

Article

Sustainable Brand Resilience: Mitigating Panic Buying through Brand Value and Food Waste Attitudes Amid Social Media Misinformation

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Abstract: This study investigates the relationship between user-generated content on social media and panic buying, with a focus on how attitudes towards food waste and brand value act as moderating variables. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), data from an online survey with 370 responses were analyzed. The findings show that user-generated content significantly contributes to the dissemination of inaccurate information, which in turn triggers panic buying. However, the impact of inaccurate information on panic buying is moderated by consumer attitudes towards food waste and brand value. Specifically, consumers with negative attitudes towards food waste and high brand trust are less likely to engage in panic buying when exposed to misinformation. These results suggest that promoting responsible consumption and leveraging brand value can mitigate the adverse effects of misinformation during crises. This study contributes to sustainability by providing insights into developing strategies for retailers and policymakers to manage consumer behavior, emphasizing the importance of accurate information and brand communication in reducing panic buying tendencies.

Keywords: brand value; panic buying; social media misinformation; food waste attitudes; crisis consumer behavior; sustainable consumption



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1. Introduction

The rapid rise in social media usage and the global transformation of our practices for sharing and accessing information have changed remarkably. Millions of people around the globe are using social platforms like Facebook, Twitter, and Instagram as integral sources of news and information in daily life [1]. Despite enabling instant communication, social media presents notable challenges, especially in terms of spreading false and misleading information [2,3]. This study explores the interaction between these factors, with a focus on their influence on consumer behavior, particularly panic buying, and the mitigating effects of attitudes towards food waste and brand value.

Especially amidst times of crisis, the spread of untrue information on social media can have significant consequences, in inciting panic buying. This provokes fear and uncertainty in consumers, leading them to rush to purchase large amounts of goods due to perceived scarcities [4]. During the COVID-19 pandemic, this behavior of panic buying prevailed worldwide, which led to shortages and interruptions in the supply chain for essential items such as toilet paper, sanitizers, and food products [5]. Understanding the reasoning behind panic buying can be quite complex, involving factors like the fear of missing out (FOMO), scarcity mindset, and social proof (i.e., individuals mimic the behavior of others when they are unsure about what to do) [6,7]. The spread of misinformation on social media indicating upcoming shortages produces increased worry and stress, which ultimately leads to unproductive actions such as panic buying. This sets off a cycle where the presence

of empty shelves and extended lines of consumers continue to confirm the false information, thus sustaining the pattern of panic buying [6,7].

The flow of misleading information on social media through user-generated content (UGC) leads to panic buying behaviors [2]. The Extended Parallel Process Model (EPPM) suggests that messages that evoke fear can result in adaptive or maladaptive responses, depending on the individual's perceived threat and coping mechanisms [8]. Often, consumers who experience rumors of an impending shortage become more terrified, hence resulting in irrational actions like panic buying [9]. An example is when empty shelves are visible and there are long queues of consumers; this makes it easier for people to believe in them and continue engaging in panic buying.

On the other hand, consumers' attitude towards food wastage also acts as a moderating factor to panic buying. There is evidence that persons with a high sense of self-efficacy and well-organized patterns of purchasing food are not inclined to panic buying [10,11]. These shoppers do not rush while shopping; thus, they cannot purchase goods that they do not need, hence reducing food wastage. Moral considerations regarding throwing away edible items strongly affect shopping behavior, as purchasers who view food waste as a negative thing consider themselves more responsible about what they buy [10,12]. People whose firmly held beliefs disapprove of wastefulness of any kind behave systematically while buying groceries, hence limiting the possibility for excessive purchasing due to sudden shocks as witnessed during panics [11]. This case underscores customer stance as a means of achieving immunity from recurring bouts of shopping sprees caused by inaccurate data widely spread on social networks.

Lehberger et al. [13] argue that consumers prioritizing reducing food waste are less prone to a scarcity mindset which is a major driver behind panic buying during shortages. Misinformation fuels a scarcity mindset, which in turn leads to stockpiling. However, such individuals who are deeply committed to minimizing food waste can question the authenticity and the shortage messages and therefore have the ability to avoid excessive buying. This resistance is supported by their structured approach to shopping and consumption, where they focus on buying only what is necessary, thus mitigating the impact of misinformation-induced panic buying [12].

Moreover, panic buying can be curbed through the food waste morality and social dimensions. This sense of duty to avoid wasteful habits is a major motivator for those consumers who find food waste morally unacceptable [14]. Therefore, this ethical position makes these customers more cautious when responding to crisis-based misinformation, since they are concerned about long-term sustainability rather than immediate panic-driven behavior. They also practice responsible consumption and waste to avoid market fluctuations and panic buying that disrupt industries' supplies. Moreover, Quested et al. [15] and Stuart [16] have shed some light on the other potential uses of food loss reduction, indicating that such goals are aligned with sustainable development and overall food security.

