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Research Hotspots and Trends in International Public Panic Buying Behavior

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ABSTRACT

This study employs bibliometric methods and knowledge mapping to analyze 164 papers on panic buying from the Science Citation Index Expanded database. It examines the research landscape, identifies key hotspots, traces evolutionary pathways, and proposes future directions. The findings reveal that: 1) Annual publication output has transitioned through three distinct phases: a low-frequency exploratory period, an explosive growth period, and a stable development period. 2) A novel method for identifying research hotspot clusters—based on core keywords, cluster labels, and central terms—is proposed, leading to the identification of four major knowledge clusters: triggering contexts, psychological drivers, behavioral manifestations, and coping strategies. 3) Research topics exhibit clear evolutionary phases: an early exploratory stage (pre-2019), a pandemic-driven systematic research stage (2020–2022), and a stage of theoretical model refinement and innovation (post-2023). 4) Future research should progress systematically along four dimensions: theoretical foundations, content expansion, methodological innovation, and practical applications.

KEYWORDS

Panic Buying Behavior; Emergencies; CiteSpace.

1. INTRODUCTION

In the contemporary risk society, shaped and intensified by digital and intelligent technologies, public panic buying has become increasingly prevalent. This trend is driven by the frequent occurrence of emergencies and the accelerated dissemination of information through social media. Notable recent examples include the 2020 “mask-buying frenzy” during the COVID-19 pandemic[1], the 2023 “panic salt-buying” spurred by Japan’s nuclear wastewater release[2], and the 2025 “U.S. stockpiling surge” influenced by tariff policy shifts[3]. Large-scale panic buying disrupts market equilibrium, erodes social trust, infringes on consumer rights, and can trigger negative psychological cascades within the population. Consequently, it has emerged as a critical interdisciplinary research topic. Although scholarly interest has grown since the COVID-19 pandemic, research remains relatively scarce and fragmented, spanning across psychology, behavioral science, management, disaster studies, and economics[4-7].A systematic synthesis of existing findings is therefore essential to guide future interdisciplinary inquiry and inform government intervention strategies. Furthermore, comprehensive reviews that map the research hotspots and evolutionary trajectory of this field are lacking. To address this gap, this paper provides a systematic review, analyzing the research landscape, key hotspots, and developmental pathways, and proposes priorities for future investigation.

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2. DATA SOURCES AND RESEARCH METHODS

Data were retrieved from the ISI Web of Science Core Collection database, a premier global citation index renowned for its academic authority, disciplinary coverage, and timeliness. A topical search was conducted on October 28, 2025, using the query: (“consumer stockpil*” OR “consumer hoard*” OR “panic buy*” OR “panic purchas*”). The search, limited to the Science Citation Index Expanded, yielded 332 academic works. After reviewing abstracts, 164 relevant publications were selected for analysis.

This study employs bibliometric methods, utilizing CiteSpace software (version 6.4.R1) for quantitative and visual analysis. The procedure involved three steps: 1) analyzing annual publication trends; 2) identifying research hotspot clusters via keyword co-occurrence and clustering knowledge graphs generated by CiteSpace; and 3) tracing the evolutionary trajectory by constructing a keyword timeline map.

Core software parameters were set as follows: Time Slicing = 1 year; Node Type = Keyword; Selection Criteria = g-index (k=25); Pruning algorithms = Pathfinder, Pruning sliced networks, and Pruning the merged network.

3. EVOLUTION OF ANNUAL PUBLICATION VOLUME ON PUBLIC PANIC BUYING BEHAVIOR

Annual publication volume reflects the academic focus on a given topic. The earliest relevant publication in our sample dates from 2010. Figure 1 illustrates the publication trend over 15 years, showing an initial rise followed by a decline. Based on publication output and content, the research evolution can be categorized into three stages.

(1) Low-frequency exploratory period (pre-2019). Research during this nascent stage was limited, with annual publications remaining consistently low. From 2010 to 2019, only seven papers were published, comprising just 4.3% of the total sample. Although consumer hoarding and panic buying were noted by some scholars, the average of 1–2 publications per year indicated a low level of sustained academic engagement. This likely reflects that panic buying during this era was typically triggered by localized or small-scale crises, failing to attract widespread global attention.

