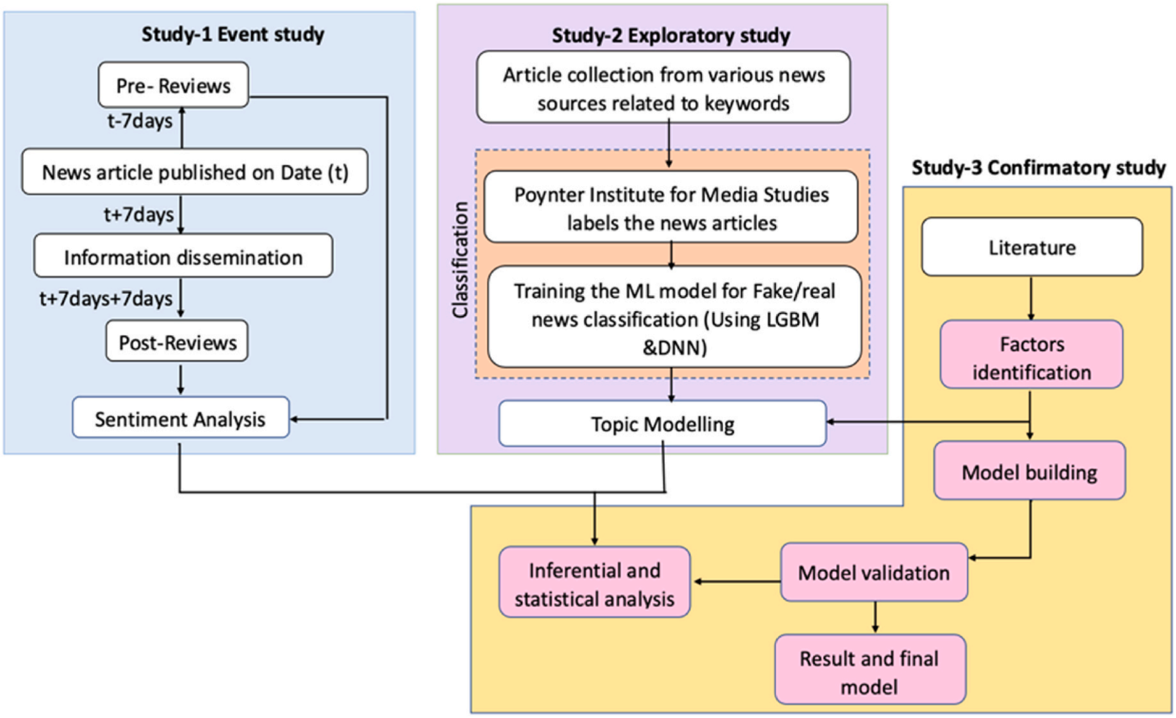

Fig. 1. Research flow.

'Medicines,' and 'Immunity.' Using these keywords, we downloaded over 7588 news articles (Table 1).

3.3. Classification and intercoder reliability

The news articles were classified manually, i.e., by supervised data, by the Coronavirus Infodemic Database by the International Fact-Checking Network (IFCN) Poynter Institute 2020. At the time of the study, i.e., until March 2023, the Poynter website included 7100 fact checks from more than 70 nations in over 40 languages. IFCN is a global body that collaborates with numerous organizations. Hence, the collected data is considered valid and reliable for measuring the propensity of fake news.

To fact-check a news article and segment the same as Fake or Genuine, the analysts of the Poynter Institute started with a keyword search of the new article. The goal is to start small and expand to a wider internet community search, involving single or multiple keywords depending on the article the team tries to verify. As part of the second step, the team attempts to subset all the search results into known news and unknown sources. They then look for trustworthy news sources among the subset of the search results.

The team subsequently looked for specific incidents and tried to see what existed outside the trustworthy news sources. They then compared the story around the incident and the original article under analysis, trying to see the overlap among the events and their sequence. The articles are classified as genuine or fake if the overlap exists beyond a certain threshold.

Two coders manually identified the products discussed in each news article. We conducted an intercoder reliability test to check the validity of the manual coding schemes. The intercoder reliability test indicated Cohen's Kappa score was 0.937, highlighting significant inter-coder reliability (Kassarjian, 1977).

These products listed in the news articles were searched for on the e-commerce platforms for analysis from the focal product pages, subsequently undertaken at the product level based on aggregated reviews and ratings. The product ratings and user experience reviews were accessed from seven popularly used e-commerce healthcare platforms, e.g., Amazon, 1 mg, Pharmeasy, Walgreens, Online Drugstore (U.S.), Chemist Direct, and Simple online pharmacy (U.K.), where reviews were predominantly given in English. Non-English studies were discarded. Reviews with similar content from the page where they were posted or similar content across multiple pages were discarded as they may be bot-generated reviews.

4. STUDY 1: does misinformation impact e-commerce product availability for customers?

4.1. Event study

Event study has been used widely in the management and economics literature (Raghu et al., 2008). It is considered suitable to assess the effects of a rare event on an individual's behavior (Wang et al., 2010). Since the pandemic was unprecedented in the era of high internet diffusion, the event study was suitable for our analysis.

Table 1
Overall description of the news articles.

Region	Number of articles	Total words	Average words	Minimum words	Maximum words	Fake/Genuine
North America	1403	26528	19	9	26	Fake
Europe	1569	30253	18	9	18	
Asia	823	18365	22	11	39	
North America	439	11793	27	5	13	Genuine
Europe	1202	17361	14	5	9	
Asia	2152	53470	25	4	12	

4.2. Event and estimation period

The timeline of this study is represented in Fig. 2. We chose these timelines for analysis to ensure that we cover the impact of COVID-19 on various news sources driving any of the implications of panic buying. As the information shared on the SM cascades quickly as soon as the event happens, we used a 43-day window ranging from twenty-eight days before the article was published (*t-28 days) to (t+ 14 days)*. The day on which the news was published was considered as *t*. We included *t-28 days* (28 days before the article was published) to capture the normal product demand, i.e., pre-reviews. *t+7 days* (7 days after the article was published) were considered the time for information dissemination; it was assumed that consumers were exposed to the news articles. Lastly, *t+14 days* (14 days after the article was published) captures people's response to information dissemination, i.e., post-reviews. The outage reviews reported are the proxies for measuring disruption, as consumers are dissatisfied with the fulfillment services. As the number of these outage reviews increased post-event compared to pre-event, it highlighted the shortage of products in the market, leading to SC disruption. Wang et al. (2019) highlighted the impact of user reviews on SC involving manufacturers and retailers, including sales, price, and quality.

4.3. Data analysis

In the event of companies experiencing a shortage of a specific product, consumers might experience a stockout of the particular product (Khan and DePaoli, 2023). When a consumer discovers that they cannot purchase a product as it is out of stock, it creates a negative effect (Khan and DePaoli, 2023). The data collection involves consumer reviews across online healthcare platforms from focal product pages, which can help measure purchase intention (Yang et al., 2016). Campo et al. (2003) highlighted that stockouts could impact three purchase decisions: reduce purchase probability, induce asymmetry, and purchase in small quantities. We considered the proportion of reviews related to ratings and comments with keywords "out of stock" for the data analysis. We compared the number of ratings/average ratings per week to estimate demand variation. To evaluate SC disruption, we compared the number of out-of-stock comments/average number of out-of-stock comments. The criterion for estimating demand variation leading to SC disruption is motivated by one assumption: the users read news articles on some topics, influencing the consumers' perception and resulting in irrational buying behavior.

Ideally, sales data are considered for accessing demand variation and SC disruption, but generally, sales data are not open to the public and are unavailable in our study. Hence, we assumed, based on past literature, that panic buying had made the products stock out, leading to SC disruption. The proxy for measuring this disruption was based on mining out-of-stock comments in user reviews. We argue that when customers read the news articles, panicked, and purchased the products in higher volumes than needed, it made products go out of stock. Then, other potential buyers started writing about the phenomenon in their reviews on multiple sites. Hence, user ratings and reviews are considered a proxy to analyze demand variation and, subsequently, the SC disruption (Kwark et al., 2021). The demand variation can be regarded as high if the average number of ratings per week after the event (news published) increased or decreased more compared to the average number of ratings before the event, where ratings become a proxy for actual purchases.

The influence of user reviews (Chen et al., 2021) and variance in the user rating (Sun, 2012) on online retail sales can predict sales volume. The erratic purchase behavior of the users causes demand variation and SC disruption estimated from the user-generated content based on natural language processing in the following manner:

$$\text{Demand variation} = \frac{\text{No. of ratings}_{t+14}}{\text{Average ratings per week}_{t-28}}$$

$$\text{Supply chain disruption} = \frac{\text{No. of out}-\text{of}-\text{stock comments}_{t+14}}{\text{Average no. of out}-\text{of}-\text{stock comments per week}_{t-28}}$$

The analysis of the study includes sentiment analysis to understand how emotions change throughout the crisis. SentiStrength is used to determine sentiment strengths. SentiStrength assesses the resilience of both happy and negative emotions (Thelwall et al., 2010). When measuring sentiment strength, we examine each online review as a separate unit before averaging the identical product strength scores for all reviews. SentiStrength assessed the strength of the text based on the most important emotional term. Multiple reviews are combined, resulting in the average score being predominated by the strongest emotional terms in the reviews. SentiStrength determines the strength of each word and the review valence using the Linguistic Inquiry and Word Count (LIWC) vocabulary using natural language processing. The output

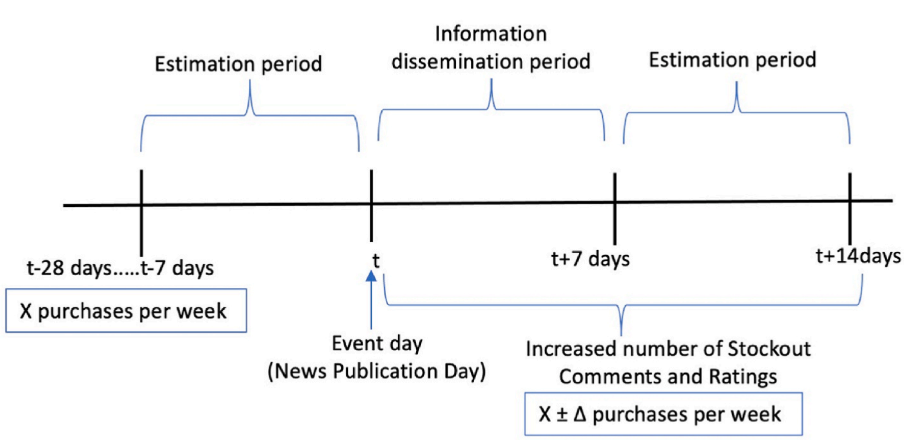

Fig. 2. Event and estimation period.

values for SentiStrength are the review's strongest positive and negative words' strength scores (Thelwall et al., 2010).