The research also contributes to expanding the current knowledge by covering several other socio-psychological aspects that aid in understanding the causes of panic buying. Thus, an all-inclusive approach is necessary to understand how fake news spreads through society via social media platforms and, thus, how it impacts negatively consumer behavior as well as the possible remedies for such acts. It also covers aspects of attitudes towards food wastage and perceived brand value concerning misconceptions on consumer behavior towards a holistic understanding of consumer responses to misleading information. Such information would then enable policymakers, retailers and brands to develop strategies that will promote responsible purchasing while mitigating the impacts of misleading information, particularly during crises. The purpose of this study is therefore to fill this gap by finding out whether user-generated content on social media contributes to spreading wrong facts that result in panic buying or not, as well as investigating how perceptions regarding food wastage or brand equity affect these results. Altogether, the main aim behind conducting such research is to gain insights into consumer behaviors during times

of crises followed by proposing effective solutions towards tackling misconceptions about purchasing trends.

2. Literature

2.1. User-Generated Content Leading to Inaccurate Information

It is evident that misinformation is constantly being generated and circulated by social media users. Generating such information often depends on the user's personal opinions rather than widely accepted facts. When inaccurate data are produced, they can lead to the spread of false and misleading information among the general population. The definition of "misinformation" is the dissemination of information by the general population with the intention of gaining popularity, while "disinformation" is defined as the deliberate distribution of false information with the aim of inducing fear [17]. Although having distinct meanings, misinformation and disinformation are closely related, and this connection will be evident in the framework referred to as "Inaccurate Information." The terms "misinformation" and "disinformation" have gained significant traction in the last few years through their widespread dissemination on social media platforms, but the fact is that they have been in use for quite a while [2].

In the early 2000s, modern social media networks began to arise, and the first social media platform that attained a million active members by 2004 was MySpace [18]. It was about 2004 that social media had become a vital part of the daily lives of millions of people globally, who use it as a prime news source. Chadwick and Vaccari [2] carried out a survey in the UK and found that 57.7% of participants observed errors in social news. Social media, in recent times, has become a platform for individuals to spread fake news, leading to misinformation [2,3].

False information abounds on social media, due to user-generated content (UGC). Vosoughi, Roy, and Aral [19] proved that false news stories are more than 70 percent likely to be retweeted compared with true ones. This rapid spreading occurs because of inherent biases and cognitive shortcuts people use when processing online information [20]. Also, the reasons behind the sharing of fake news make it worse. Tandoc, Lim, and Ling [21] identified key drivers like self-promotion, ideological reinforcement, and entertainment that cause people to share fake news. Together with the echo chamber effect depicted by Garrett [22], motivations such as these have led into an environment facilitating growth of misinformation.

Technological solutions are not easy tasks as well when it comes to counteracting misinformation. Zhou and Zafarani [23] identified that, with a large number of UGC, it would be challenging for current filtering approaches to adequately eliminate fake news. Nonetheless, the current and emerging issues in fake news present major challenges even with the current progress in machine learning and AI. Shu et al. [24] have found out that though the effects of misinformation can be reduced through fact-checking and user education, the two approaches are not perfect. The urgency rate of such information and people's rather shallow interactions with the material do not allow for the effectiveness of such actions. Taken together, these studies indicate that the issue is complex and requires a more advanced level of analysis. Users' everyday actions, cognitive biases, social incentives, and technology flaws form the coinciding conditions that allow for misinformation distribution. As the use of social media platforms escalates, the amount of UGC generated escalates as well, meaning that sorting the real and fake news becomes even harder. Hence, it is suggested that:

H1. *User-generated content will have a positive impact on inaccurate information.*

2.2. Inaccurate Information and Panic Buying

The phenomenon of panic purchasing is mostly driven by the profound psychological effects resulting from the dissemination of false information, particularly on social media platforms. Social media platforms often serve as amplifiers of false information, spreading

unverified or exaggerated claims about product shortages or crises. It is suggested in EPPM (Extended Parallel Process Model) that either adaptive or maladaptive responses are induced as a result of fear-promoting messages based on individuals' assessment of the hazard and their ability to handle it [8]. People may experience amplified fear and severe anxiety when they receive misinformation indicating forthcoming goods shortages, which ultimately leads to maladaptive behaviors such as panic buying and goods storing [4,8].

