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Applying K-Means Clustering to Analyze the Contextual Impact of Failure Severity on Dissatisfied E-Consumers.

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Abstract

This research offers insights into the dynamics of online service failures and recovery. Failures occur frequently, yet consumers generally do not anticipate them. Their baseline expectation is that no failure will occur, making failures particularly disappointing and, at times, shocking when a purchased product does not meet expectations. While failures create a sense of imbalance, recovery services aim to restore fairness by compensating dissatisfied customers.

However, companies must proceed with caution, as unhappy customers closely observe how their concerns are addressed. Research has shown that the severity of a failure negatively impacts customer satisfaction during the recovery process. This study further explores how the context of a failure influences this relationship, employing the k-means clustering method. Data were collected from 355 online consumers who experienced dissatisfaction following a problematic purchase, allowing the identification of distinct consumer profiles based on their reactions to failure and recovery strategies.

Keywords

Failure Severity; Satisfaction Recovery; Negative Effect; Contextual Effect; K-Means Clustering

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1. Introduction

Identical phenomena and similar events often lead to differing interpretations. Some failures are perceived as tolerable, while others are deemed intolerable. The literature highlights two perspectives on failures: the “attenuated” view and the “amplified” view. Some individuals regard failures as serious, whereas others dismiss them as normal and insignificant. Various sources from which individuals derive explanations exist, including their beliefs and motivations.

For our purposes, we are particularly interested in the impact of failure severity. This concept stems from the literature on the consequences of failure, suggesting that any negative event can be subjectively evaluated by individuals who assign varying levels of severity to it. Notably, this variable pertains more to the individual than to the organization, complicating control from a managerial perspective.

Perceived failure severity refers to the extent of loss customers experience during an unsatisfactory service encounter. Similarly, Zarrouk (2015) describes failure severity as the perceived intensity of loss felt by the customer in such situations. Hess et al. (2003) characterize failure severity as the extent of the damage incurred. However, the ambiguity surrounding failure severity lies in its role as a precursor to other consequences.

This variable provides insight into how dissatisfied individuals react and express their perceptions in the context of failure. More specifically, failure severity influences how recovery efforts are evaluated (Migacz, 2018).

For example, receiving shoes in the wrong size is disappointing, while discovering that the cell phone ordered has arrived in a faulty version is frustrating. What about being served cold food in a restaurant? Or experiencing a transport breakdown during a long journey? Whether related to services or products, failures and incidents are ubiquitous in the supply chain. These examples lead us to acknowledge a fundamental truth: every exchange context is fraught with vulnerabilities and the potential for failure.

We will focus on the context of product returns, particularly in e-commerce, where such incidents can proliferate. The inability to physically try products and the lack of tangible contact heighten the risk of misunderstandings (Dissanayake, 2007; Zerhouni, 2009), leading to highly subjective expectations (Migacz, 2018).

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Researchers assert that effective management of returns is crucial for recovering customer satisfaction. However, it is important to note that in many cases, efforts to recover satisfaction fall short (Migacz, 2018). This observation highlights a significant gap that underpins the central question of this article.

This article contributes to the literature on consumer-perceived failures, with a particular focus on the role of perceived failure severity in product return situations. The objective of this research is to analyze, using a quantitative approach, the influence of perceived failure severity on the evaluation of recovery efforts. To achieve this objective, the article is structured as follows: the first section presents the literature review and the conceptual framework; the second section is devoted to the quantitative methodology adopted; the third section presents and discusses the results of the statistical analyses, followed by a conclusion that synthesizes the main contributions of the study.

1.1 Research gap

A review of the literature reveals numerous conclusions that are both insufficient and contradictory, highlighting significant gaps.

Specifically, our literature review found that many researchers have linked offsets to satisfaction without considering the context of failure. It is important to note that every context encompasses so-called "circumstantial" variables, which stem from the specific characteristics of the environment and are not to be overlooked. Ignoring these variables fails to provide a complete understanding of practical implications. In other words, environmental characteristics significantly influence recovery (Riscinto-Kozub, 2008). As Migacz (2018) asserts, no analysis should occur outside of context. To address this gap, we will focus on examining the relationship between failure severity and satisfaction recovery.

