



EXPLORING ONLINE COMPLAINT BEHAVIOR DIMENSIONS: A SCALE DEVELOPMENT AND VALIDATION STUDY

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Abstract:

The primary goal of this study is to develop and validate a measurement tool that assesses consumers' online complaint behavior. The study employed a mixed-methods approach, beginning with in-depth interviews of eight (8) e-commerce users, which resulted in the formulation of 36 item statements capturing the different motivations behind online complaints. Afterwards, Exploratory Factor Analysis (EFA) was conducted on a sufficiently large sample (n=250), revealing a three-factor structure: Emotionally Driven Complaining, Empowered and Advocacy-Based Complaining, and Complaint Resolution Expectations. In addition, the final model (Model 3), as confirmed by conducting Confirmatory Factor Analysis (CFA), shows strong fit indices, confirming the robustness of the three-factor structure and strong convergent validity. Overall, the results revealed that the scale created is psychometrically valid and effectively captures the complexities of online complaint behavior. The validated instrument is a valuable tool for educators, researchers, and practitioners who aim to understand the motivations behind online complaints. Moreover, this research contributes to achieving the United Nations Sustainable Development Goal 12 (Responsible Consumption and Production) by promoting consumer empowerment, accountability, and transparency in digital marketplaces. Future studies should investigate the reliability of the scale in measuring across various demographic groups and its ability to predict customer loyalty and brand perception.

Keywords: online complaint behavior, scale validation, sequential exploratory mixed-method, exploratory factor analysis, confirmatory factor analysis

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1. Introduction

In today's digital world, social media platforms offer businesses a great chance to boost their brand visibility. At the same time, these platforms provide customers with a crucial means to express their concerns, particularly when they encounter issues with products or services. Rather than resolving issues privately, many customers choose to voice their displeasure online, bypassing the traditional face-to-face methods for voicing dissatisfaction, potentially damaging the company's reputation.

In the Philippines, social media engagement continues to grow, offering Filipino consumers more convenient avenues for lodging complaints. According to a 2024 report, the Philippines boasts approximately 86.98 million active internet users, placing it fourth globally in terms of social media usage (Kemp, 2024). The report reveals compelling statistics regarding active social media users in the country, with prominent platforms including Facebook (86.75 million users), YouTube (58.10 million users), TikTok (49.09 million users), and Instagram (21.35 million users).

Daily, Filipinos dedicate around 3 hours and 34 minutes to social media (Howe, 2024), which facilitates their ability to voice complaints and poses risks of brand damage, while also encouraging others who may have similar grievances to come forward. Given the high social media usage in the Philippines, the trend profoundly affects how consumers lodge online complaints. Consequently, comprehending customer complaint behavior, along with the responses from businesses, is critical to customer retention, the cultivation of customer relationships, and significantly influences consumers' online shopping decisions (Angelovska, 2021).

Scholarly efforts in the field of consumer behavior, particularly in the Asia region, have explored various factors influencing consumer complaint behavior (Simanjuntak and Shahirah, 2024; Yulianti and Simanjuntak, 2024; Azizah *et al.*, 2022; Preuss and Marconatto, 2022; Morgeson *et al.*, 2020). However, these studies predominantly examine complaint behavior in traditional markets, leaving a notable gap regarding online environments, particularly in the Filipino context. Although these studies provide insights into consumer complaint behavior, they may not fully encompass the social and cultural dimensions specific to the Philippine setting, particularly in Region 12.

In addition, studies on online complaint behavior have focused primarily on traditional, western, and other Asian contexts (Ally *et al.*, 2020; Sann *et al.*, 2022; Armstrong and Brennan, 2021. Azemi and Howell, 2020; Shin and Larson, 2020) leaving a significant gap in validated culturally relevant measurement scales that capture the unique dimensions of online complaint behavior among Filipino consumers in the rapidly evolving e-commerce landscape.

1.2 Research Objectives

The primary objective of this research is to develop and validate an alternative scale for measuring online complaint behavior within the Philippine context. Specifically, this

study aims to explore the various dimensions of online complaint behavior among Filipino consumers and to gain insights into the factors that influence these behaviors.

The study aims to address the following question:

- 1) What are the primary factors that motivate consumers to lodge online complaints?
- 2) How do contextual variables influence the nature and intensity of these complaints?
- 3) Can an alternative scale be developed to accurately capture these dimensions within the Philippines' unique socio-economic and cultural landscape?