Panic buying is intensified by the rapid amplification of misinformation by social media users. This leads to actions like stockpiling of essentials. This behavior may be attributed to the psychological phenomenon of scarcity, when the fear of missing out (FOMO) and the need to acquire resources hinder rational decisionmaking [7]. This results in reinforcement of the panic buying cycle, emptiness of shelves and long queues, thus supporting the misinformation [9]. The influence of social proof in social media cannot be underrated. The term social proof refers to the psychological behavior in which individuals imitate the actions of others as the correct conduct in a given situation. This influence becomes especially strong during times of crisis [6]. People acquire motivation after observing their fellows or prominent figures on social media being engaged in panic-buying, and they consider this behavior as suitable and essential. This behavior was clearly observed during the COVID-19 pandemic. Misinformation about the possibility of lockdowns and interruptions in the supply chain caused worldwide panic buying of essential items such as masks, food items, pain killers, sanitizers, etc. [5].

H2. *Inaccurate information will have a positive impact on panic buying.*

2.3. Food Waste and Brand Values

Panic buying appeared as a global phenomenon during the COVID-19 epidemic. It can be simply defined as a sudden boom in purchasing behavior often provoked by some crises. This is directly related to individuals' attitudes and behaviors towards food waste. Panic buying behaviors are much reduced by consumers' behavior towards food waste. Consumers who have organized food-related routines and strong behavioral control are less likely to be involved in panic buying. These consumers have a tendency to be more cautious and organized in their buying habits, and as a result reduce the chances of food waste and avoid needless stockpiling [11]. One more factor that has a significant influence on consumers' shopping behaviors is moral attitudes towards food waste. People who view food waste as negative behavior tend to be more conscientious in their purchasing routines [10,12].

Stancu et al. [11] conducted a study to illustrate the indirect relationship between planning routines and food waste. It revealed that consumers with controlled food and shopping organization have fewer chances to be subjected to panic buying, and this is because of their systematic purchasing habits. Roka [10] suggests that consumers have low engagement in panic buying owing to their ethical stance towards wasting foods in the process. Therefore, avoiding panic-buying leads to moral, social, and environmental responsibility and promotes the disadvantages of food waste. Promotional offers could present potential significant effects to consumers especially in the area of food waste. Such promotional incentives, for instance, "Buy Two Get One Free", may make the customers buy more than what is required, thus leading to more food wastage [12]. This indicates that it is important for business to be very careful when coming up with promotions that in essence lead to wastage of food.

Perceived food waste avoidance behaviors are significantly related to the level of environmental concern among consumers with environmental consciousness. They look for approaches and techniques to minimize food waste in order to avoid things such as panic buying [25]. In addition, it has been observed that concerns about the potential failure of products and a lack of commitment to environmental sustainability contribute to the accumulation of excess inventory, eventually leading to the wastage of food [13]. Hence, it is plausible to hypothesize that:

H3. *Attitudes towards food waste act as a moderating variable between the dissemination of inaccurate information on social media and panic buying behavior.*

During times of crisis, consumers often rely on well-established brands to alleviate fear [26]. There is a positive effect on behavioral control due to brand value that makes the consumer feel more capable of making a rational choice, with or without deceptive information [27]. Moreover, the long-standing image of a company's brand and products can also contribute to reducing the negative emotions of consumers when facing fake news that may strengthen consumers' restraint and prevent hasty purchase decisions [28]. For example, in situations of information conflict, the consumers are more likely to rely on well-known brands which they can trust, thereby decreasing the probabilities of panic buying [29]. This further means that when it comes to brand reliability, it can greatly affect the consumer decision making, even in unfavorable external conditions.

It becomes problematic when ambiguous information circulates on social media, leading to the mass dissemination of fear and mistrust. These effects can be moderated by a high brand value, since it increases consumers' confidence in the availability and quality of goods. Furthermore, when high-value companies effectively communicate during crises, they may rectify any misunderstandings that customers may have, providing them with accurate information and discouraging panic purchasing [30]. Hence, it is plausible to hypothesize that:

H4. *Brand values is the moderator variable between the communication of misinformation on social networks and the panic buying.*

This study investigates the relationship between inaccurate information and panic buying, focusing on the influence of attitudes toward food waste and brand value. Based on the findings of the existing literature, a conceptual model was constructed to guide the research, as presented in Figure 1.