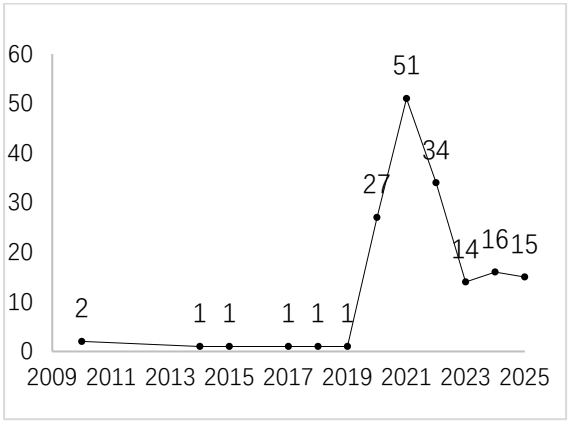


Fig 1. A nnual publication volume of the sample literature

(2) Explosive growth period (2020–2022). This stage marked a phase of rapid development, with 112 publications accounting for 68.3% of the total sample—an average of 37 papers per year, far surpassing the previous period. The primary catalyst was the COVID-19 pandemic, which triggered frequent panic buying episodes worldwide. The surge in real-world cases propelled the phenomenon to the forefront of academic discourse. Figure 1 shows a dramatic, “jump-growth” trend from 2020–2022 compared to 2019, underscoring the direct impact of major public health events on research

agendas and highlighting the reactive nature of academic inquiry in response to emergent social phenomena.

(3) Stable development period (2023–present). In this phase, 45 papers have been published (27.4% of the total), with output stabilizing at around 15 papers annually. While research intensity has declined from its pandemic peak, it remains at a level significantly higher than the pre-2020 era. This stability stems from two factors: first, the normalization of pandemic containment measures reduced the incidence of panic buying and the immediate demand for crisis-response research; second, the research focus has gradually shifted from acute crisis response to deeper theoretical exploration, leading to longer research cycles and a more measured pace of publication, as discussed in the evolutionary analysis below.

4. ANALYSIS OF RESEARCH HOTSPOT KNOWLEDGE CLUSTERS BASED ON KEYWORD CO-OCCURRENCE AND CLUSTERING

This section outlines a method for identifying research hotspot clusters based on three elements: core keywords, cluster label terms, and cluster core terms. The procedure is as follows: First, core keywords are identified using co-occurrence networks and centrality measures. Second, cluster label terms and core terms are extracted using the Log-Likelihood Ratio (LLR) and Mutual Information (MI) algorithms, respectively. Finally, research hotspot knowledge clusters are inductively summarized and categorized.

4.1. Identification of Core Keywords

Keywords are pivotal indicators of research focus. Visualizing their co-occurrence (Figure 2) helps identify core concepts within a field. Node size corresponds to frequency. The 16 most frequent keywords are: panic buying, behavior, consumer behavior, COVID-19, impact, consumption, food waste, risk, health, social media, management, model, COVID-19 pandemic, crisis, anxiety, and attitudes.

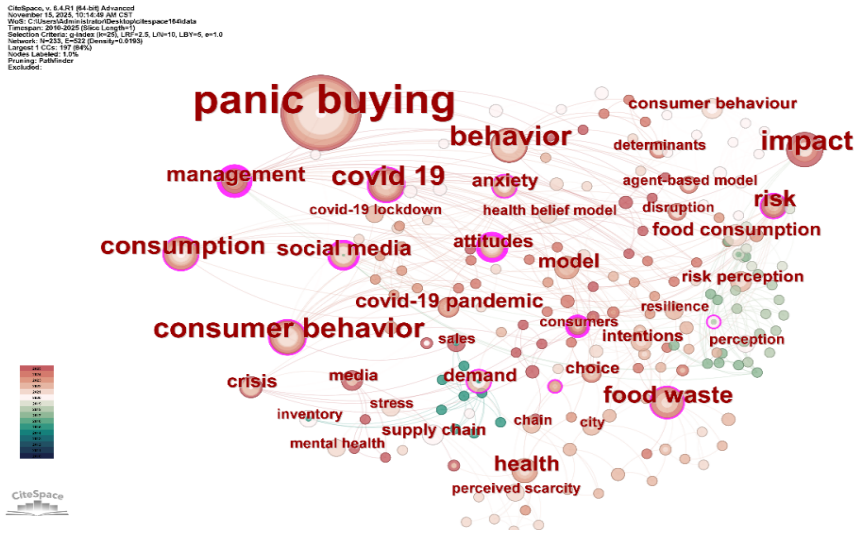


Fig 2. Keywords knowledge graph of sample literature

Beyond frequency, a keyword's influence within the co-occurrence network—measured by its centrality—is also critical. Keywords with centrality ≥ 0.1 are considered highly influential[8]. As

shown in Table 1, 11 high-frequency keywords meet this threshold: attitudes, management, social media, COVID-19, consumer behavior, consumption, anxiety, food waste, risk, health, and crisis. These are identified as the core keywords in panic buying research.