We analyzed pre and post-reviews based on the average sentiments of the reviews, using the paired *t*-test to test the rating behavior due to fake and authentic information. Researchers widely use paired t-tests to evaluate the significant statistical mean difference (Lam, 2004). To analyze post behavior between factual information and misinformation, we used the Games-Howell post hoc test to assess rating behavior. We used this test because of its ability to compare multiple groups (Games and Howell, 1976).

4.4. Event study findings

The study examines how news articles alter demand variation from unplanned purchases. To better understand customer behavior during the crisis, we analyzed the user reviews in three ways. First, we divided customer reviews into two groups, pre-reviews, and post-reviews, of the products identified from the fake news articles for analysis. Second, we split customer reviews into two groups, pre-reviews, and post-reviews, of the products identified from the factual news articles for the study. Lastly, customer reviews were divided into two groups: post reviews of the products identified from the fake news and post reviews of the products identified from the factual information for the analysis.

We needed to determine whether the difference in means between fake and authentic news is significantly different. We compared pre and post-reviews of the products mentioned in the fake news articles using paired t-tests. The review scores are mostly normally distributed and equal across pre and post-events. However, in the case of post-event for both fake and real news, the review scores had heterogeneous variance; hence, we considered the Games-Howell post hoc test.

We compared pre and post-reviews of the products mentioned in the fake news articles using paired t-tests. The results highlighted a significant difference between the rating behavior before and after the article was published ($p < 0.05$) (Table 2). We highlighted the changes in the average sentiments of reviews on the focal product page, providing a visual representation based on fake news (Fig. 3).

In the case of assessing the changes in the rating behavior due to factual news articles published based on user reviews, we employed a paired *t*-test. The results have outlined a significant difference in the rating behavior before and after the true news article was published ($p < 0.05$) (Table 3).

We further highlight the changes in the aggregate sentiments through polarity analysis, as it provides a visual representation of the outcomes of the events (Fig. 3). In the case of fake news, there has been a sharp decline in the sentiment score leading to negative sentiment in a pre-review phase. Fake news has more negative sentiment scores in post reviews, which suggests that after reading the fake news, readers experience higher negative emotions expressed in reviews. However, in the case of post reviews, there has been a steady decline, and after t+7 days, a somewhat flat trend was observed, majorly representing a negative sentiment score. In the case of true news, positive sentiment has been observed in both the pre-review and post-review phases. This suggests that after reading true news, more positive words and emotions are perceived by the readers and expressed in reviews.

While comparing customers' post behavior, we employed the Games-Howell post hoc test to assess demand variation. It is observed from the magnitude of the reported significant level ($p < 0.005$) that there is a substantial difference between the post-post behavior of fake news and true news (Table 4). In particular, it suggests that information and misinformation impact user rating behavior on e-commerce platforms.

Table 2
Changes in rating behavior due to misinformation.

Post vs. Pre Event	Mean diff.	Standard Error	Significance	95% Conf. Interval LL	UL
	0.54	0.5287	0	16.36	18.23

5. STUDY 2: which factors determine how online misinformation impacts SC disruption?

5.1. Exploratory study

An exploratory study is performed when there are limited studies or historical data to analyze; it is committed to understanding the nature of the research question (Kushwaha et al., 2021). We collected the data from various news sources and applied computationally intensive big data-driven methods.

5.2. Topic modeling

Topic modeling was employed to analyze the relationship and group the data's emerging topics. An LSTM-based topic modeling approach was employed to uncover hidden themes or topics that news articles used in pandemic-related news items. We extracted ten topics, each with ten words, for 100 words. The topics extracted from the topic modeling are accessed for feature identification based on the similarity of the words from the data text. For model generation in Study 2, the extracted features were correlated to the topics of the factors identified in the literature. Subsequently, these factors were used for model validation in Study 3.

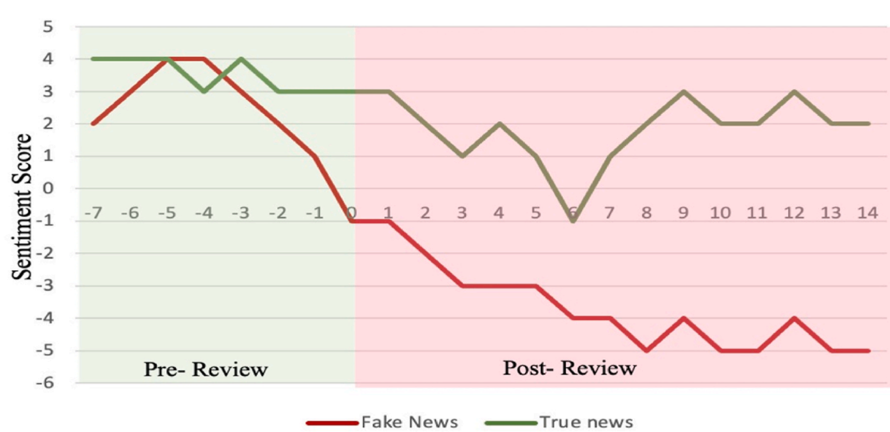

Fig. 3. Sentiment changes in reviews due to misinformation and real information.

Table 3
Changes in rating behavior due to true information.

Post vs. Pre Event	Mean diff.	Standard Error	Significance	95% Conf. Interval	
				LL	UL
	0.38	0.457	0	12.54	13.24

Table 4
Changes in rating behavior due to true information and misinformation.

Post vs. Post Event *(misinformation vs. information)*	Mean diff.	Standard Error	Significance	95% Conf. Interval	
				LL	UL
	0.58	0.028	0	0.377	0.565

5.3. *Exploratory findings*

User evaluations are evaluated in this research to provide insights into SC disruption, using online news articles from various sources, classification accuracy, and content analysis using SMA and NLP approaches for statistical analysis and model validation. Multiple regressions were utilized in the statistical study.

5.3.1. *Topic modeling insights*

The N-gram analysis is a common approach used for textual analysis (Sidorov et al., 2014). The analysis makes it easy to understand the lexicon of words and provides insight into the meaning of word sequence linked to each word (Saura et al., 2022). Fig. 4 Bigram network diagram highlights negative connotations of the reviews, like "disappoint," "aggressive," "losing," "harsh," "mistake," etc. However, N-grams lack the meaning of the phrases and relationships in the data. Hence, we used scattered network diagrams and hierarchical clustering to understand the data comprehensively.

The conventional topic modeling approach, like Latent Dirichlet Allocation (LDA), summarises the text corpus in a few representative topics. While LDA is efficient in terms of execution time, it comes with a significant limitation of needing help to handle correlations between the emerging topics post-summarization. LDA is also heuristic when choosing the number of topics for human interpretable results. The state-of-the-art neural network frameworks add value to address these limitations of LDA. The sequential-based learning of the topics from a corpus of text using recurrent neural network (RNN) family models helps to retain the correlation among the topics, helping to maintain the context of themes emerging through these topics. The efficient model framework among the RNN family of models, LSTM, is used to run topic modeling in this study to identify latent topics or themes used by news providers in their pandemic-related news items.

We combined all identified themes and created a scattered network diagram, as shown in Fig. 5, based on the association between words in specific subjects (Kar, 2021). We can examine 14 clusters with different colors in Fig. 5, where each color denotes a term co-occurring in the topic. After connecting the output from both sections, we mapped the factors arising from the literature. For instance, cyan color words including "fear," "death," "hurricane," and "negative" could be mapped with the *fear appeal*. Topics associated with words like "wrong news," "misunderstanding," "sharing," and "authenticity" could be related to *unverified information sharing*. Hierarchical clustering was developed to understand natural grouping. The benefit of using LSTM here for the network diagram is that linguistic association over a large corpus of text can be handled without facing the challenges of vanishing gradient due to verbosity within the text.

5.3.2. *Hierarchical clustering analysis insights*

We employed an agglomerative hierarchical clustering technique to find the latent structure within the news articles. Fig. 6 shows a tree diagram of comparable terms and their similarity. For instance, "help" and "question" are grouped, representing that the people have a few queries and problems associated with the situation. Similarly, "never" and "except" are joined, representing desperation amongst the consumers. We vertically sliced the tree diagram from 0.3 to find seven groups to classify the words into themes. There are no set criteria for assigning the line (Tullis and Albert, 2013); however, Kushwaha et al. (2021) suggested finding the average number of clusters based on word proximity scores as one option. Further, the segregation needs to have face validity, which we evaluated independently between 3 researchers in the team (Kar and Dwivedi, 2020). We developed a hypothesis based on the topics and variables mentioned in the literature.