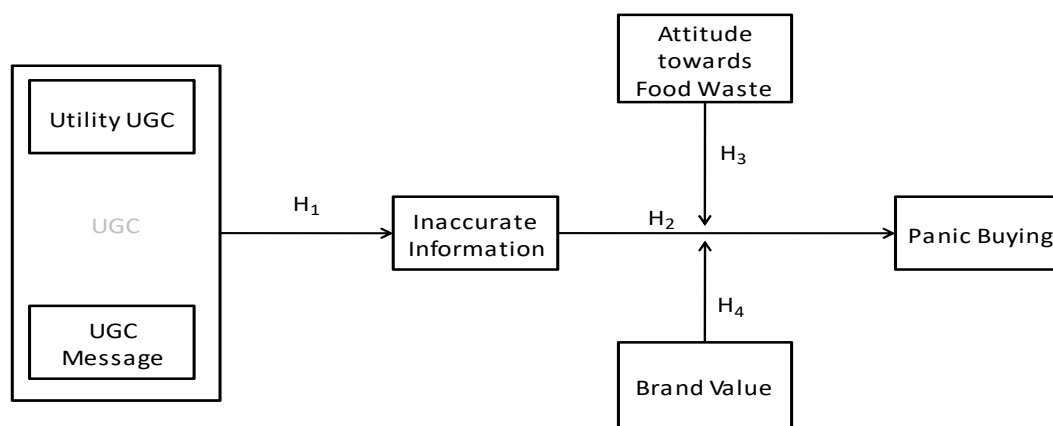


Figure 1. Conceptual model.

3. Materials and Methods

3.1. Data Collection

The study used an online self-administered questionnaire to investigate users' panic buying behavior, which was controlled by their attitude towards food waste and brand value. Data were collected during the autumn of 2023 via the Google Forms platform, with the survey link distributed through social media, where users create and share their content. A total of 370 responses were gathered and deemed usable for analysis following a pilot test and necessary adjustments to the questionnaire.

The sample for this study was chosen using a purposive sampling strategy, a sampling technique guided by specific criteria specific to the research goals [31]. The non-probability

sampling technique of purposeful sampling was utilized, specifically targeting social media users with active participation to ensure the relevance and depth of the data collected. As defined by Bougie and Sekaran [32], purposeful sampling is the technique of selecting information-rich participants who could have been chosen because of age, gender, status, or experience with the phenomenon. In circumstances where a random sampling strategy is not feasible or might compromise the depth of insights, a purposive sampling strategy can be adapted to yield rich and context-specific data [33]. For this reason, the purposeful sampling technique by which the researchers found participants who actively participated on social media (informed daily about the news, following brand and news fan pages) was essential to obtain the information needed to design an accurate survey. Thus, two screening questions were asked about users' social media daily activity and their interaction with other social media users' content to ensure qualified respondent recruitment.

3.2. Measures and Measurement

A quantitative survey utilized a questionnaire to collect data from social media users, structured into three parts. The first section explored users' generated content and the impact of inaccurate information. The UGC variable was measured with two constructs, the utility of the UGC and the UGC message, adapted from Kim et al. [34] and Kim and Johnson [35], and for inaccurate measurement, the adopted scale from Tan et al. [36] and Hossain et al. was used [37]. The second part dealt with panic buying, which described the consumers' reaction after the inaccurate information (modified from Tan et al. [36]). Hence, the second part covered attitudes towards food waste (adapted from Stancu et al. [11]) and brand value (Coelho et al. [38]), examining customers' intentions not to waste food and the benefits they receive from consuming specific brands. The final section depicted the demographic profile of the respondents, encompassing characteristics such as gender, age, educational level, and marital status. All items, except the demographics section, were measured using a five-point Likert scale, where one indicated "Strongly disagree" and five indicated "Strongly agree" [39].

Validity and reliability were ensured through measurement scales previously examined in other studies. The Cronbach's Alpha reliability coefficient further bolstered the tool's reliability. The coefficient for the entire questionnaire was 0.884 (22 items), indicating a very high level of reliability at a statistical level of 0.000 (Hotelling's T-squared: 4.22244; F: 190.17; $p < 0.001$). In addition, a Confirmatory Factor Analysis was used to validate the research constructs, using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, which was 0.836, and Bartlett's Test of sphericity was significant ($\chi^2 = 3.02753$, $p < 0.001$). For the UGC construct, the standardized factor loadings ranged from 0.607 to 0.715; for the Inaccurate Information construct, the standardized factor loadings were between 0.700 and 0.799; and for the Panic Buying construct, the standardized factor loadings ranged from 0.761 to 0.815. Moreover, for the Attitude towards food waste construct, the standardized factor loadings ranged from 0.635 to 0.841 and for the Brand value construct, the standardized factor loadings were between 0.761 and 0.815. All standardized loadings were above 0.60 and statistically significant ($p < 0.001$), indicating that the items reliably measure the respective factor according to values that Field [40] has set.

3.3. Methods of Analysis

The data analysis employed Partial Least Squares (PLS) Structural Equation Modeling (SEM) using SmartPLS software 4th edition [41]. PLS is distinguished as an alternative to variance-based SEM, oriented on prediction rather than causal model/theory testing [42,43]. Unlike other methods [44], PLS maximizes the explained variance of endogenous latent variables by iteratively evaluating partial model relationships through ordinary least squares regressions [45]. PLS-SEM is adaptable for complex models, non-parametric data, and small sample sizes.