Table 1. The centrality of high-frequency keywords

Number	Keywords	frequency	centrality	order number	Keywords	frequency	centrality
1	attitudes	5	0.44	9	risk	8	0.11
2	management	7	0.43	10	health	7	0.1
3	social media	7	0.21	11	crisis	5	0.1
4	covid 19	14	0.15	12	behavior	15	0.09
5	consumer behavior	15	0.13	13	model	6	0.05
6	consumption	11	0.13	14	covid-19 pandemic	6	0.05
7	anxiety	5	0.13	15	panic buying	60	0.04
8	food waste	9	0.12	16	impact	14	0.03

4.2. Identification of Cluster Label Terms and Cluster Core Terms

To delineate research hotspot clusters precisely, core keyword analysis must be supplemented with the identification of formal cluster labels and their underlying core terms.

(1) Cluster Label Terms via LLR. The LLR algorithm effectively identifies the most representative label for each cluster. A cluster structure is considered significant when the modularity Q-value > 0.3 and the mean silhouette S-value > 0.7[9]. For our panic buying keyword cluster map (Figure 3), Q = 0.7978 and S = 0.9254, confirming a robust and reliable cluster structure. The LLR algorithm yielded 11 cluster labels: consumption, panic buying, perceived risk, consumer behaviour, media exposure, food waste, fake news, behavior change, information transmission rates, and emergency response.

(2) Cluster Core Terms via MI. While LLR finds representative labels, the MI algorithm detects terms highly specific to a cluster, even if less frequent, thereby revealing its nuanced thematic character. The 11 core terms identified by MI are listed in Table 2.

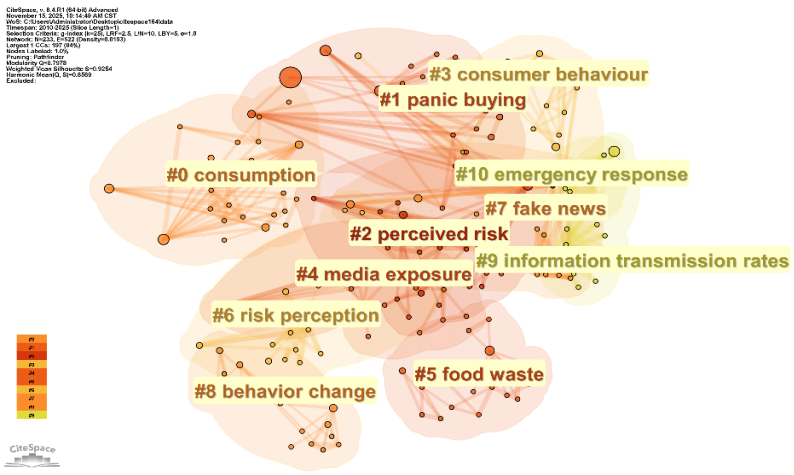


Fig 3. Keywords clustering knowledge map of sample literature

4.3. Division of Research Hotspot Knowledge Clusters

Integrating the core keywords, LLR cluster labels, and MI core terms, four primary research hotspot clusters in international panic buying behavior research are inductively identified (Table 3): Triggering Contexts, Psychological Drivers, Behavioral Manifestations, and Coping Strategies.

Table 2. Core terms of clustering

number	Core Term	MI price	number	Core Term	MI value
0	Mortality salience	0.57	6	Trust	0.10
1	Signal Theory	1.20	7	Resilience	0.09
2	Proactive hoarding	0.22	8	Intolerance of uncertainty	0.22
3	Financial crisis	0.15	9	Sourcing Strategy	0.13
4	Waste Management	0.12	10	Support	0.03
5	Psychological panic	0.18	/	/	/