2. Literature review

The quest for understanding motivates individuals to ask numerous questions in any given environment. In every situation, people ponder the causes behind their experiences and contemplate their own attitudes, as well as those of others around them. Through this inquiry, they construct their own worldview based on the interpretations they assign to events.

The foundational theories in this field emphasize that attribution stems from the consequences of social events, where individuals naturally seek to identify perceived causes behind behaviors

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and occurrences. Attribution involves assigning meaning to events by interpreting them through a lens of causality. Rather than focusing solely on what is being attributed, more recent perspectives highlight the importance of understanding when and how individuals engage in the attribution process. Thus, in certain contexts, individuals tend to ask numerous questions about the facts. Attributions become especially prominent in specific situations, particularly in the face of failure. When negative or undesirable events occur, people often seek explanations, asking many questions to understand why the event happened.

This theory supports the argument that the context of failure can significantly influence recovery. It is important to note that failure represents a deviation from the expected normal functioning of a system.

In our study, the severity of failure is identified as a key variable, operating within a framework of consequences rather than causes. Ye and Luo (2016) conclude that failure severity is a subjective assessment that varies from one customer to another, reflecting the judgment of the loss experienced by the dissatisfied. This subjective nature of failure severity underscores the importance of addressing customer perceptions in the challenging context of failure. Researchers have recognized the need to conceptualize and understand satisfaction following dissatisfaction, leading to the term "satisfaction recovery" being associated with this field. This term is used in situations where a company aims to transform dissatisfied customers into satisfied ones. In this framework, researchers emphasize that satisfaction recovery arises from the paradigm of unmet expectations.

Several scholars view satisfaction recovery as part of a broader value recovery process. Maxham and Netemeyer (2002) suggest that it involves restoring value to the customer through targeted efforts, while Cho et al. (2017) emphasize that effective recovery experiences can enhance customer satisfaction, indicating that positive interactions can trigger strong emotional responses. We adopt the definition by Choi and La (2013), which frames satisfaction recovery as the assessment of how well a service provider addresses a failure, underscoring that post-negative experience satisfaction hinges on the vendor’s response.

However, we note that while satisfaction recovery aligns with the expectations-confirmation paradigm, the specific elements of confirmation and comparison are often unclear, particularly in atypical situations. Aigbavboa and Thwala (2013) stress the need for a deeper understanding of the evaluation process. Context significantly influences this evaluation, especially in

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satisfaction recovery. Our study aims to analyze the negative impact of failure severity and its moderating effects, as failures create an imbalance for consumers when their expectations are not met (Ye and Luo, 2016). Research indicates that severe failures directly hinder the likelihood of satisfactory recovery.

In a study involving 556 dissatisfied customers, Matos et al. (2012) employed regression analysis and found that the introduction of the failure severity variable significantly affected post-recovery satisfaction (Beta = -0.08, p = 0.037). They noted that when a failure is perceived as major, customer satisfaction declines.

It is important to recognize that the assessment of failure severity is subjective and influences consumers' perceptions of the company’s recovery efforts, particularly regarding compensation. Cho et al. (2017) assert that the intensity of a failure affects the effectiveness of the recovery solutions implemented. They explain that when the damage is perceived as substantial, achieving satisfaction recovery becomes more challenging. This is supported by Weun et al. (2004), who investigated the impact of failure magnitude on recovery efforts, demonstrating that a high perception of severity reduces the effectiveness of compensation in enhancing satisfaction.

When losses are perceived as significant, consumers tend to be less satisfied with the recovery solution provided. Additionally, the perceived value of compensation decreases as the severity of the failure increases.

3. Methodology

Our quantitative approach involved administering a questionnaire to online consumers who had previously experienced a failure situation, specifically those who had returned a product in e-commerce. The sample size consisted of 355 participants (N=355). For data analysis, we will employ the k-means clustering method using SPSS.

Responses were collected on a 5-point Likert scale. The k-means clustering approach is suitable for our data, which is "successive," meaning it was collected based on different response modalities. Used in customer segmentation, this method plays a key role in understanding customer behavior (Zhao, 2024). Clustering will allow us to group the responses according to the provided modalities. More specifically, the scale we utilized, ranging from 1 to 5, will facilitate the formation of distinct response groups. In this regard, Moreau et al. (2000)

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recommended using clustering to enhance comparison. We will apply the k-means algorithm, taking into account two key variables: failure severity and satisfaction recovery.