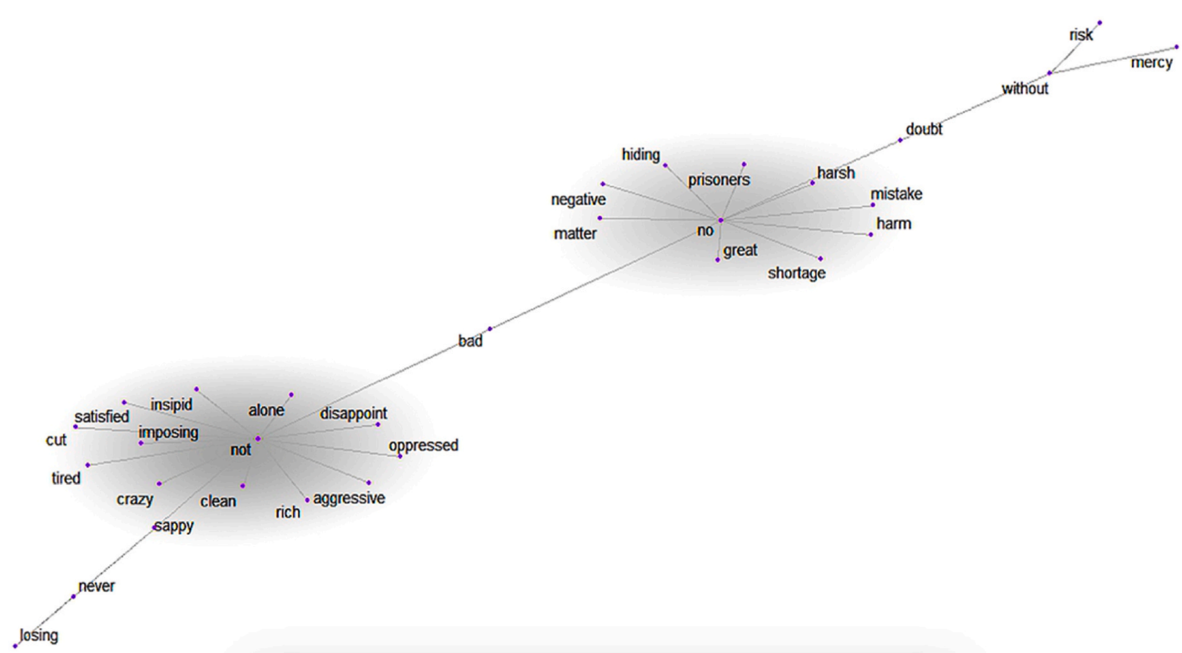

Fig. 4. Bigram network diagram based on reviews.

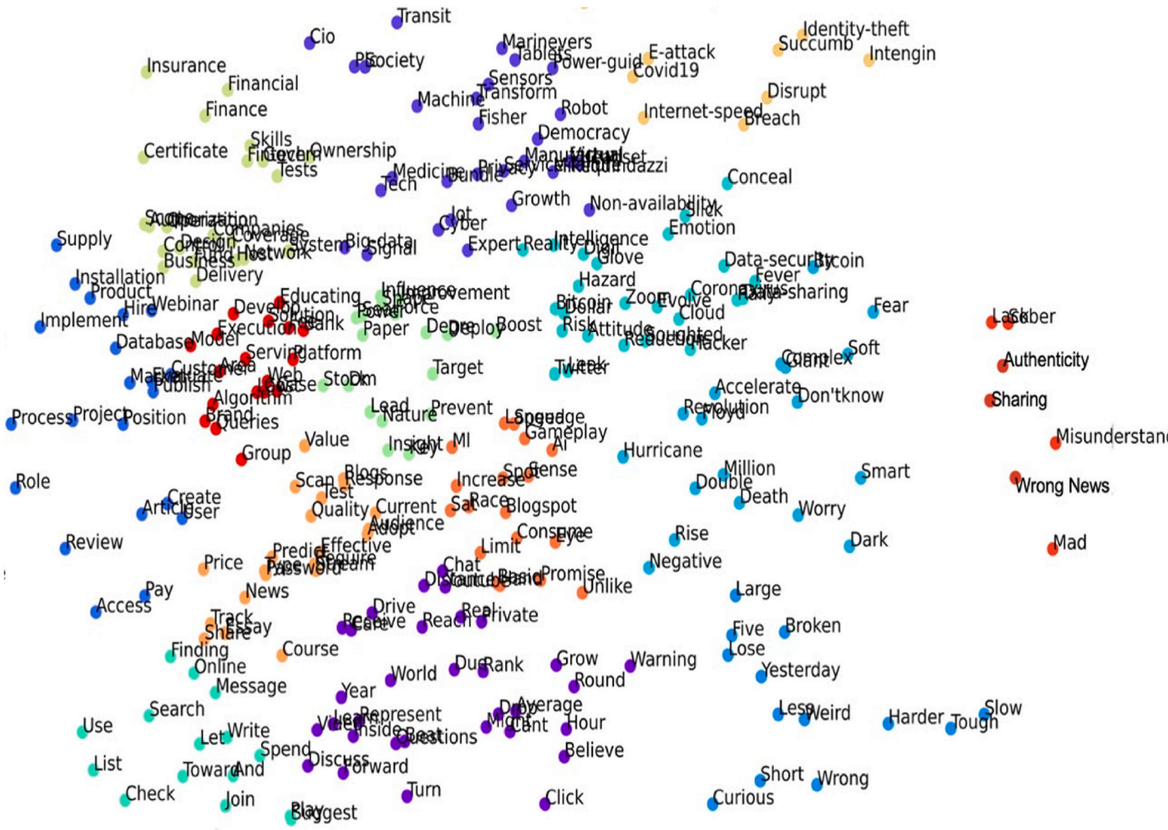

Fig. 5. Scattered Network Diagram using LSTM.

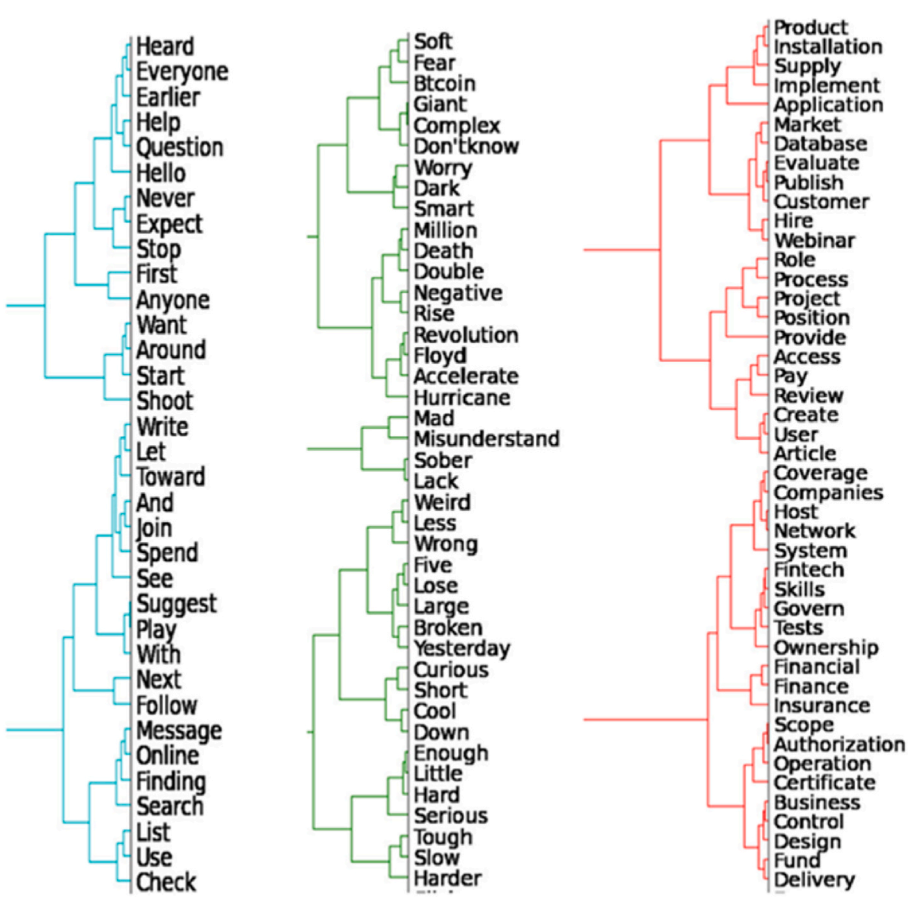

Fig. 6. Hierarchical clustering of themes based on word proximity.

5.3.3. *Unverified information sharing (UIS)*

The topics identified in the corpus have helped develop a variable of *UIS* amongst users. Two social sharing websites, sharedcount.com and sharesscores.com, were determined to understand the sharing pattern of news articles across the internet (Table 5). Python code was developed to access the propagation of news articles across the internet. Each news article was checked on social sharing websites to validate the results, and the social sharing scores across counters were averaged. *UIS* was measured based on social shares on Twitter, Facebook, and Instagram posts. The *t*-test results highlighted a significant mean difference between sharing fake and genuine news articles, i.e., Table 6.

The results highlighted that genuine news articles were shared less on SM than on fake news articles. Fake news articles' higher propagation on the internet could be because people's trust in the traditional media is low and highly polarised, highlighting deeper structural problems (Shirish et al., 2021). Users should rely on the source of information that can act as an authenticator for genuine news articles.

6. STUDY 3: how do these factors cause SC disruption because of online news sharing?

6.1. *Confirmatory study*

In this study, we initially developed hypotheses aligned with our research questions by drawing upon the foundation provided by existing literature. Secondly, the MISCD model was developed, followed by the methods employed for hypothesis validation. Finally, the confirmatory study's findings were reported.

6.2. *Theoretical model development*

In this section, we discuss how we generated the theoretical model, namely MISCD, based on Study 2.