Conducting this study is urgent due to the rapidly increasing importance of digital platforms in consumer interactions and the need for businesses to manage online complaints effectively. In the Philippines, where internet penetration and social media usage are among the highest in the world, understanding online complaint behavior is crucial for businesses aiming to maintain their reputation and customer satisfaction. Existing scales developed in Western contexts may not fully capture the nuances of Filipino consumer behavior, highlighting the need for a context-specific tool. By addressing this gap, the study will provide businesses with valuable insights into managing online complaints, ultimately leading to better customer service and enhanced brand loyalty.

1.3 Theoretical Framework

Understanding the dimensions of online complaint behavior can be effectively framed using several theoretical lenses. One such theory is the Social Exchange Theory, which posits that human interactions are based on the exchange of resources, and individuals seek to maximize their benefits while minimizing their costs (Homans, 1958). In the context of online complaint behavior, consumers may lodge complaints online as a way to gain resolution or compensation for perceived grievances. The costs associated with this behavior include time, effort, and emotional stress, while the benefits could include problem resolution, monetary compensation, or a sense of justice and empowerment. This theory helps explain why consumers choose to complain online rather than using other channels, and it can also shed light on the factors influencing the intensity and persistence of their complaints.

Another relevant framework is the Expectancy-Disconfirmation Theory, which suggests that customer satisfaction is determined by the gap between the customer's expectations and the actual performance. When there is a significant discrepancy between what consumers expect and what they experience, negative disconfirmation occurs, prompting them to voice their dissatisfaction through complaints (Oliver, 1977). This theory can help analyze the triggers of online complaint behavior by examining the expectations consumers have before making a purchase and how those expectations are not met. It also provides insight into the emotional responses of consumers and the subsequent actions they take to address their dissatisfaction, such as posting online reviews or complaints.

1.4 Conceptual Framework

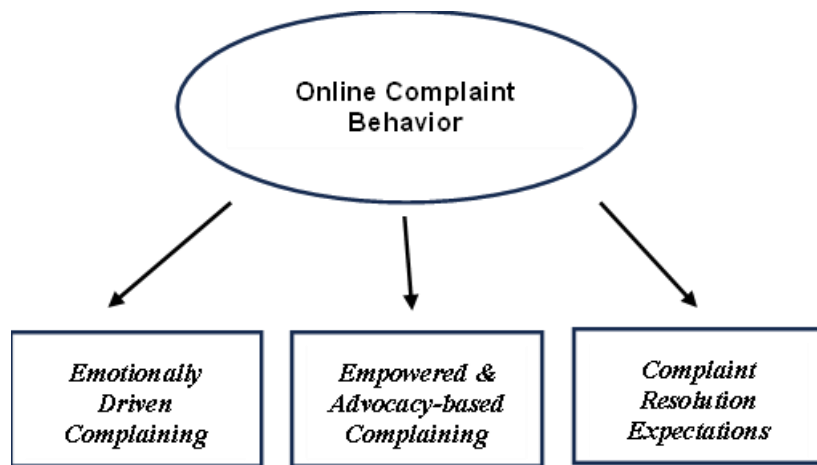


Figure 1: Conceptual Framework of the Study

Figure 1 presents the conceptual framework of the study. It illustrates the core construct of online complaint behavior, alongside its latent variables: emotionally driven complaining, advocacy-based complaining, and complaint resolution expectations. These online complaint behavior dimensions were identified through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), statistical techniques used for scale development and validation.

The first dimension, labeled as emotionally driven complaining, demonstrates online consumers' tendency to lodge complaints as a result of anger, disappointment, and frustration over product or service failures. This dimension underscores the critical role of emotion in shaping consumer behavior in an online setting, emphasizing that complaints are psychological in nature.

In addition, the second dimension, labeled as empowered and advocacy-based complaining, explains consumer use of digital platforms in expressing displeasure as a medium of consumer empowerment to hold businesses accountable. This dimension goes beyond individual dissatisfaction, often advocating consumer rights and raising awareness to influence others' purchasing intentions.

Lastly, complaint resolution expectations demonstrate consumers' desire for prompt and fair resolution of their complaints. It highlights complaint motivations that consumers expect a concrete response when raising complaints.

2. Literature Review

Using internet platforms to voice displeasure with a product, service, or experience is known as online complaint behavior. The way customers voice their displeasure has changed significantly in the digital age, mainly due to the influence of technology (Kumar and Kaur, 2020). With the rise of social media and online review platforms, the landscape of complaint behavior has evolved away from traditional techniques like face-to-face

contacts or phone calls and toward more public venues (Azemi *et al.*, 2020; Mei *et al.*, 2019; Frasquet *et al.*, 2019).