Moreover, it can handle both metric and categorical indicators, enabling the simultaneous assessment of reflective latent variables (RLVs) and formative latent variables

(FLVs) [46]. According to criteria set by Hair et al. [45], in formative constructs, the latent variable is a consequence of its indicators, meaning that changing an indicator alters its meaning. Indicators in formative constructs do not need to be highly correlated. In contrast, reflective constructs view indicators as consequences of the latent variable, making them interchangeable and often correlated. Reflective constructs exist independently of their measures, aligning with many business methodologies. However, formative constructs depend on specific interpretations and have limited examples in social science literature. Reflective constructs require high correlation among items, while formative constructs do not, and a change in one formative indicator does not necessarily affect others [47]. In this study, PLS-SEM was deemed appropriate due to the inclusion of reflective and formative constructs [44] and its recent application in panic buying and food waste papers [48,49]. This approach allows for robust analysis and interpretation of the relationships between variables in the research context.

4. Results

4.1. Sample Profile

As depicted in Table 1, the sample is evenly distributed by gender; almost 70% of participants are between 26 and 45 years old. Participants worked as employees (44.6% private and 25.1% public sector workers), earning 601–1200 (47.3%) euros.

Table 1. Sample Profile.

Item	Characteristic	Frequency	Percentage
Gender	Male	181	48.9%
	Female	189	51.1%
Age	16–25	24	6.5%
	26–35	117	31.6%
	36–45	148	40.0%
	46–55	54	14.6%
	56+	27	7.3%
Occupation	Unemployed	6	1.6%
	Public Worker	93	25.1%
	Private Worker	165	44.6%
	Entrepreneur/Self-employed	79	21.4%
	Student	6	1.6%
	Retiree	21	5.7%
Income(EUR) (Monthly)	0–300	63	17.5%
	301–600	21	5.8%
	601–900	72	19.9%
	901–1200	99	27.4%
	1201–1500	52	14.4%
	1501–1800	42	11.6%
	+1801	12	3.3%

4.2. Measurement Model Assessment

The study implemented validation procedures to assess the reliability and validity of reflective and formative measurement scales [50]. The assessments of reflective and formative constructs are different approaches.

The reflective latent variables considered were the Inaccurate Information and the Brand Value. The Composite reliability, as shown in Table 3, was scrutinized to assess RLV reliability and validity and was calculated as 0.868 for Inaccurate Information and 0.773 for Brand Value, exceeding the threshold of 0.7 [45,51,52]. Convergent validity was affirmed through AVE values for reflective variables. The results revealed that all reflectively measured constructs have AVE values of 0.568 (Inaccurate Information) and 0.535 (Brand Value), and all the variables were higher than the threshold of 0.5, demonstrating the

robustness of the measurement model. Discriminant validity was rigorously assessed using the Fornell–Larcker criteria and the Heterotrait–Monotrait Ratio (HTMT) [45], as shown in Table 2. All HTMT ratios were below 0.85, confirming discriminant validity within the measurement model [45,53].

Table 2. Measurement model assessment (discriminant validity).

	Heterotrait–Monotrait Ratio (HTMT)—Matrix				Fornell–Larcker Criterion	
	BV	Inaccurate	BV × Inaccurate	AFW × Inaccurate	BV	Inaccurate
BV					0.647	
Inaccurate	0.580				0.430	0.754
BV × Inaccurate	0.119	0.419				
AFW × Inaccurate	0.129	0.455	0.708			

In addition, to evaluate the FLV measures, the assessment procedure for the formative measurement models was followed according to Hair et al. [45]. Convergent and discriminant validity tests were conducted, alongside examining construct weights, to evaluate the indicators' reliability. Firstly, the formative constructs' convergent validity was examined, carrying out separate redundancy analyses for each construct. The results of redundancy analyses concurred with the convergent validity. Consequently, it should be ensured that no collinearity issues exist. Multicollinearity is a concern in formative models due to the lack of overlap between explanatory variables. Table 3 shows the structural model's collinearity test results; the highest VIF value for formative constructs was 1.41. Hence, VIF scores were below the 3.3 threshold, indicating no collinearity issues [54]. Therefore, the collinearity values did not reach critical levels in any formative or reflective constructs.

Another crucial step in the evaluation process was the confirmation of the statistical significance of the loadings/weights. This was achieved through bootstrapping with 5000 iterations, a method that ensures the robustness of the evaluation process. The results, as shown in Table 3, revealed all *p*-values to be <0.05 [45], thereby validating the robustness of the evaluation process and allowing to proceed with the evaluation of the structural model.

Table 3. Measurement model assessment (reliability and validity).