6.2.1. *Social influence and panic buying*

The larger group's opinions, beliefs, and attitudes can impact an individual's decisions (Zheng et al., 2021). In response to social situations, individuals adjust their behavior, known as a social influence (Prakash and Das, 2021). Studies have outlined that extensive exposure to information related to COVID-19 potentially leads to rash decision-making (Samson and Kostyszyn, 2015), suggesting that cognitive overload can contribute to fake news sharing (Bermes, 2021). Moreover, fake news sharing is not an individual's response to information overload (Talwar et al., 2019) but is also subjected to other influences, particularly SM (Naeem and Ozuem, 2021). In a circumstance like COVID-19, an individual may be influenced to panic buy rather than trust their judgment. Hence, based on the literature, it was hypothesized.

Table 5
Count of information sharing.

Country/Region	Number of Social shares	Fake/Genuine
North America	958,249	Fake
Europe	1,198,716	
Asia	680,621	
North America	19,755	Genuine
Europe	68,514	
Asia	90,384	

Table 6
Independent sample *t*-test for information sharing.

	Number of Articles	Mean	SD	t value	p
Fake	3795	46.2	4.5	10.15	0.002
Genuine	3793	31	6.42		

H1. Social Influence is positively associated with panic buying behavior.

6.2.2. *Perceived threat and panic buying*

The perceived threat reflects the threat's subjective perception rather than the objective perception of the actual threat (Tomaka et al., 1993). The perceived threat to freedom is a core antecedent of reactance, which aims to explain an individual's response (Brehm and Brehm, 1981). Researchers have highlighted the role of the perceived threat and negative outcome in promoting panic buying among people to protect themselves from negative situations after the COVID-19 outbreak (Yuen et al., 2020). An individual's risk perception is based on their judgment of the outburst of threat, based on susceptibility and severity of an occurrence (Yoo et al., 2021). Hence, based on the literature, it was hypothesized.

H2. The perceived threat is positively associated with panic buying behavior.

6.2.3. *Perceived scarcity and panic buying*

External circumstances influence an individual's buying behavior. In retail (Parker and Lehmann, 2011), perceived scarcity significantly impacts an individual's purchase intentions. Reactance theory highlights that when an individual's freedom to perform a particular task is threatened, that task becomes more appealing and motivates individuals to regain their sense of freedom (Brehm, 1966). Perceived scarcity is associated with the reactance theory; it highlights that people feel constrained, which creates an urgency to buy, and hoarding behavior might be triggered by psychological reactance, like panic buying (Sterman and Dogan, 2015). Furthermore, the more scarcity is perceived, the more unprotected and susceptible customers would feel about the COVID-19 virus. Hence, based on the literature, it was hypothesized.

H3. The perceived scarcity of goods is positively associated with panic buying behavior.

6.2.4. *Fear appeal and panic buying*

During a disease outbreak, people experience mental distress, such as stress and fear; during a pandemic, the risk to life and property may enhance an individual's fear perception (Omar et al., 2021). Ambiguity causes people to contemplate and imagine the worst cases, developing fear (Kemp et al., 2014). The fear appeal can trigger reactance and threaten freedom (Ratcliff, 2021), influencing buying behavior (Omar et al., 2021). Sneath et al. (2009) highlighted that people are compelled to buy as it provides a sense of security, momentary escape, and comfort. As a result, we have hypothesized.

H4. The fear appeal is positively associated with panic buying behavior.

6.2.5. *Information overload and panic buying*

CLT states that when an individual is exposed to excessive information, overload happens due to an individual's limited cognitive capacity (Sweller, 2011). During COVID-19, inaccurate information leads to cognitive overload among consumers. The overload causes stress and showcases consumers engaging in irrational buying behaviors (Kar et al., 2022). Past studies have discovered that pandemic-induced fear had increased media information overload, linked to panic buying essential supplies. Hence, the hypothesis framed is as follows.

H5. Information overload is positively associated with panic buying behavior.

6.2.6. *Moderating effect of UIS*

SMPs are widely used for information sharing (Appel et al., 2020), which leads to information overload due to limited cognitive resources, which hampers the information verification ability of a user (Bright et al., 2015). We used CLT to understand this relationship. UIS represents SM's role users in spreading information lacking verification (Laato et al., 2020b). Laato et al. (2020b) outlined that individuals are less likely to verify the information source when experiencing information overload. Chatterjee et al. (2022) highlighted that fake news impacts SC resilience and uncertainty, moderated by technology capabilities, ultimately affecting organizations' performance. Hence, based on the literature, it was hypothesized.

H6. UIS moderates the relationship between (a) social influence, (b) perceived threat, (c) perceived scarcity, (d)fear appeal, (e) information overload, and panic buying.

Hence, in Fig. 7, we have developed the study's conceptual model.

6.3. Research methods

We assigned all news articles a coefficient based on a word score using topic modeling analysis, which was then employed in regression analysis to develop and test a hypothesis. Finally, each document (news line) was assigned to the closest themes and rated using a Likert scale. In content analysis methodologies, multiple regression analysis is adequate for empirical studies and is free of low multicollinearity impacts (Kar, 2021). We initially kept an out-of-sample portion to evaluate the model on an unknown dataset. To assess the robustness of the proposed model results, we used techniques such as k-fold cross-validation. We divided the analysis sample into multiple cross-validation folds, which were utilized to check the stability and robustness of the result (Appendix A1).

6.4. Confirmatory findings

6.4.1. Multiple regression analysis

We have used multiple regression to predict the value of the variables based on the value of two or more independent variables. Using literature to create six hypotheses based on selected theories, we tested ideas separately using Pearson's chi-square to calculate the p-value. The factors with a p-value less than 0.05 have been highlighted in Table 7 for hypothesis validation (95% acceptance rate).

$$\begin{aligned}\text{Panic buying} = {} & \alpha + \beta_1.\text{Perceived Threat} + \beta_2.\text{Perceived scarcity} \\ & + \beta_3.\text{Fear Appeal} + \beta_4.\text{Social Influence} + \beta_5.\text{Information Overaload} \\ & + \beta_6.\text{UIS} + \beta_7.\text{UIS.Percived Threat} + \beta_8.\text{UIS.Percived Scarcity} \\ & + \beta_9.\text{UIS.Percived Threat} + \beta_{10}.\text{UIS.Information Overload} \\ & + \beta_{11}.\text{UIS.Social Influence} + \varepsilon\end{aligned}$$

Where α indicates the constant intercept, $\beta_1 \ldots \beta_{11}$ regression coefficients, and ε is random error.

The MISCD model specifies if panic buying can be explained by social influence, perceived threat, perceived scarcity, fear appeal, and information overload. Four main significant effects, i.e., perceived threat, perceived scarcity, fear appeal, and information overload, influence consumers' panic buying behavior. Hence, hypotheses 2,3,4, and 5 are

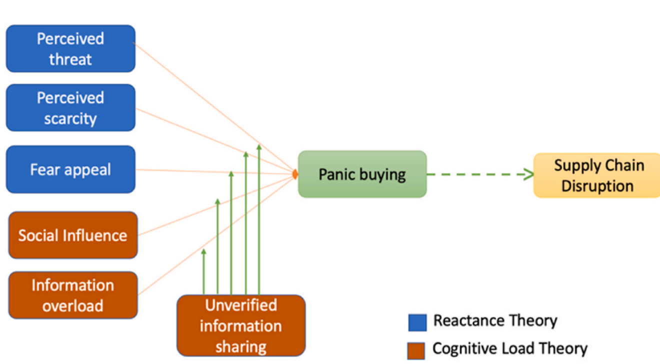

Fig. 7. Conceptual model for MISCD.

Table 7
Main and moderating effect results.

Coefficients	Estimate	Std. Error	t-value	P-value
Main Effect				
Intercept	9.58	1.4	4.9	0.00006
Social Influence	−0.0007	0.002	0.437	0.662
Perceived Threat	−0.1387	0.023	10.99	0.006
Perceived Scarcity	−0.1689	0.01	−5.706	0
Fear Appeal	−0.0085	0.004	1.612	0.007
Information Overload	0.1875	0.024	−11.419	0.002
UIS	−0.0085	0.018	−0.037	0.001
Moderating Effect				
UIS x Perceived Threat	−0.0896	0.006	−6.032	0
UIS x Perceived Scarcity	−0.1289	0.062	−1.258	0.008
UIS x Fear Appeal	−0.5784	0.035	2.1	0.003
UIS x Information Overload	0.0038	0.002	0.26	0.005
UIS x Social Influence	−10.287	1.347	−4.973	0.25

supported. These results have rejected the null hypothesis and accepted the alternative hypothesis. The regression results highlighted that perceived threat impacts panic buying as misinformation creates more engagement (Zannettou, 2021) and develops irrational buying behavior amongst users. In the case of perceived scarcity and fear appeal, misinformation can create an environment of restricted availability and anxiety, developing a sense of psychological reactance amongst customers (Sterman and Dogan, 2015), which promotes panic buying behavior. Further, information overload impacts panic buying as customers want to determine their scope of risk mitigation (Laato et al., 2020a).

However, unexpectedly, the impact of social influence on the panic-buying behavior of the users is insignificant. Thus, Hypothesis 1 is not supported (Table 7). Hence, we accepted the null hypothesis and rejected the null hypothesis, i.e., social influence does not impact panic buying behavior amongst users due to the rational decision-making process. Silvera et al. (2008) highlighted that impulsive buying is inconsistent with the rational choices model.

6.4.2. Moderating effect of UIS

Finally, integration moderation was used to test whether UIS had any moderating impact on the users' predictor and panic buying behavior. The primary effects of independent factors linked with UIS and the result of interaction terms are shown in Table 7. UIS did not have a significant impact on social influence. Hence, the moderating of *UIS* on social influence and panic buying was insignificant. In contrast, UIS significantly modifies the perceived threat, perceived scarcity, fear appeal, and information overload ($p < 0.05$).

7. Discussion

In this digital era, information sharing is just a few clicks away; however, sharing information without verification could be detrimental (Talwar et al., 2020). Due to COVID-19, fake news sharing exacerbated the situation, jeopardized public health, and impacted their buying behavior (Kar et al., 2022). Hence, UIS was one of the most critical challenges for customers and policymakers in fighting the virus. In this context, we developed the MISCD framework for explaining the impacts of misinformation on supply chain disruption.