From an epistemological standpoint, this research adopts a post-positivist stance. After conducting a qualitative contextualization study aimed at gaining a deeper understanding of the phenomenon of consumer-perceived failures in product return situations within e-commerce and refining the constructs employed, we subsequently pursued the analysis through a quantitative study.

3.1. The k-means clustering method

Clustering is a method employed in data analysis (Huang et al., 2007; Xu and Lange, 2019) that involves grouping similar objects together. The K-means method overcomes the limitations of traditional marketing approaches by providing more precise consumer segmentation based on objective data analysis (Chen, 2024).

eans clustering is the most commonly used clustering technique. This algorithm groups (n) objects into (k) clusters based on specified criteria (Moreau et al., 2000) and is classified as an "unsupervised" approach (Huang et al., 2007).

K-means is particularly effective for organizing observations from large datasets, with the goal of understanding data heterogeneity. By utilizing this statistical model, we will identify subgroups to explore the contextual effects of failure severity. It is important to note that the presence of dissimilarities among responses is a critical factor that justifies the application of the clustering method.

4. Results

4.1. Chi-square test for satisfaction recovery

We conducted a chi-squared test to analyze the distribution of cyberconsumer responses regarding the variable of satisfaction recovery.

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Table -1 : Chi-square test for satisfaction recovery; SPSS output.

	SAT_REC1	SAT_REC2	SAT_REC3	SAT_REC4
Chi-Square	179,944	210,451	184,225	226,282
df	4	4	4	4
Asymp. Sig.	,000	,000	,000	,000

The chi-squared test indicates a significant difference between the responses ($p < 0.05$) (Table1). This suggests that it would be valuable to conduct clustering analysis.

4.2. Chi-square test for failure severity

In line with this logic, the preliminary results of the chi-squared test for failure severity indicate the distribution of responses from online consumers.

Table -2 : Chi-square test for failure severity; SPSS output.

	FAI_SEV
Chi-Square	75,296
df	4
Asymp. Sig.	,000

The Chi-square test shows that there is a significant difference between responses ($p<5\%$) (table2). This means that the clustering condition is met.

4.3. Results of the k-means clustering test

The data will be organized into two clusters containing similar elements. We present the clusters obtained for both variables.

- *Satisfaction recovery*

For the "satisfaction recovery" variable, the clustering test grouped the responses into two clusters (table3):

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Table -3 : Grouping the data in two for satisfaction recovery ; SPSS output.

	Groups obtained	
	Groupe 1	**Groupe 2**
SAT_REC1	4*	2***
SAT_REC2	5**	2
SAT_REC3	4	2
SAT_REC4	5	2
*4th response mode of the 5-point Likert-type scale **5th response mode of the 5-point Likert-type scale ***2nd response mode of the 5-point Likert-type scale		

Now we'll have to go back to the Likert scale to give each group its proper designation.

Response modalities 4 and 5 tend towards "high satisfaction", while response modality 2 tends towards "low satisfaction". The final result of the K-means test is summarized as follows:

Table -4 : Groups obtained for satisfaction recovery; SPSS output.

The two groups obtained (2 clusters)	
Groupe 1	High satisfaction group
Groupe 2	Low satisfaction group
Valid	355,000
Missing	,000

- *Failure severity*

For the "failure severity" variable, the clustering test was used to group responses into two groups (table5):

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Table -5 : Grouping the data into two for failure severity ; SPSS output

	Groups obtained	
	Groupe 1	**Groupe 2**
FAI_SEV	4*	1**
*4th response mode of the 5-point Likert-type scale **1st response mode of the 5-point Likert-type scale		

Now, we will return to the Likert scale to assign appropriate designations to each group. Response modality 4 corresponds to "very serious failure," while response modality 1 relates to "not very serious failure." The final results of the k-means test are summarized as follows:

Table -6 : Groups obtained for failure severity; SPSS output

The two groups obtained (2 clusters)	
Group 1	Very severe failure group
Group 2	Less severe failure group
Valid	355,000
Missing	,000