Table 3. A list of main knowledge group with keywords and clustering support

Knowledge Group	Content	kernel keyword	LLR clustering identifier term	MI Core Terms
Triggering contexts	This study examines the interaction between external crisis events (such as pandemics and financial crises) and media information dissemination (including social media and fake news), analyzing how these factors trigger and amplify panic buying behaviors through mechanisms like information propagation rates and signal theory.	social media COVID-19 risk crisis	media exposure fake news information-transmission rates	signalling theory financial crisis
Psychological drivers	This study delves into the mechanisms of individual psychological responses to external stimuli, focusing on how key psychological factors—such as risk perception, mortality awareness, and intolerance to uncertainty— drive anxiety, shifts in attitude, and psychological panic, ultimately leading to panic-driven purchasing decisions.	Attitudes Anxiety health health	perceived risk	trust mortality salience intolerance of uncertainty psychological Panic
Behavioral manifestations	This systematic study examines specific behavioral patterns driven jointly by external environments and internal psychological factors, including typical manifestations such as proactive stockpiling and changes in consumption behaviors, thereby revealing the distinctive characteristics and evolutionary patterns of panic buying at the consumer behavior level.	consumer behavior consumption	panic buying consumer behavior Consumption behavior change	proactive hoarding
Coping strategies	From a management perspective, this study examines how to effectively mitigate the social impacts of panic buying and enhance societal resilience through systematic measures such as improving supply chain resilience, optimizing procurement strategies, strengthening waste management, and enhancing emergency response capabilities.	management food waste	food waste emergency response	waste management resilience sourcing strategy support assistance

4.4. Analysis of Core Content within the Knowledge Clusters

(1) Triggering Contexts Cluster

This cluster delineates the external precipitating conditions (Table 3). Core keywords point to specific crises (COVID-19, crisis, risk) and a key dissemination channel (social media). LLR labels specify attributes of the information environment (media exposure, fake news, information transmission rates) that act as triggering mechanisms. MI terms provide theoretical underpinnings; signaling theory explains how crisis information acts as a signal affecting public judgment, while financial crisis exemplifies another major crisis type, confirming the behavior's generality across different emergencies.

The cluster framework reveals that major crises like COVID-19 and financial disruptions are common triggers. Concurrently, an information ecosystem defined by exposure, misinformation, and speed of dissemination creates a fertile ground for panic. Signaling theory is central here: consumers interpret media reports of scarcity as macro-signals of an impending crisis, prompting preemptive buying[10]. Empirical work supports this; for instance, Arafat et al. (2021) found a strong positive correlation ($r = 0.84$) between social media use and panic buying in Iraqi Kurdistan during COVID-19, with panic-inducing content heightening public risk perception[11]. This confirms the information environment's role as a critical trigger, aligning with signaling theory's explanatory power. Thus, this cluster provides a coherent theoretical framework for understanding the genesis of panic buying.

(2) Psychological Drivers Cluster

This cluster probes the internal cognitive and affective mechanisms. Core keywords (anxiety, attitudes, health) denote basic emotional and cognitive states. The LLR label perceived risk highlights a key evaluative variable. MI terms uncover deeper motivational constructs (trust, mortality salience, intolerance of uncertainty, psychological panic).

The research in this domain follows a layered progression from basic emotion to deep motivation. Studies begin with core affective states like anxiety and panic. They then examine cognitive appraisal through perceived risk, attitudes, and trust, explaining how threats are evaluated and intentions formed. Finally, they reach the motivational level, revealing panic buying as a compensatory strategy driven by mortality salience, health concerns, and intolerance of uncertainty—essentially an effort to maintain health, confront existential threats, and restore a sense of control.

This "emotion-cognition-motivation" pathway is empirically validated. Poulis et al. (2024) demonstrated that high brand trust can buffer against panic induced by misinformation[12]. Yuen et al. (2020) 's review identified perceived threat, fear, compensatory motivation, and social learning as key drivers[13], aligning closely with the layered framework identified here and providing robust empirical support for the psychological drivers model.

(3) Behavioral Manifestations Cluster

This cluster defines the observable outcomes of panic buying. The core keywords consumer behavior and consumption set the broad scope. The LLR label panic buying is the central behavior, examined through detailed patterns of consumer behavior and consumption changes. The MI term proactive hoarding offers a specific, goal-oriented behavioral paradigm.

The research trajectory within this cluster is clear: it first establishes the broad domains of consumer behavior and consumption. It then zooms in on the core phenomenon of panic buying. Finally, it dissects specific action patterns, with proactive hoarding serving as a concrete exemplar. This framework captures the behavioral reality of crises. For example, Güney and Sangün (2021) [14] documented widespread hoarding tendencies and shifts in consumption patterns among Turkish consumers during the pandemic. Such findings illustrate the specific behavior of proactive hoarding while fully capturing the broader transformation in consumer behavior, providing empirical evidence for the diverse manifestations of panic buying.