CLT (Sweller, 2011) and reactance theory (Brehm and Brehm, 1981) are used in the study to understand consumer behavioral responses during COVID-19. Based on these theories, the data of this study indicated irrational buying behavior, i.e., panic buying. As per CLT, consumers experience cognitive overload due to excessive information due to the limited cognitive capacity of the human brain. Cognitive load causes stress to individuals, which instigates irrational buying behavior. The study highlighted that information overload significantly affects panic buying behavior among users. The extent of ambiguity surrounding COVID-19 determines consumers' scope of risk mitigation

(Laato et al., 2020a), increasing their dependability on online information sources. People may experience a high volume of health information related to COVID-19, which leads to psychological strain on customers (Kar et al., 2022). Due to customers' limited cognitive capacity, the brain suffers from a cognitive load, leading to irrational buying behavior (Laato et al., 2020a).

The moderating effect of UIS worsens the situation, leading to panic buying. Fake news spreads like wildfire on SMP (Ramanathan et al., 2017). These platforms developed an echo chamber highlighting a narrow vision amongst individuals, leading to panic buying behavior. There was misinformation surrounding COVID-19 remedies, treatments, vaccination side effects, etc. Panic buying behavior highlighted the demand variation escalated due to UIS on SM and news platforms, leading to SC disruption. Zheng et al. (2021) demonstrated that consumers' purchasing decisions are frequently affected by the choices of their peers. Social learning triggers customers about anticipated supply scarcity based on their peers' stockpiling, leading to panic buying behavior. However, our results have highlighted that social influence does not significantly impact panic buying behavior amongst users.

As per reactance theory, COVID-19 leads to multiple restrictions ranging from leaving one's home to wearing masks, avoiding social events, etc., leading to a worldwide experience of reactance. Due to the omnipresence of reactance, fear appeal, perceived scarcity, and perceived threat have been used to evaluate behavioral restrictions due to the pandemic. Certain aspects of COVID-19, such as the ambiguity (Kemp et al., 2014) regarding how it spreads, evolves, or the immunity of those who have been infected, as well as the unavailability of a vaccine to battle the illness, have sparked widespread fear, resulting in panic buying (Naeem, 2021). Information asymmetry was one of the significant causes of fear among customers during the pandemic. Over-purchasing helped customers in relieving fear induced due to fake news circulation.

Further, perceived threat significantly affects panic buying by the users. When fake online news is circulated on SM surrounding COVID-19, it causes distress. Zannettou (2021) highlighted that misinformation generates more engagement than regular tweets. During the pandemic, these social interactions created an echo chamber (Kar et al., 2022), leading to irrational customer buying behavior. The social interactions during the crisis trigger hoarding and over-purchasing amongst customers due to a rational survival strategy.

Furthermore, perceived scarcity substantially affects users' panic buying behavior. The news surrounding toilet paper shortages or uncertainty about lockdowns contributed to erratic consumer behavior. Our findings also suggested that fake news articles created a sense of restricted availability, developing a perception of scarcity. Fake news articles trigger psychological reactance among customers (Sterman and Dogan, 2015) as consumers with a hedonic mindset seek gratification in owning a scarce product.

Lastly, fear appeal in online news articles about COVID-19 significantly affects users' panic buying behavior. Certain aspects of COVID-19, such as the ambiguity (Kemp et al., 2014) regarding how it spreads, evolves, or the immunity of those who have been infected, as well as the unavailability of a vaccine to battle the illness, have sparked widespread fear, resulting in panic buying (Naeem, 2021). Information asymmetry was one of the primary causes of fear among customers during the pandemic. Over-purchasing helped customers in relieving fear induced due to fake news circulation. Customers purchasing behavior was impacted by the uncertain economic conditions caused due to the pandemic. The final model of our research contributes to the management literature, including all the factors that influence panic buying behavior moderated by UIS, leading to SC disruption (as presented in Fig. 8).

7.1. Theoretical implications

The research is based on the honest signals of multiple stakeholders,

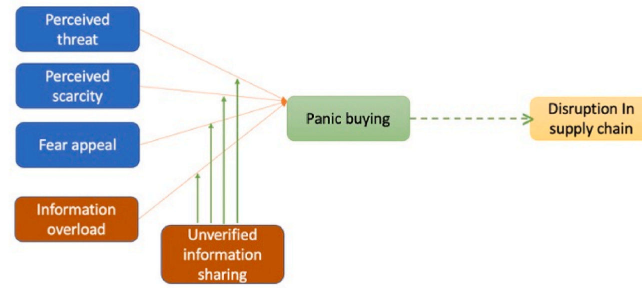

Fig. 8. Validated model for MISCD.

i.e., media, customers, and prior literature, included in three studies complementing the output and strengthening the understanding to develop the MISCD model by integrating RT and CLT. The study offers three contributions to the literature. First, the study established that panic buying leads to SC disruption moderated by misinformation through the event study. The primary driving factors for panic buying due to misinformation are perceived threat, perceived scarcity, fear appeal, information overload, and *UIS*. To reduce their trips to crowded places, panic buying could be attributed to users' self-protecting mechanisms (Prentice et al., 2020). Users' dependency on online shopping platforms minimizes the likelihood of coming in contact with the virus, highlighting excess buying behavior due to anticipated supply shortages.

The second contribution concerns CLT, which highlights information overload and *UIS*. The study incrementally contributes toward the studies on individual factors augmenting COVID-19-related information sharing on multiple platforms. The quantity of information shared on SMP bombards customers, leading to cognitive overload and instigating irrational buying behavior (Zaky et al., 2022). The study found a vital role of *UIS* as a moderator to panic buying. *UIS* triggers uncertainty amongst customers, leading to demand variations. These small retail demand fluctuations progressively result in demand fluctuation at multiple levels of distributors, wholesalers, manufacturers, and raw material suppliers, causing a bullwhip effect. The bullwhip effect depends not solely on demand variations but also on an organization's internal factors like the degree of operational level, share price, and debt (Scarpin et al., 2022).

Lastly, the crucial contribution to reactance theory is that perceived scarcity, perceived threat, and fear appeal to panic buying moderated by *UIS*. The rampant usage of SM and news platforms created an atmosphere of ambiguity and uncertainty. Fear-induced negative perception, fear of the unknown, and coping mechanisms lead to excess buying behavior. The study has highlighted the role of misinformation in serving as a conduit to demand variations during COVID-19. Sharma et al. (2022) outline that customer information sharing can lead to changes in demand and supply, which can influence SC performance. The study offers a theoretical foundation to understand misinformation disrupting the SC.

7.2. Practical implications

The pandemic triggered social and economic disruption globally; it highlighted the structural problems in SC management. It upset the demand-supply equilibrium in the market, caused by transportation and logistics bottlenecks, limited plant operations due to the social distancing norms, plant closures due to limited labor availability, and the bullwhip effect in SC. These unforeseen circumstances led to a perceived threat, perceived scarcity, fear appeal, and information overload amongst customers, increasing the dependence on the information being circulated online. The misinformation circulated fueled the panic buying behavior among customers. The companies experienced a sudden increase in product demand, which made it difficult for the organizations to keep up with the demand variations, disrupting the entire SC.

By monitoring these factors, firms can minimize SC disruption. First, the firms must understand that accurate retail demand information can combat the bullwhip effect. Demand information accuracy can help avoid over-ordering and repeat ordering, preventing organizations from overcorrecting for disruption while building the capacity to fulfill rising global demand. Organizations need to be resilient against SC disruptions; they need to be ready for the challenges of new product introduction, erratic demand behavior, and growing customer expectations. Employing smart manufacturing capabilities (Bianco et al., 2023), i.e., the practices accessible by Industry 4.0, helps develop smart capabilities and build resilience (El Baz and Ruel, 2021). The pandemic has emphasized the importance of developing a global SC and resilience. In a highly disruptive scenario, SC alertness can influence SC resilience (Queiroz et al., 2022).

Second, a crucial role of the government is in combating misinformation during a crisis. The skepticism around the situation can lead to mass irrational behavior. Hence, the government must educate users to be mindful of misinformation. The policymakers should nudge customers and platform firms digitally, whereby using user interface designs may influence users' input in online platforms (Weinmann et al., 2016). Educating users will stimulate them to think rationally and not make knee-jerk decisions based on misinformation.

8. Conclusion

Uncertainties during disasters like a pandemic can change customer behavior, significantly impacting SC management. There is an evident need for organizations to plan and invest in the tools to identify and manage misinformation. We present the MISCD model that can be used to analyze misinformation sharing in online platforms and its impact on SC. We analyzed the data from multiple news sources and user comments from numerous e-commerce websites across three studies for big data-driven computationally intensive theory building.

Our findings indicated that the primary cause of this disruption is *UIS* on the internet amongst users, contributing to demand variation that disrupts the entire SC. We highlight how organizations should proactively manage misinformation in SC through monitoring SMP, collaborating with fact-checking organizations, and collaborating with SC partners. Following these strategies could be helpful for organizations to promote accurate information exchange through SC. Further, news publishing houses need to focus on publishing articles and have a news management division that could concentrate on misinformation.