	Dimensions and Items	CR	AVE	t-Value	VIF
	User- Generated Content	N/A	N/A		
UTI_1	I use the UGC on the social media for my personal satisfaction.			3.259 (0.001)	1.140
UTI_2	I use the UGC on the social media to get more viewpoints.			5.533 (0.000)	1.124
UTI_3	I use the UGC on the social media to exchange useful information freely.			3.101 (0.000)	1.152
UTI_4	I use the UGC on the social media to generate ideas.			2.184 (0.001)	1.161
UGC_RM_1	The postings that appear on the social media describe information about brands and news.			3.818 (0.000)	1.141
UGC_RM_2	The postings that appear on the social media fan pages describe values of the featured brands and products.			1.979 (0.048)	1.117
UGC_RM_3	The postings that appear on the social media fan pages describe benefits of the featured brands and products.			3.262 (0.000)	1.137

Table 3. Cont.

	Dimensions and Items	CR	AVE	t-Value	VIF
	Inaccurate Information	0.868	0.568		
InacInfo1	I check the source of online news content. (r)			25.217 (0.000)	1.437
InacInfo2	I always read the contents of online news, not just the headlines. (r)			17.177 (0.000)	1.946
InacInfo3	I usually check the date of online news to make sure the story is up to date. (r)			12.297 (0.000)	1.908
InacInfo4	I cross-check social media news against official media.(r)			20.846 (0.000)	2.158
InacInfo5	I seek expert opinions on the authenticity of online news. (r)			27.205 (0.000)	2.070
	Panic Buying	N/A	N/A		
PB1	I buy because everyone is buying.			5.221 (0.000)	1.290
PB2	I buy food and nonfood items more than what I normally bought			3.774 (0.000)	1.405
PB3	I buy according to how I feel			7.520 (0.000)	1.292
	I shop in the supermarket without thinking much *removed*				
	Attitude towards Food Waste	N/A	N/A		
AFW1	In my opinion, wasting food is not at all negative (1) to extremely negative (5)			7.586 (0.000)	1.034
AFW2	I intend not to throw food away			4.022 (0.000)	1.347
AFW3	My goal is to throw food away. (r)			4.974 (0.000)	1.326
	Brand Value	0.773	0.535		
BV1	What I get from this brand is worth the cost.			2.312 (0.021)	1.091
BV2	All things considered (price, time, and effort), this brand is a good buy			15.926 (0.000)	1.182
BV3	Compared to other brands, this brand is good value for the money.			28.164 (0.000)	1.232
BV4	When I use this brand, I feel I am getting my money's worth.			10.205 (0.000)	1.214

4.3. Structural Model and Hypotheses Testing

Evaluating the proposed model by estimating the standardized path coefficients, UGC explains 40.3% of inaccurate information positively, supporting the H1. The standardized path coefficient for UGC (0.880) is significant at $p < 0.001$. Inaccurate information mediates the influence on panic buying, as shown in Figure 2. The Attitude towards Food Waste and Brand Value variables were added to the measurement model as moderators. The moderation effects of attitude towards food waste and brand value with the direct influence of inaccurate information explain 57.2% of panic buying (path coefficient 0.125, p -value 0.025). The path from inaccurate information to panic buying is significant, supporting H2. Table 4 presents all the results in detail.

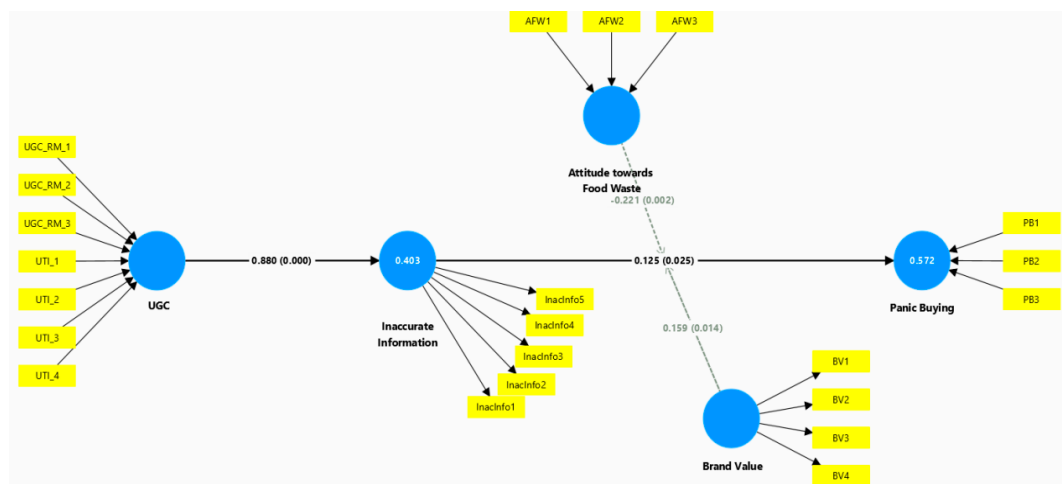


Figure 2. Structural Model.

Table 4. Structural model results.