(4) Coping Strategies Cluster

This cluster addresses managerial and systemic responses. Core keywords management and food waste define the problem space. The LLR label emergency response indicates a primary management approach, while the reappearance of food waste underscores its salience. MI terms specify actionable measures: waste management addresses a direct consequence; sourcing strategy and resilience target supply chain robustness; and support denotes social-level intervention.

Research in this cluster systematically constructs a multi-tiered response framework. It starts by identifying challenges related to management and food waste. It then identifies emergency response as a key modality. Finally, it articulates concrete measures—waste management, sourcing strategy, resilience, support—that together form an integrated strategy from waste handling to social support.

This framework is reflected in diverse practical recommendations. Li et al. (2022) argue for dynamic retailer procurement and inventory strategies calibrated to consumer panic levels[15]. Brugarolas et al. (2020) suggest that food producers can build supply chain resilience through strategies like long-shelf-life food reserves[16]. Babbitt et al. (2021) highlight the importance of household-level management, such as meal planning, to reduce waste, suggesting avenues for household-society collaboration[17]. Furthermore, government-led acceleration of emergency production and distribution underscores the critical role of emergency response. Wu et al. (2024) advocate for a tripartite public-media-government collaboration mechanism for prevention and response through support and informed guidance[18]. These multi-level strategies collectively chart a comprehensive path for mitigating panic buying.

5. EVOLUTIONARY PATHWAY ANALYSIS BASED ON KEYWORD TIME ZONES

A keyword time-zone map (Figure 4) visualizes the thematic evolution of the field, which can be divided into three distinct stages.

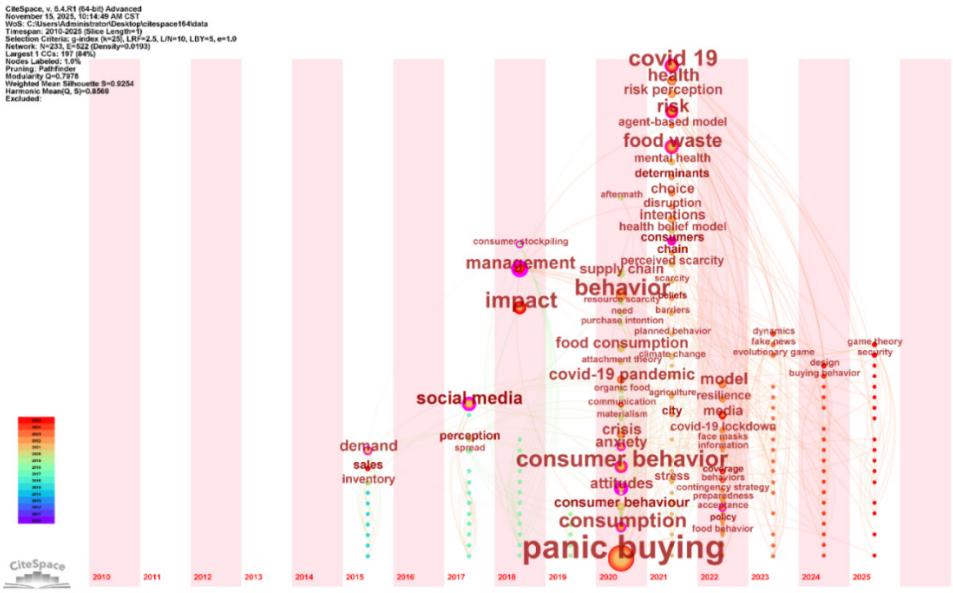


Fig 4. Sample literature keywords time zone diagram

(1) Early Exploratory Stage (pre-2019). Research in this phase was exploratory, focusing on market impacts and behavioral mechanisms. Keywords like demand, sales, and inventory (appearing circa 2015) reflect a market-oriented perspective. Studies examined how proactive hoarding disrupted demand patterns, created sales peaks, and strained inventories, impacting market systems[19] and prompting supply chain adaptations[20]. Research also explored meeting abnormal demand through

product substitution[21]. The focus later expanded to behavioral drivers, marked by keywords like social media and perception (2017). Scholars used social media data to model risk perception and predict buying behavior[22]. By 2018, keywords like impact and management came to the fore, with studies identifying factors such as supplier flexibility as key to mitigating panic buying's market effects[23]. This stage thus evolved logically from describing market phenomena to analyzing behavioral mechanisms and, finally, to exploring management levers.