Our study has some limitations; first, the study explains consumers' panic buying during COVID-19 based on empirical data to enhance generalizability. Future researchers could test the generalizability of our model in the context of other disasters, which may create an infodemic (Ansar and Goswami, 2021; Vasist and Sebastian, 2022). Second, we have considered the news resources from Asia, Europe, and North America only; researchers also can explore other regions. Furthermore, a cross-national investigation of false news propagation could offer exciting results that can assist policymakers. Third, the study has considered only English news sources and customer reviews; however, inspecting the non-English news sources and reviews may help gain deeper insights. Fourth, prior research has highlighted that seller ratings impact customer behavior (Hong and Cha, 2013); hence, the study initially intended to consider seller ratings as a control variable in the study. However, the data was only available on very few e-commerce platforms. Hence, future researchers can introduce more control variables for future research, provided the online platforms start capturing the data across platforms. Finally, the recent advances in Generative Artificial Intelligence (Dwivedi et al., 2023a, 2023b; Richey et al.,) may further amplify the phenomenon of fake news and misinformation. This could make it much more difficult to detect and might have a detrimental impact on various areas, including consumer behavior and supply chain disruptions. Future research should examine how to identify fake news, misinformation, and fake reviews generated by Generative Artificial Intelligence, as well as the potential impacts they might have on consumers, businesses, and society.

Data availability

Data will be made available on request.

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•The authors have no conflict of interests to declare.

•All authors have contributed, and all contributors have been listed as authors.

Appendix

Cross-validation 1

Coefficients	Estimate	Std. Error	Z-value	P-value
Main Effect				
Intercept	8.96	1.9	6.2	0.00004
Social Influence	−0.0010	0.045	0.876	0.981
Perceived Threat	−0.1976	0.058	14.78	0.0008
Perceived Scarcity	−0.2398	0.2	−6.789	0.01
Fear Appeal	−0.0031	0.039	2.587	0.0002
Information Overload	0.2187	0.987	−12.789	0.001
UIS	−0.0059	0.031	−0.042	0.0006
Moderating Effect				
UIS x Perceived Threat	−0.1329	0.045	−5.980	0.002
UIS x Perceived Scarcity	−0.4478	0.139	−2.378	0.004
UIS x Fear Appeal	−0.9480	0.098	1.9	0.025
UIS x Information Overload	0.0057	0.007	0.89	0.035
UIS x Social Influence	−12.538	1.879	−3.786	0.34

Cross-validation 2

Coefficients	Estimate	Std. Error	Z-value	P-value
Main Effect				
Intercept	9.43	1.3	4.9	0.00010
Social Influence	−0.0012	0.0018	0.674	0.734
Perceived Threat	−0.2197	0.027	11.33	0.0009
Perceived Scarcity	−0.1844	0.007	−6.887	0.004
Fear Appeal	−0.0045	0.0033	1.584	0.0008
Information Overload	0.1779	0.0019	−12.365	0.017
UIS	−0.0112	0.022	−0.047	0.0008
Moderating Effect				
UIS x Perceived Threat	−0.0045	0.0008	−5.775	0.007
UIS x Perceived Scarcity	−0.1865	0.056	−1.467	0.015
UIS x Fear Appeal	−0.4487	0.041	2.44	0.019
UIS x Information Overload	0.0041	0.0008	0.34	0.0008
UIS x Social Influence	−12.114	1.2754	−4.545	0.46

Cross-validation 3

Coefficients	Estimate	Std. Error	Z-value	P-value
Main Effect				
Intercept	8.89	1.5	4.24	0.00030
Social Influence	−0.0023	0.0027	0.588	0.547
Perceived Threat	−0.3166	0.046	12.77	0.0013
Perceived Scarcity	−0.1278	0.005	−8.449	0.003
Fear Appeal	−0.0032	0.0022	1.867	0.0012
Information Overload	0.2188	0.0009	−13.154	0.006
UIS	−0.0255	0.031	−0.046	0.0012
Moderating Effect				
UIS x Perceived Threat	−0.0051	0.0010	−6.312	0.0001
UIS x Perceived Scarcity	−0.1678	0.006	−1.853	0.003
UIS x Fear Appeal	−0.6439	0.038	3.03	0.004
UIS x Information Overload	0.0031	0.0014	0.45	0.0007
UIS x Social Influence	−13.341	2.006	−3.871	0.54

References

Adams, R.J., Smart, P., Huff, A.S., 2017. Shades of grey: guidelines for working with the grey literature in systematic reviews for management and organizational studies. Int. J. Manag. Rev. 19, 432–454. https://doi.org/10.1111/ijmr.12102.

Allcott, H., Gentzkow, M., 2017. Social media and fake news in the 2016 election. J. Econ. Perspect. 31, 211–236. https://doi.org/10.1257/jep.31.2.211.

Ansar, W., Goswami, S., 2021. Combating the menace: a survey on characterization and detection of fake news from a data science perspective. Int. J. Info. Manag. Data Insights 1, 100052. https://doi.org/10.1016/j.jjimei.2021.100052.

AON, 2020. COVID-19 Related Cyber Fraud and Misinformation Campaigns Disrupt Critical Industries.

Appel, G., Grewal, L., Hadi, R., Stephen, A.T., 2020. The future of social media in marketing. J. Acad. Market. Sci. 48, 79–95. https://doi.org/10.1007/s11747-019-00695-1.

Argouslidis, P., Skarmeas, D., Kühn, A., Mavrommatis, A., 2018. Consumers' reactions to variety reduction in grocery stores: a freedom of choice perspective. Eur. J. Market. 52, 1931–1955. https://doi.org/10.1108/EJM-12-2016-0844.

Aswani, R., Kar, A.K., Ilavarasan, P.V., 2019a. Experience: managing misinformation in social media—insights for policymakers from twitter analytics. J. Data and Info. Q. 12 (6), 1–6. https://doi.org/10.1145/3341107, 18.

Aswani, R., Kar, A.K., Ilavarasan, P.V., 2019b. Experience: managing misinformation in social media—insights for policymakers from twitter analytics. J. Data and Info. Q. 12 (6), 1–6. https://doi.org/10.1145/3341107, 18.

Berente, N., Seidel, S., Safadi, H., 2019. Research commentary—data-driven computationally intensive theory development. Inf. Syst. Res. 30, 50–64. https://doi.org/10.1287/isre.2018.0774.

Bermes, A., 2021. Information overload and fake news sharing: a transactional stress perspective exploring the mitigating role of consumers' resilience during COVID-19. J. Retailing Consum. Serv. 61, 102555 https://doi.org/10.1016/j.jretconser.2021.102555.

Bianco, D., Bueno, A., Godinho Filho, M., Latan, H., Miller Devós Ganga, G., Frank, A.G., Chiappetta Jabbour, C.J., 2023. The role of Industry 4.0 in developing resilience for manufacturing companies during COVID-19. Int. J. Prod. Econ. 256, 108728 https://doi.org/10.1016/j.ijpe.2022.108728.

Brehm, J.W., 1966. A Theory of Psychological Reactance, A Theory of Psychological Reactance. Academic Press, Oxford, England.

Brehm, S.S., Brehm, J.W., 1981. Psychological Reactance: A Theory of Freedom and Control. Academic Press.

Bright, L.F., Kleiser, S.B., Grau, S.L., 2015. Too much Facebook? An exploratory examination of social media fatigue. Comput. Hum. Behav. 44, 148–155. https://doi.org/10.1016/j.chb.2014.11.048.

Campo, K., Gijsbrechts, E., Nisol, P., 2003. The impact of retailer stockouts on whether, how much, and what to buy. Int. J. Res. Market. 20, 273–286. https://doi.org/10.1016/S0167-8116(03)00037-5.

Chatterjee, S., Chaudhuri, R., Vrontis, D., 2022. Role of fake news and misinformation in supply chain disruption: impact of technology competency as moderator. Ann. Oper. Res. https://doi.org/10.1007/s10479-022-05001-x.

Chen, H., Duan, W., Zhou, W., 2021. When products receive reviews across platforms: studying the platform concentration of electronic word-of-mouth. Inf. Manag. 58, 103532 https://doi.org/10.1016/j.im.2021.103532.

Choi, T.Y., Rogers, D., Vakil, B., 2020. Coronavirus is a wake-up call for supply chain management. Harv. Bus. Rev. 27 (1), 364–398.

Chopra, S., Sodhi, M., Lücker, F., 2021. Achieving supply chain efficiency and resilience by using multi-level commons. Decis. Sci. J. 52, 817–832. https://doi.org/10.1111/deci.12526.

Chowdhury, P., Paul, S.K., Kaisar, S., Moktadir, MdA., 2021. COVID-19 pandemic related supply chain studies: a systematic review. Transport. Res. E Logist. Transport. Rev. 148, 102271 https://doi.org/10.1016/j.tre.2021.102271.

Coleman, A., 2020. Hundreds Dead" Because of Covid-19 Misinformation. BBC News.

Dolgui, A., Ivanov, D., Rozhkov, M., 2020. Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain. Int. J. Prod. Res. 58, 1285–1301. https://doi.org/10.1080/00207543.2019.1627438.

Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K., et al., 2023a. "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. Int. J. Inf. Manag. 71, 102642.

Dwivedi, Y.K., Pandey, N., Currie, W., Micu, A., 2023b. Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda. Int. J. Contemp. Hospit. Manag. https://doi.org/10.1108/IJCHM-05-2023-0686.

Dwivedi, Y.K., Hughes, D.L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J.S., et al., 2020. Impact of COVID-19 pandemic on information management research and practice: transforming education, work and life. Int. J. Inf. Manag. 55, 102211.

Dwivedi, Y.K., Kelly, G., Janssen, M., Rana, N.P., Slade, E.L., Clement, M., 2018. Social media: the good, the bad, and the ugly. Inf. Syst. Front 20, 4419–4423. https://doi.org/10.1007/s10796-018-9848-5.

El Baz, J., Ruel, S., 2021. Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. Int. J. Prod. Econ. 233, 107972 https://doi.org/10.1016/j.ijpe.2020.107972.

Figl, K., Kießling, S., Remus, U., 2023. Do symbol and device matter? The effects of symbol choice of fake news flags and device on human interaction with fake news on social media platforms. Comput. Hum. Behav. 144, 107704 https://doi.org/10.1016/j.chb.2023.107704.

Fitzsimons, G.J., 2000. Consumer response to stockouts. J. Consum. Res. 27, 249–266. https://doi.org/10.1086/314323.