Relationship	Standard Bootstrap Results				Percentile Bootstrap Quartiles		R ²	f ²	Conclusion
	Path Coefficient	Std. Error	t-Stat	p-Value (2-Sided)	2.50%	97.50%			
UGC → Inaccurate Information	0.880	0.067	13.153	0.000	0.754	1.018	0.403	0.674	Supported
Inaccurate Information → Panic Buying	0.125	0.056	2.240	0.025	0.009	0.229	0.572	0.016	Supported
Attitude towards Food Waste × Inaccurate Information → Panic Buying	−0.221	0.072	3.095	0.002	−0.363	−0.076		0.031	Supported
Brand Value × Inaccurate Information → Panic Buying	0.159	0.065	2.461	0.014	0.031	0.288		0.020	Supported
Attitude towards Food Waste → Panic Buying	0.252	0.079	3.192	0.001	0.096	0.403		0.036	
Brand Value → Panic Buying	0.659	0.060	11.015	0.000	0.553	0.789		0.582	

Following Hair et al. [45], the appropriate tests for moderation were carried out, and support for H3 and H4 was established. Attitude towards Food Waste acted as a moderator of inaccurate information on Panic Buying, with negative strong strength (path coefficient −0.221, statistical significance 0.002) as supported in H3, indicating that the sensitivity toward food waste acts negatively on stockpiling food which may not be consumed by the consumers, so they avoid panic buying. Brand Value also acts as a moderator, with positive medium strength of the relationship between inaccurate information and panic buying (path coefficient 0.159, statistical significance 0.014), confirming H4, indicating that consumers have brand sensitivity and prefer to stock their favorite brand products.

Table 4 displays the f^2 value, illustrating the effect when exogenous variables are excluded. The interactions had a medium effect size, given that f^2 was estimated to be 0.020 and 0.031, based on the formula and thresholds set by Chin et al. [55] and Cohen [56] (pp. 407–414). Therefore, the relationship between inaccurate information and panic buying is moderated by attitude towards food waste and panic buying, suggesting a moderate explanatory power. Figures 3 and 4 display the results of the moderation effects.

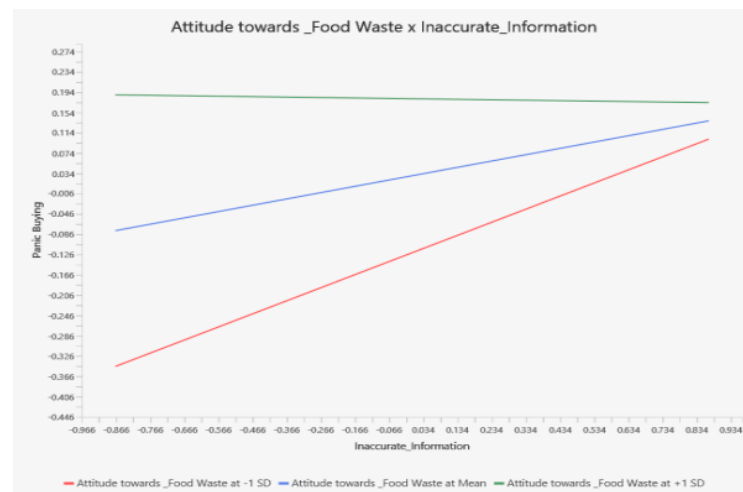


Figure 3. Moderation Effect (Attitude towards Food Waste).

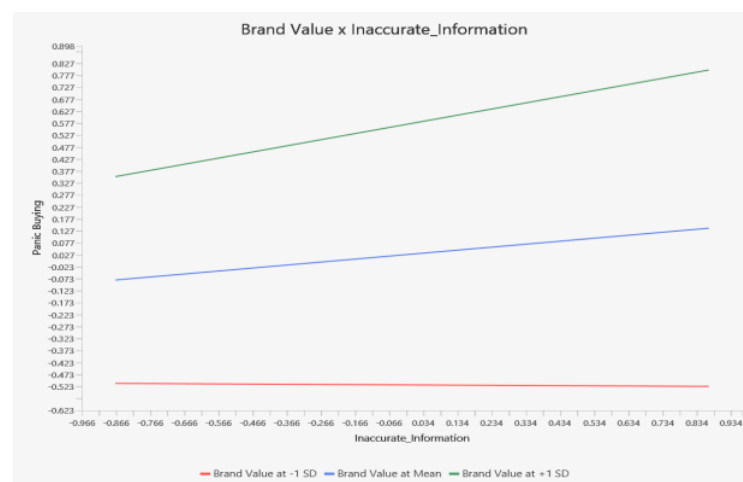


Figure 4. Moderation Effect (Brand Value).