(2) Pandemic-Driven Systematic Research Stage (2020–2022). The COVID-19 pandemic catalyzed systematic, theory-informed research. Early efforts focused on identifying the key determinants of panic buying[24,25], often leveraging established theoretical frameworks like the Health Belief Model[26] and the Theory of Planned Behavior[27]. Research thoroughly examined external catalysts, confirming the catalytic role of media reports on shortages[28] and unraveling the interplay between rumor dissemination and purchasing behavior[29,30]. The focus simultaneously turned inward to psychological mechanisms, signaled by keywords like attitudes, risk perception, and anxiety (2021–2022). Studies documented how perceived health risks and scarcity[31], fueled by anxiety[32], led to excessive buying as a coping mechanism to regain contro[33], shifting consumption attitudes from need-based to precautionary. This shift, ironically, often resulted in significant food waste[34], exposing the rationality-irrationality paradox in crises. This stage established a dual-path analysis (external environment/internal psychology), advancing the field from description to mechanistic explanation.

(3) Stage of Theoretical Model Refinement and Innovation (post-2023). This phase is characterized by theoretical refinement and methodological innovation. Continued scrutiny of buying behavior explores its fundamental transformation in the post-pandemic landscape[35]. Methodologically, the adoption of evolutionary game theory[36] and other game-theoretic models[37], integrated with dynamic analysis frameworks, marks a paradigm shift from static analysis to dynamic modeling and simulation. This theoretical and methodological advancement deepens the understanding of panic buying's formation and evolution and expands the research scope to include system optimization and governance strategy design.

6. RESEARCH PROSPECTS

Synthesizing the hotspot clusters and evolutionary pathway, this study identifies several promising directions for advancing the field from explanation toward prediction and intervention.

Theoretical Development: Future work must transcend disciplinary silos to develop integrated models. Macroscopically, theories should connect the full "cognition-behavior-system feedback" loop. Mesoscopically, cross-cultural comparative studies are needed to test the generalizability of psychological drivers (e.g., anxiety, risk perception). Integrating theories like the Health Belief Model, the Theory of Planned Behavior, and Terror Management Theory (TMT) is a promising path. Microscopically, research should build on signaling theory and dynamic modeling to decipher the interaction effects and feedback mechanisms between different types of information (e.g., social media, fake news) in triggering panic.

Content Expansion: The research scope requires broadening and deepening. Macroscopically, contexts should expand beyond pandemics to include other emerging crises such as extreme climate events. Mesoscopically, studies should investigate behavioral specificity across different consumer segments (e.g., varying income levels, family structures). Microscopically, longitudinal research is crucial to uncover the critical conditions and dynamic pathways translating psychological drivers into action, and to assess the long-term impacts of panic buying on supply chain resilience and social trust.

Methodological Innovation: A multi-method collaborative paradigm is needed. Macroscopically, interdisciplinary teams should blend methods from psychology (experiments), sociology (network analysis), and operations research (modeling). Mesoscopically, complex systems methods like

evolutionary game theory and system dynamics should be widely employed to simulate the effects of multi-agent governance strategies. Microscopically, leveraging AI and big data analytics can foster tools for information filtering, misinformation correction, and predictive modeling, while rigorous field experiments can provide causal evidence.

Practical Application: Research should be systematically integrated into the full disaster management cycle. In mitigation, focus on building societal resilience through routine risk education and strategic reserves. In preparedness, develop big data-based early warning systems and information monitoring tools informed by triggering context research. In response, refine crisis communication strategies, material distribution mechanisms, and develop targeted behavioral intervention toolkits. In recovery, evaluate the cost-effectiveness of emergency policies to build an evidence-based "policy toolbox" for multi-stakeholder, resilience-focused governance.

Adopting this multi-level, full-cycle perspective will significantly enhance the theoretical explanatory power and practical utility of panic buying research, propelling the field into a more mature and impactful stage of development.

REFERENCES

[1] Shi, M. J. (2022). Analysis of supply and demand changes in the mask market under the COVID-19 pandemic. *Economic Research Guide*, (16), 28–30, 51.

[2] Li, Y. M. (2024). Industry supply-demand balance and future development trend stabilization—Analysis of China's salt industry operation in the first half of 2024. *China Salt Industry*, (15), 32–34.

[3] Su, L. J., & Liang, J. S. (2021). Political economy input-output analysis of constructing domestic and international economic dual circulation. *The Journal of Quantitative & Technical Economics*, *38*(9), 3–24.