Due to its accessibility, this trend has expanded significantly. Customers can easily share their experiences on forums, review websites, and social media. Additionally, people can air their grievances online without worrying about face-to-face conflict (Huang and Ha, 2020). Online complaints also offer the solace of community support, as many people turn to others who may have gone through similar experiences for validation and encouragement.

A sense of community and support from those who have similar frustrations can be obtained by sharing experiences (Golmohammadi *et al.*, 2021; Mei *et al.*, 2019; Johnen and Schnittka, 2019). Consequently, online complaints can have significant implications for companies, both positive and negative. Negative reviews can harm a company's reputation, affecting potential customers' perceptions. Conversely, effective handling of complaints can enhance a brand's image (Hwang and Mattila, 2020). Responding promptly and professionally to complaints can demonstrate a company's commitment to customer satisfaction and lead to increased loyalty. Further, online complaints can serve as valuable feedback, helping businesses identify areas for improvement (Ku *et al.*, 2021; Guo *et al.*, 2020; Cooper *et al.*, 2019).

In addition, the shift to online complaint behavior reflects changing customer expectations in several ways. Today's consumers expect quick resolutions. With the immediacy of online platforms, waiting for traditional customer service responses can be frustrating (Fuoli *et al.*, 2021). Moreover, consumers increasingly seek transparency from brands. They want to see how companies handle complaints publicly, influencing their purchasing decisions. Online platforms give consumers a voice and a sense of power. They can mobilize support and create significant pressure on companies to address issues (Singh *et al.*, 2022; Awa *et al.*, 2021; Yang *et al.*, 2019).

If companies fail to address online customer complaints, they risk significant long-term consequences, including loss of revenue and erosion of brand loyalty. Research consistently demonstrates the critical role of customer service in shaping consumer behavior and brand perception. For instance, 83% of consumers feel more loyal to brands that actively respond to and resolve complaints, underscoring the importance of timely and effective complaint management (Khoros, 2024). Effective strategies for addressing complaints include acknowledging the issue, providing a solution, and following up to ensure customer satisfaction. Failure to prioritize customer service can also result in diminished lifetime customer value, as evidenced by Bain and Company's (2015) findings that a promoter's lifetime value is between 600% and 1,400% higher than that of a detractor, highlighting the financial implications of converting dissatisfied customers into advocates.

Furthermore, customer retention is directly tied to profitability, as noted by Bain & Company. Increasing retention rates by just 5% can lead to profit increases of between 25% and 95% (Reichheld, 2001), suggesting that ignoring complaints can stymie potential revenue growth. Additionally, in the case of Invesp, the costs associated with customer

acquisition are far higher than those for retention, with new customer acquisition estimated to be between 5 and 25 times more costly than maintaining existing relationships (Saleh, 2024). These findings underscore that neglecting online complaints can have cascading adverse effects on a company's financial performance and reputation, highlighting the urgency of addressing online complaints.

In the Philippines, the rising trend in consumer complaints underscores the importance of effective online customer complaint management, particularly in light of the rapid shift to digital commerce. In 2022, consumer complaints reported to the Department of Trade and Industry (DTI) reached 27,947, more than doubling from the pre-pandemic total of approximately 10,000 in 2019, illustrating the growing challenges companies face in maintaining service quality on digital platforms. Notably, 44% of these complaints, or approximately 12,200 cases, involved online transactions, ranging from product defects to service imperfections, as evidenced by consumers receiving torn clothing or damaged goods (Monzon, 2023).

Additionally, over 2,200 complaints were linked to deceptive practices where customers never received their purchased items, raising concerns about consumer protection and trust in online commerce. Misleading advertisements and fraudulent promotional practices also surfaced, with 450 complaints reported regarding denied discounts during advertised promotions, underscoring the impact of unmet expectations on brand reputation. This surge in complaints indicates that companies must prioritize transparent communication and quality service in digital transactions to maintain consumer trust and loyalty.

While online complaints can pose challenges, addressing them effectively can yield substantial benefits. Customers who feel heard and valued are more likely to remain loyal to a brand, even after a negative experience (Labrecque *et al.*, 2022). Feedback from online complaints can highlight areas for product and service improvement, leading to better offerings and enhanced customer satisfaction. Lastly, successfully resolving complaints can turn dissatisfied customers into advocates who share positive experiences, helping to restore and even enhance a brand's reputation (Mishra, 2022; Simanjuntak, 2019; Whiting *et al.*, 2019).