Games, P.A., Howell, J.F., 1976. Pairwise multiple comparison procedures with unequal N's and/or variances: a Monte Carlo study. J. Educ. Stat. 1, 113–125. https://doi.org/10.3102/10769986001002113.

Goodman, P.S., 2021. How the Supply Chain Broke, and Why it Won't Be Fixed Anytime Soon. The New York Times.

Hausman, A., 2000. A multi-method investigation of consumer motivations in impulse buying behavior. J. Consum. Market. 17, 403–426. https://doi.org/10.1108/07363760010341045.

Ho, W., 2020. The COVID-19 Shock to Supply Chains.

Hong, I.B., Cha, H.S., 2013. The mediating role of consumer trust in an online merchant in predicting purchase intention. Int. J. Inf. Manag. 33, 927–939. https://doi.org/10.1016/j.ijinfomgt.2013.08.007.

Horowitz, I.A., Gumenik, W.E., 1970. Effects of the volunteer subject, choice, and fear arousal on attitude change. J. Exp. Soc. Psychol. 6, 293–303. https://doi.org/10.1016/0022-1031(70)90064-8.

Hossain, M.A., Sabani, A., Bandyopadhyay, A., Raman, R., Goyal, D.P., Dwivedi, Y.K., 2023a. Investigating the effect of social media fake news on consumer behavior: an empirical study with multiple moderations. J. Strat. Market. 1–18. https://doi.org/10.1080/0965254X.2023.2253824.

Hossain, M.A., Chowdhury, M.M.H., Pappas, I.O., Metri, B., Hughes, L., Dwivedi, Y.K., 2023b. Fake news on Facebook and their impact on supply chain disruption during COVID-19. Ann. Oper. Res. 327 (2), 683–711.

Islam, A.K.M.N., Laato, S., Talukder, S., Sutinen, E., 2020. Misinformation sharing and social media fatigue during COVID-19: an affordance and cognitive load perspective. Technol. Forecast. Soc. Change 159, 120201. https://doi.org/10.1016/j.techfore.2020.120201.

Islam, T., Pitafi, A.H., Arya, V., Wang, Y., Akhtar, N., Mubarik, S., Xiaobei, L., 2021. Panic buying in the COVID-19 pandemic: a multi-country examination. J. Retailing Consum. Serv. 59, 102357 https://doi.org/10.1016/j.jretconser.2020.102357.

ITU, 2021. Pandemic in the Internet Age: from Second Wave to New Normal, Recovery, Adaptation and Resilience [WWW Document]. ITU Hub. URL. https://www.itu.int/hub/publication/d-pref-ef-pandemic_01-2021/, 4.15.23.

Ivanov, D., Dolgui, A., Sokolov, B., 2015. Supply chain design with disruption considerations: review of research streams on the ripple effect in the supply chain. In: IFAC-PapersOnLine, 15th IFAC Symposium onInformation Control Problems inManufacturing, 48, pp. 1700–1707. https://doi.org/10.1016/j.ifacol.2015.06.331.

Kar, A.K., 2021. What affects usage satisfaction in mobile payments? Modelling user generated content to develop the "digital service usage satisfaction model.". Inf. Syst. Front 23, 1341–1361. https://doi.org/10.1007/s10796-020-10045-0.

Kar, A.K., Angelopoulos, S., Rao, H.R., 2023. Guest Editorial: big data-driven theory building: philosophies, guiding principles, and common traps. Int. J. Inf. Manag. 71, 102661 https://doi.org/10.1016/j.ijinfomgt.2023.102661.

Kar, A.K., Dwivedi, Y.K., 2020. Theory building with big data-driven research – moving away from the "What" towards the "Why.". Int. J. Inf. Manag. 54, 102205 https://doi.org/10.1016/j.ijinfomgt.2020.102205.

Kar, A.K., Tripathi, S.N., Malik, N., Gupta, S., Sivarajah, U., 2022. How does misinformation and capricious opinions impact the supply chain - a study on the impacts during the pandemic. Ann. Oper. Res. https://doi.org/10.1007/s10479-022-04997-6.

Kassarjian, H.H., 1977. Content analysis in consumer research. J. Consum. Res. 4, 8–18. https://doi.org/10.1086/208674.

Kelley, A., 2020. Attacks on Asian Americans Skyrocket to 100 Per Day during Coronavirus Pandemic (Text). The Hill.

Kemp, E., Kennett-Hensel, P.A., Williams, K.H., 2014. The calm before the storm: examining emotion regulation consumption in the face of an impending disaster. Psychol. Market. 31, 933–945. https://doi.org/10.1002/mar.20744.

Khan, U., DePaoli, A., 2023. Brand loyalty in the face of stockouts. J. Acad. Market. Sci. https://doi.org/10.1007/s11747-023-00924-8.

Kleitman, S., Fullerton, D.J., Zhang, L.M., Blanchard, M.D., Lee, J., Stankov, L., Thompson, V., 2021. To comply or not comply? A latent profile analysis of behaviours and attitudes during the COVID-19 pandemic. PLoS One 16, e0255268. https://doi.org/10.1371/journal.pone.0255268.

Kogan, K., Herbon, A., 2022. Retailing under panic buying and consumer stockpiling: can governmental intervention make a difference? Int. J. Prod. Econ. 254, 108631 https://doi.org/10.1016/j.ijpe.2022.108631.

Kushwaha, A.K., Kumar, P., Kar, A.K., 2021. What impacts customer experience for B2B enterprises on using AI-enabled chatbots? Insights from Big data analytics. Ind. Market. Manag. 98, 207–221. https://doi.org/10.1016/j.indmarman.2021.08.011.

Kwark, Y., Lee, G.M., Pavlou, P.A., Qiu, L., 2021. On the spillover effects of online product reviews on purchases: evidence from clickstream data. Inf. Syst. Res. 32, 895–913. https://doi.org/10.1287/isre.2021.0998.

Laato, S., Islam, A.K.M.N., Farooq, A., Dhir, A., 2020a. Unusual purchasing behavior during the early stages of the COVID-19 pandemic: the stimulus-organism-response approach. J. Retailing Consum. Serv. 57, 102224 https://doi.org/10.1016/j.jretconser.2020.102224.

Laato, S., Islam, A.K.M.N., Islam, M.N., Whelan, E., 2020b. What drives unverified information sharing and cyberchondria during the COVID-19 pandemic? Eur. J. Inf. Syst. 29, 288–305. https://doi.org/10.1080/0960085X.2020.1770632.

Lam, M., 2004. Neural network techniques for financial performance prediction: integrating fundamental and technical analysis. In: Decision Support Systems, Data mining for financial decision making, 37, pp. 567–581. https://doi.org/10.1016/S0167-9236(03)00088-5.

Lampos, V., Majumder, M.S., Yom-Tov, E., Edelstein, M., Moura, S., Hamada, Y., Rangaka, M.X., McKendry, R.A., Cox, I.J., 2021. Tracking COVID-19 using online search. NPJ Digit Med 4, 17. https://doi.org/10.1038/s41746-021-00384-w.

Lazer, D.M.J., Baum, M.A., Benkler, Y., Berinsky, A.J., Greenhill, K.M., Menczer, F., Metzger, M.J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S.A., Sunstein, C.R., Thorson, E.A., Watts, D.J., Zittrain, J.L., 2018. The science of fake news. Science 359, 1094–1096. https://doi.org/10.1126/science.aao2998.

Lufkin, B., 2020. Coronavirus: the Psychology of Panic Buying. BBC.

Margherita, A., Heikkilä, M., 2021. Business continuity in the COVID-19 emergency: a framework of actions undertaken by world-leading companies. Bus. Horiz. 64, 683–695. https://doi.org/10.1016/j.bushor.2021.02.020.

Miranda, S., Berente, N., Seidel, S., Safadi, H., Burton-Jones, A., 2022. Computationally intensive theory construction: a primer for authors and reviewers. MIS Q. 46.

Murray, K.B., Häubl, G., 2011. Freedom of choice, ease of use, and the formation of interface preferences. MIS Q. 35, 955–976. https://doi.org/10.2307/41409968.

Naeem, M., 2021. Do social media platforms develop consumer panic buying during the fear of Covid-19 pandemic. J. Retailing Consum. Serv. 58, 102226 https://doi.org/10.1016/j.jretconser.2020.102226.

Naeem, M., Ozuem, W., 2021. Customers' social interactions and panic buying behavior: insights from social media practices. J. Consum. Behav. 20, 1191–1203. https://doi.org/10.1002/cb.1925.

Nagurney, A., 2021. Optimization of supply chain networks with inclusion of labor: applications to COVID-19 pandemic disruptions. Int. J. Prod. Econ. 235, 108080 https://doi.org/10.1016/j.ijpe.2021.108080.

Omar, N.A., Nazri, M.A., Ali, M.H., Alam, S.S., 2021. The panic buying behavior of consumers during the COVID-19 pandemic: examining the influences of uncertainty, perceptions of severity, perceptions of scarcity, and anxiety. J. Retailing Consum. Serv. 62, 102600 https://doi.org/10.1016/j.jretconser.2021.102600.

Parker, J.R., Lehmann, D.R., 2011. When shelf-based scarcity impacts consumer preferences. J. Retailing 87, 142–155. https://doi.org/10.1016/j.jretai.2011.02.001.

Paul, S.K., Sarker, R., Essam, D., 2016. Managing risk and disruption in production-inventory and supply chain systems: a review. J. Ind. Manag. Optim.

Pennycook, G., McPhetres, J., Zhang, Y., Lu, J.G., Rand, D.G., 2020. Fighting COVID-19 misinformation on social media: experimental evidence for a scalable accuracy-nudge intervention. Psychol. Sci. 31, 770–780. https://doi.org/10.1177/0956797620939054.

Prakash, A.V., Das, S., 2021. Medical practitioner's adoption of intelligent clinical diagnostic decision support systems: a mixed-methods study. Inf. Manag. 58, 103524 https://doi.org/10.1016/j.im.2021.103524.