[4] Billore, S., & Anisimova, T. (2021). Panic buying research: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, *45*(4), 777–804. https://doi.org/10.1111/ijcs.12675.

[5] Arafat, S. Y., Kar, S. K., Singh, R., et al. (2022). Panic buying research: A bibliometric review. *Nepal Journal of Epidemiology*, *12*(3). https://doi.org/10.3126/nje.v12i3.37928.

[6] Bentall, R. P., Lloyd, A., Bennett, K., et al. (2021). Pandemic buying: Testing a psychological model of over-purchasing and panic buying using data from the united kingdom and the republic of ireland during the early phase of the COVID-19 pandemic. *PLOS ONE*, *16*(1), e0245338. https://doi.org/10.1371/journal.pone.0245338.

[7] Dulam, R., Furuta, K., & Kanno, T. (2021). Quantitative decision-making model to analyze the post-disaster consumer behavior. *International Journal of Disaster Risk Reduction*, *61*, 102387. https://doi.org/ 10. 1016/ j.ijdrr. 2021.102387.

[8] Li, J., & Chen, C. M. (2022). *CiteSpace: Scientific text mining and visualization* (3rd ed.). Capital University of Economics and Business Press.

[9] Chen, Y., Chen, C. M., Liu, Z. Y., et al. (2015). The methodological function of CiteSpace knowledge maps. *Studies in Science of Science*, *33*(2), 242–253.

[10] Cao, C., Chu, C., & Yang, J. (2023). "If you don't buy it, it's gone!": The effect of perceived scarcity on panic buying. *Electronic Research Archive*, *31*(9), 5222–5238. https://doi.org/10.3934/era.2023229.

[11] Arafat, S. M. Y., Ahmad, A. R., Murad, H. R., et al. (2021). Perceived impact of social media on panic buying: An online cross-sectional survey in iraqi kurdistan. *Frontiers in Public Health*, *9*, 695309. https://doi.org/ 10.3389/fpubh.2021.695309.

[12] Poulis, A., Theodoridis, P., & Chatzopoulou, E. (2024). Sustainable brand resilience: mitigating panic buying through brand value and food waste attitudes amid social media misinformation. *Sustainability*, *16*(15), 6521. https://doi.org/10.3390/su16156521.

[13] Yuen, K. F., Wang, X., Ma, F., et al. (2020). The psychological causes of panic buying following a health crisis. *International Journal of Environmental Research and Public Health*, *17*(10), 3595. https://doi.org/ 10.3390/ ijerph 17103595.

[14] Güney, O. I., & Sangün, L. (2021). How COVID-19 affects individuals' food consumption behaviour: a consumer survey on attitudes and habits in Turkey. *British Food Journal*, *123*(7), 2557–2573. https://doi.org/10.1108/BFJ-07-2020-0631.

[15] Li, S., He, Y., & Zhou, L. (2022). Dynamic sourcing strategies for supply disruptions under consumer stockpiling. *Complex & Intelligent Systems*, *8*(6), 4829–4847. https://doi.org/10.1007/s40747-022-00732-6.

[16] Brugarolas, M., Martínez-Carrasco, L., Rabadán, A., et al. (2020). Innovation Strategies of the Spanish Agri-Food Sector in Response to the Black Swan COVID-19 Pandemic. *Foods*, *9*(12), 1891. https://doi.org/ 10. 3390/ foods9121891.

[17] Babbitt, C. W., Babbitt, G. A., & Oehman, J. M. (2021). Behavioral impacts on residential food provisioning, use, and waste during the COVID-19 pandemic. *Sustainable Production and Consumption*, *28*, 315–325. https://doi.org/ 10.1016/j.spc.2021.06.018.

[18] Wu, H., Xie, R., Ding, L., et al. (2024). Study on the influencing factors and intervention strategies of public panic buying during public health emergencies. *BMC Public Health*, *24*(1), 1283. https://doi.org/10.1186/s12889-024-17761-1.

[19] Byrne, D. P., Leslie, G. W., & Ware, R. (2015). How do consumers respond to gasoline price cycles? *The Energy Journal*, *36*(1), 115–147. https://doi.org/10.5547/01956574.36.1.5.

[20] Yoon, J., Narasimhan, R., & Kim, M. K. (2018). Retailer's sourcing strategy under consumer stockpiling in anticipation of supply disruptions. *International Journal of Production Research*, *56*(10), 3515–3532. https://doi.org/10.1080/00207543.2017.1403145.