5. Discussion

The objective of this study was to examine the extent to which COVID-19 and panic purchasing have been exacerbated by social media, and how they influence attitudes towards food waste and brand value in mitigating this phenomenon. Such findings can turn out to be useful in making attempts at understanding these dynamics and deriving principles of intervention in consumer behavior in crises. The findings shown here give support to the fact that the level of social media UGC is directly proportional to the level of misinformation, thus confirming hypothesis H1. This affirms previous work conducted by Chadwick and Vaccari [2], which did suggest that social media platforms undermined credible information because of the growth and reach of the platforms and user-generated content. Likewise, Allcott and Gentzkow [3] suggest that it is possible for unverified or fake news to spread rapidly within the social media.

The information generated through personal experience during the crisis situation directs the behavior to panic buying, thus supporting Hypothesis H2. Such a perception aligns with Witte's [8] Extended Parallel Process Model (EPPM), which asserts that the messages in question result in panic buying. In addition, we analyze how social media amplifies this behavior, as mentioned earlier, by using the scarcity theory. We also emphasize the obvious signs of stockpiling [7,9]. This research further validates that the attitudes towards food waste have a moderating role, as per hypothesis H3, regarding the dissemination of incorrect information via advertising and the resulting panic purchasing. There can be security-conscious customers who are unlikely to participate in the transgression. These individuals are cautious, perceptive, and thoughtful shoppers who consistently examine the risks associated with food wasting. The discovery aligns with the research undertaken by Le Borgne, Sirieix, and Costa [12], which concluded that discovering free promotions that may lead to food wasting as suspicious might help eliminate impulsive shopping behavior. Hypothesis H4 posits that brand value plays a role in influencing panic purchasing caused by erroneous information. Consumers with high trust and familiarization with the brand are less vulnerable to panic buying which the misinformation seeks to create, since they are loyal to brands they know well during a crisis. The current study aligns with the thoughts of Aaker and Joachimsthaler [29] and Chaudhuri and Holbrook [57] that identified brand trust as a core determinant of consumer buying behavior, especially during a period of economic instability.

The application of these recommendations certainly holds significant implications, and they can be applied meaningfully by different retailers and policymakers so as to come up with strategies that can assist in the elimination of panic buying. This should ensure that the stakeholders provide accurate information on the issues of food waste and also put effort into changing consumer habits to observe positive impacts on the environment and the community. Furthermore, organizations that are impacted by the problem of false news may mitigate the most negative consequences by enhancing their communication strategy to bolster customer trust.

Finally, this research highlights the significance of consumer perceptions of food wastage and brand value when it comes to reducing the effect of misinformation on panic buying behavior. These results enhance our understanding of consumers' behavior during a crisis and create further knowledge on which appropriate marketing strategies and interventions can be designed to stabilize the internal and external markets as well as to encourage consumers to act responsibly. Furthermore, this study has contributed to the existing body of knowledge by elucidating the mechanics of consumer panic purchasing during specific crises such as energy, military, nuclear, financial, and health crises. Additionally, it assists both academics and businesses in predicting client behavior and meeting their demands during such situations. The research also examined the effects of scarcity on consumer consuming behavior, specifically focusing on how scarcity and time constraints affect customer decision-making. The research also examined how advertising appeals influenced buyers' consuming behavior. Specifically, the study used scarcity and timing elements in the promotional messaging to encourage competitive purchasing, since the fashion goods were expected to sell out quickly. This method is consistent with the findings of Islam et al. [58], Laato et al. [4], and Lehberger et al. [13], all of whom highlighted the impact of scarcity on consumer behavior.

6. Limitations and Future Research Directions

This study offers significant insights into the relationship between user-generated content on social media, misinformation, and panic buying, moderated by attitudes towards food waste and brand value. However, two primary limitations must be acknowledged. First, although the sample is adequate for the study's analysis, it limits the generalizability of the findings. A larger and more diverse sample would provide a more comprehensive understanding of these phenomena across different demographics and regions. Second, the study's focus on a specific geographic and cultural context constrains the applicability of

the results to other settings. The impact of misinformation and consumer behavior can vary widely across different cultural and geographic contexts, suggesting a need for broader and more diverse geographical studies.

In terms of future research, longitudinal studies are recommended to capture the evolving nature of consumer behavior and misinformation over time, particularly in response to different types of crises. Moreover, future studies should explore the interplay between misinformation and other moderating variables such as socioeconomic status, education level, and digital literacy, to develop a deeper understanding of the factors influencing panic buying. Incorporating experimental designs could also provide more robust evidence of causality between misinformation and consumer behavior. Lastly, integrating qualitative methods, such as interviews or focus groups, could offer deeper insights into the motivations and perceptions driving consumer behavior in response to misinformation, thus enriching the quantitative findings with contextual depth. By addressing these directions, future research can build on the current study's findings and contribute to more effective strategies for mitigating the adverse effects of misinformation on consumer behavior.

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