Prentice, C., Chen, J., Stantic, B., 2020. Timed intervention in COVID-19 and panic buying. J. Retailing Consum. Serv. 57, 102203 https://doi.org/10.1016/j.jretconser.2020.102203.

Queiroz, M.M., Fosso Wamba, S., Chiappetta Jabbour, C.J., Machado, M.C., 2022. Supply chain resilience in the UK during the coronavirus pandemic: a resource orchestration perspective. Int. J. Prod. Econ. 245, 108405 https://doi.org/10.1016/j.ijpe.2021.108405.

Raghu, T.S., Woo, W., Mohan, S.B., Rao, H.R., 2008. Market reaction to patent infringement litigations in the information technology industry. Inf. Syst. Front 10, 61–75. https://doi.org/10.1007/s10796-007-9036-5.

Ramanathan, U., Subramanian, N., Parrott, G., 2017. Role of social media in retail network operations and marketing to enhance customer satisfaction. Int. J. Oper. Prod. Manag. 37, 105–123. https://doi.org/10.1108/IJOPM-03-2015-0153.

Ratcliff, C.L., 2021. Characterizing reactance in communication research: a review of conceptual and operational approaches. Commun. Res. 48, 1033–1058. https://doi.org/10.1177/0093650219872126.

Rathore, A.K., Kar, A.K., Ilavarasan, P.V., 2017. Social media analytics: literature review and directions for future research. Decis. Anal. 14, 229–249. https://doi.org/10.1287/deca.2017.0355.

Richey Jr, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. J. Bus. Logist., doi: https://doi.org/10.1111/jbl.12364.

Ross, G.M., 2023. Now that everyone else has panicked, well… I have to panic: regulatory focus predicts panic buying during COVID-19. J. Consum. Market. https://doi.org/10.1108/JCM-06-2022-5409.

Samson, K., Kostyszyn, P., 2015. Effects of cognitive load on trusting behavior – an experiment using the trust game. PLoS One 10, e0127680. https://doi.org/10.1371/journal.pone.0127680.

Saura, J.R., Ribeiro-Soriano, D., Zegarra Saldaña, P., 2022. Exploring the challenges of remote work on Twitter users' sentiments: from digital technology development to a post-pandemic era. J. Bus. Res. 142, 242–254. https://doi.org/10.1016/j.jbusres.2021.12.052.

Scarpin, M.R.S., Scarpin, J.E., Krespi Musial, N.T., Nakamura, W.T., 2022. The implications of COVID-19: bullwhip and ripple effects in global supply chains. Int. J. Prod. Econ. 251, 108523 https://doi.org/10.1016/j.ijpe.2022.108523.

Sharma, M., Alkatheeri, H., Jabeen, F., Sehrawat, R., 2022. Impact of COVID-19 pandemic on perishable food supply chain management: a contingent Resource-Based View (RBV) perspective. Int. J. Logist. Manag. 33, 796–817. https://doi.org/10.1108/IJLM-02-2021-0131.

Shearer, E., 2018. Social Media Outpaces Print Newspapers in the U.S. As a News Source.

Shen, Z.M., Sun, Y., 2023. Strengthening supply chain resilience during COVID-19: a case study of JD.com. J. Oper. Manag. 69, 359–383. https://doi.org/10.1002/joom.1161.

Shirish, A., Srivastava, S.C., Chandra, S., 2021. Impact of mobile connectivity and freedom on fake news propensity during the COVID-19 pandemic: a cross-country empirical examination. Eur. J. Inf. Syst. 30, 322–341. https://doi.org/10.1080/0960085X.2021.1886614.

Sidorov, G., Velasquez, F., Stamatatos, E., Gelbukh, A., Chanona-Hernández, L., 2014. Syntactic N-grams as machine learning features for natural language processing. In: Expert Systems with Applications, Methods and Applications of Artificial and Computational Intelligence, 41, pp. 853–860. https://doi.org/10.1016/j.eswa.2013.08.015.

Silvera, D.H., Lavack, A.M., Kropp, F., 2008. Impulse buying: the role of affect, social influence, and subjective wellbeing. J. Consum. Market. 25, 23–33. https://doi.org/10.1108/07363760810845381.

Smelser, N., Baltes, P., 2015. International Encyclopedia of the Social & Behavioral Sciences, second ed. Elseviers.

Sneath, J.Z., Lacey, R., Kennett-Hensel, P.A., 2009. Coping with a natural disaster: losses, emotions, and impulsive and compulsive buying. Mark Lett 20, 45–60. https://doi.org/10.1007/s11002-008-9049-y.

Sterman, J.D., Dogan, G., 2015. "I'm not hoarding, I'm just stocking up before the hoarders get here.": behavioral causes of phantom ordering in supply chains. J. Operations Manag., Syst. Dynam.: Emergence, Reinfor., Adaptation and Traps 39–40, 6–22. https://doi.org/10.1016/j.jom.2015.07.002.

Sun, M., 2012. How does the variance of product ratings matter? Manag. Sci. 58, 696–707. https://doi.org/10.1287/mnsc.1110.1458.

Sweller, J., 2011. Cognitive load theory. In: Mestre, J.P., Ross, B.H. (Eds.), Psychology of Learning and Motivation. Academic Press, pp. 37–76. https://doi.org/10.1016/B978-0-12-387691-1.00002-8.

Talwar, S., Dhir, A., Kaur, P., Zafar, N., Alrasheedy, M., 2019. Why do people share fake news? Associations between the dark side of social media use and fake news sharing behavior. J. Retailing Consum. Serv. 51, 72–82. https://doi.org/10.1016/j.jretconser.2019.05.026.

Talwar, S., Dhir, A., Singh, D., Virk, G.S., Salo, J., 2020. Sharing of fake news on social media: application of the honeycomb framework and the third-person effect hypothesis. J. Retailing Consum. Serv. 57, 102197 https://doi.org/10.1016/j.jretconser.2020.102197.

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., Kappas, A., 2010. Sentiment strength detection in short informal text. J. Am. Soc. Inf. Sci. Technol. 61, 2544–2558. https://doi.org/10.1002/asi.21416.

Times, T.S., 2020. New York City Sees Increase in Cases of People Ingesting Household Cleaners after Trump's Disinfectant Gaffe. The Straits Times.

Tomaka, J., Blascovich, J., Kelsey, R.M., Leitten, C.L., 1993. Subjective, physiological, and behavioral effects of threat and challenge appraisal. J. Pers. Soc. Psychol. 65, 248–260. https://doi.org/10.1037/0022-3514.65.2.248.

Tullis, T., Albert, B., 2013. Measuring the user experience (second edition) chapter 9 - special topics. In: Tullis, T., Albert, B. (Eds.), Measuring the User Experience, second ed., Interactive Technologies. Morgan Kaufmann, Boston, pp. 209–236. https://doi.org/10.1016/B978-0-12-415781-1.00009-1.

Vasist, P.N., Sebastian, M.P., 2022. Tackling the infodemic during a pandemic: a comparative study on algorithms to deal with thematically heterogeneous fake news. Int. J. Info. Manag. Data Insights 2, 100133. https://doi.org/10.1016/j.jjimei.2022.100133.

Vishwanath, A., 2015. Diffusion of deception in social media: social contagion effects and its antecedents. Inf. Syst. Front 17, 1353–1367. https://doi.org/10.1007/s10796-014-9509-2.

Wang, M., Liu, B., Hua, X.-S., 2010. Accessible image search for colorblindness. ACM Trans. Intell. Syst. Technol. 1 (8), 1–8. https://doi.org/10.1145/1858948.1858956, 26.

Wang, X., Leng, M., Song, J., Luo, C., Hui, S., 2019. Managing a supply chain under the impact of customer reviews: a two-period game analysis. Eur. J. Oper. Res. 277, 454–468. https://doi.org/10.1016/j.ejor.2019.02.033.

Weinmann, M., Schneider, C., Brocke, J. vom, 2016. Digital nudging. Bus Inf Syst Eng 58, 433–436. https://doi.org/10.1007/s12599-016-0453-1.

Yang, J., Sarathy, R., Lee, J., 2016. The effect of product review balance and volume on online Shoppers' risk perception and purchase intention. Decis. Support Syst. 89, 66–76. https://doi.org/10.1016/j.dss.2016.06.009.

Yoo, C.W., Lee, J., Yoo, C., Xiao, N., 2021. Coping behaviors in short message service (SMS)-based disaster alert systems: from the lens of protection motivation theory as elaboration likelihood. Inf. Manag. 58, 103454 https://doi.org/10.1016/j.im.2021.103454.

Yuen, K.F., Tan, L.S., Wong, Y.D., Wang, X., 2022. Social determinants of panic buying behaviour amidst COVID-19 pandemic: the role of perceived scarcity and anticipated regret. J. Retailing Consum. Serv. 66, 102948 https://doi.org/10.1016/j.jretconser.2022.102948.

Yuen, K.F., Wang, X., Ma, F., Li, K.X., 2020. The psychological causes of panic buying following a health crisis. Int. J. Environ. Res. Publ. Health 17, 3513. https://doi.org/10.3390/ijerph17103513.

Zaky, A., Mohamed, H., Saxena, G., 2022. Conceptualising the panic buying phenomenon during COVID-19 as an affective assemblage. Eur. J. Market. 56, 3313–3346. https://doi.org/10.1108/EJM-11-2020-0796.

Zannettou, S., 2021. "I won the election!": an empirical analysis of soft moderation interventions on twitter. In: Proceedings of the International AAAI Conference on Web and Social Media, pp. 865–876. https://doi.org/10.1609/icwsm.v15i1.18110.

Zheng, R., Shou, B., Yang, J., 2021. Supply disruption management under consumer panic buying and social learning effects. Omega 101, 102238. https://doi.org/10.1016/j.omega.2020.102238.