[21] Tsao, Y. C., & Pushpa Raj, P. V. R. (2019). Product substitution with customer segmentation under panic buying behavior. *Scientia Iranica*, 26(6), 3591–3602. https://doi.org/10.24200/sci.2019.21533.

[22] Gao, C., & Liu, J. (2017). Network-Based Modeling for Characterizing Human Collective Behaviors During Extreme Events. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *47*(1), 171–183. https://doi. org/ 10. 1109/TSMC.2015.2496335.

[23] Yoon, J., Narasimhan, R., & Kim, M. K. (2018). Retailer's sourcing strategy under consumer stockpiling in anticipation of supply disruptions. *International Journal of Production Research*, *56*(10), 3515–3532. https:// doi. org/ 10.1080/00207543.2017.1403145

[24] Chua, G., Yuen, K. F., Wang, X., et al. (2021). The determinants of panic buying during COVID-19. *International Journal of Environmental Research and Public Health*, *18*(6), 3247. https://doi.org/10.3390/ijerph18063247.

[25] Ritzel, C., Ammann, J., Mack, G., et al. (2022). Determinants of the decision to build up excessive food stocks in the COVID-19 crisis. *Appetite*, *176*, 106130. https://doi.org/10.1016/j.appet.2022.106130.

[26] Wang, F., Yuan, Y., & Lu, L. (2021). Dynamical prediction model of consumers' purchase intentions regarding anti-smog products during smog risk: taking the information flow perspective. *Physica A: Statistical Mechanics and its Applications*, *563*, 125427. https://doi.org/10.1016/j.physa.2020.125427.

[27] Rosu, M. M., Ianole-Calin, R., Dinescu, R., et al. (2021). Understanding consumer stockpiling during the COVID-19 outbreak through the theory of planned behavior. *Mathematics*, *9*(16), 1950. https://doi.org/ 10.3390/ math9 161950.

[28] Coleman, P. C., Dhaif, F., & Oyebode, O. (2022). Food shortages, stockpiling and panic buying ahead of brexit as reported by the british media: A mixed methods content analysis. *BMC Public Health*, *22*(1), 206. https://doi. org/ 10.1186/s12889-022-12633-7.

[29] Mao, Q. H., Hou, J. X., & Xie, P. Z. (2022). Dynamic Impact of the Perceived Value of Public on Panic Buying Behavior during COVID-19. *Sustainability*, *14*(9), 5178. https://doi.org/10.3390/su14095178.

[30] Cambridge Core. (2025). Influences of news and social media on food insecurity and hoarding behavior during the COVID-19 pandemic [Electronic resource]. *Disaster Medicine and Public Health Preparedness*.

[31] Cambridge Core. (2025). Factors affecting consumers' purchasing of suboptimal foods during the COVID-19 pandemic [Electronic resource].

[32] Lee, Y. C., Wu, W. L., & Lee, C. K. (2021). How COVID-19 triggers our herding behavior? Risk perception, state anxiety, and trust. *Frontiers in Public Health*, *9*, 712213. https://doi.org/10.3389/fpubh.2021.712213.

[33] Cheng, C., Wang, H. Y., & Chan, L. (2021). Multiple forms of mass anxiety in coronavirus disease-2019 pandemic. *Journal of Affective Disorders*, *291*, 338–343. https://doi.org/10.1016/j.jad.2021.04.065.

[34] Ben Hassen, T., El Bilali, H., & Allahyari, M. S. (2020). Impact of COVID-19 on food behavior and consumption in Qatar. *Sustainability*, *12*(17), 6927. https://doi.org/10.3390/su12176927.

[35] El Baba, W., & Fakih, A. (2023). COVID-19 and consumer behavior: Food stockpiling in the US market. *Agribusiness*, *39*(2), 515–534. https://doi.org/10.1002/agr.22786.

[36] Wang, X., Zhang, N., Zhou, H., et al. (2023). Multi-agent evolutionary game analysis of group panic buying in China during the COVID-19 pandemic. *Mathematics*, *11*(13), 3012. https://doi.org/10.3390/math11133012.

[37] Jie, X., He, X., & Cheng, T. C. E. (2025). Retailer hoarding in emergency situations: A game-theoretic analysis. *Transportation Research Part E: Logistics and Transportation Review*, *200*, 104156. https://doi.org/ 10. 1016/ j. tre. 2025. 104156.