4.4. Final clustering results

Now we need to address the following question: Which of the two groups in the failure severity variable will be paired with the two groups in the satisfaction recovery variable? Table 7 shows the results obtained for each variable:

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Table -7 : Combinations obtained; Output. SPSS

Variables	The two groups obtained (2 clusters)
Satisfaction recovery	G1 : High satisfaction / G2 : Low satisfaction
Failure severity	G1: Very serious failure / G2: Not very serious failure

The algorithm will suggest combinations based on the data from each group. Each combination will include two groups, allowing us to interpret the connections between the two variables. Table 8 illustrates the results of the clustering:

Table -8 : Combinations obtained; Output. SPSS

	Final groups k = 4			
	Combination A	**Combination B**	**Combination C**	**Combination D**
Satisfaction recovery	Low satisfaction group	High satisfaction group	High satisfaction group	Low satisfaction group
Failure severity	Very severe failure group	Not very severe failure group	Very severe failure group	Not very severe failure group
Lifted effect	Direct effect Direct	Direct effect Direct	Contradictory effect	Contradictory effect
N = 355				

For Combination A, this group consists of less satisfied cyber-consumers who viewed the failure as very serious. This illustrates the negative impact of failure severity on satisfaction recovery.

In Combination B, the respondents felt that their satisfaction had been largely restored, while they rated the severity of the failure as not very serious. This supports the idea that when failure severity is perceived as low, satisfaction tends to be high. Combination C presents a scenario where both the severity of the failure and satisfaction recovery are rated as high. This indicates

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that within our dataset, various behaviors overlap, revealing dilemmas and contradictions. These discrepancies may stem from the participants' misunderstanding of the questions, a mismatch between the respondents and the study focus, or a lack of attention to the questionnaire. Additionally, researchers may overlook other significant variables. Lastly, in Combination D, satisfaction recovery is perceived as low, while the failure is considered not serious. This finding does not support a direct relationship between failure severity and satisfaction recovery.

6. Discussion and conclusion

Neglecting contextual factors often results in incomplete or weakened explanations within social science research. According to recent studies (Sidhu et al., 2023), the concept of contextual effect highlights how the severity of a failure directly shapes the process of satisfaction recovery. In essence, as the severity of the failure increases, it becomes more difficult to restore customer satisfaction effectively.

Our findings align with those of Weun et al. (2004), Hess et al. (2003), Zarrouk (2015), and Shin and al. (2018) and Hwang et al. (2024) all of which indicate that failure severity adversely affects recovery efficiency. Understanding the conditions for recovery is crucial (Ikponmwen, 2011). Considering contextual effects enhances our grasp of how to improve satisfaction recovery. Additionally, some causal relationships require specific frameworks to be fully understood.

The negative impact of failure severity on satisfaction recovery suggests that cyber-consumers have varying recovery needs. When failures are perceived as severe, companies' efforts often seem inadequate to address dissatisfaction.

Building on the idea of exceeding expectations, it can be argued that when failure severity is high, companies should not only offer compensation but also engage in friendly gestures to enhance satisfaction recovery. Examples of such gestures might include gifts, vouchers, or discounts. Zarrouk (2015) highlights the importance of mobilizing extra effort in these scenarios.

However, some studies caution against the effectiveness of such measures, suggesting that for certain consumers, these actions may only mitigate the negative impact rather than fully resolve the issue. This sentiment is echoed by McCollough et al. (2000), who argue that, for instance,

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compensation cannot fully mitigate the repercussions of a significant delay on an important business trip.

It is essential to carefully consider the influence of the failure context, as company efforts may fall short in restoring satisfaction. The context of failure serves as a benchmark for evaluating expectations. Thus, the classical model, which posits that satisfaction recovery hinges solely on the comparison between expectations and perceived service quality, is inadequate.

Moreover, examining certain contextual effects brings attention to dilemmas that may arise in dyadic relationships. According to Hwang et al. (2024), dissatisfied individuals often remember typical negative experiences, which can have lingering effects.

From a methodological standpoint, the k-means clustering method has primarily revealed qualitative insights, prioritizing "meaning" over mere numerical data. By applying this method, organizations can uncover hidden patterns in customer data, leading to more informed and strategic decision-making (Zhao, 2024; Chen, 2024).

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