As online complaint behavior continues to evolve, businesses must adapt to these changes to remain competitive in the marketplace. It is well established that by actively listening to customers, engaging transparently, and responding promptly, brands can transform potential crises into opportunities for growth and loyalty (Zhao *et al.*, 2020). In the digital age, managing online complaints effectively is not just about damage control – it is about building lasting relationships with consumers. Above all, online complaint behavior is an inherent aspect of modern consumer culture (Ravichandran and Deng, 2023; Bacile, 2020; Quesenberry, 2020).

Reviewing relevant studies on online customer complaint behavior reveals that several studies have discussed the possible forms and sources of online complaint behavior. One possible factor influencing online complaint behavior is the motivation behind complaints. Understanding the motivations behind these behaviors and

implementing effective management strategies will enable businesses to turn potential challenges into opportunities for growth and improvement (Shin and Larson, 2020). Embracing transparency and engaging with customers can foster loyalty and enhance brand reputation in an increasingly digital marketplace (Arruda Filho and Barcelos, 2021; Prodanova and Van Looy, 2019; Frasquet *et al.*, 2019).

Some key motivations for online complaints are the consumers' desire for resolution. Many consumers take their complaints online in the hope of receiving a prompt resolution (Hutzinger and Weitzl, 2021). The expectation is that the public visibility will compel brands to act quickly. When traditional channels fail, consumers may feel that escalating their complaint to a public forum will garner more attention and urgency from the company. Emotional relief is also believed to be a key motivation for online complaints. Expressing dissatisfaction can serve as a cathartic outlet. Sharing grievances allows individuals to articulate their feelings and receive validation from others (Yesiloglu *et al.*, 2021; Mousavi *et al.*, 2020; Sanchez-Casado *et al.*, 2019).

Succinctly put, online complaint behavior is driven by a complex interplay of motivations, ranging from the desire for resolution to the need for validation and social recognition. Businesses can more effectively navigate the digital landscape and transform potential catastrophes into opportunities for growth and connection by being aware of these motivations. Customers' online voices continue to hold considerable power, so businesses that pay attention and react carefully will be well-positioned to forge enduring bonds and improve.

Another possible factor influencing online complaint behavior is the choice of complaint channels. In the digital age, consumers have a variety of channels at their disposal for expressing dissatisfaction with products and services. Online complaint channels have revolutionized the way feedback is communicated and addressed, providing both challenges and opportunities for businesses (Frasquet *et al.*, 2019). Online complaint channels are not just platforms for consumers to vent their frustrations; they play a critical role in shaping a brand's image and customer loyalty. With consumers increasingly relying on online interactions, businesses must understand and adapt to this evolving landscape (Heriyanto *et al.*, 2022; Yan *et al.*, 2021; Golmohammadi *et al.*, 2021).

Most online complaint channels are user-friendly, allowing consumers to share their experiences quickly and efficiently. This accessibility encourages more feedback, both positive and negative (Hutzinger and Weitzl, 2021). Unlike traditional customer service, online platforms allow consumers to voice their complaints at any time, making it easier for them to seek resolutions outside of business hours. Platforms like Twitter, Facebook, and Instagram allow users to post complaints publicly. Businesses often monitor these channels to respond in real-time (Bacile *et al.*, 2020; Dyussebayeva *et al.*, 2020; Weitzl and Einwiller, 2020).

Generally, online complaint channels have transformed the way consumers interact with businesses, offering multiple avenues for feedback. By understanding the various platforms available and implementing effective engagement strategies, businesses can transform complaints into opportunities for improvement and foster

stronger relationships with their customers. In an era where customer voices can resonate widely, proactive management of online complaints is essential for maintaining a positive brand reputation. For consumers, knowing how to navigate these channels can lead to more successful outcomes. Ultimately, both parties benefit from constructive dialogue and prompt resolutions, fostering a more positive relationship in the digital marketplace.

Complaint frequency is another possible indicator of online complaint behavior. As digital communication continues to evolve, the frequency of online complaints has emerged as a vital metric for businesses seeking to understand consumer behavior (Angelovska, 2021). With numerous platforms available for expressing dissatisfaction, understanding how often consumers voice their grievances online is crucial for businesses to address these concerns effectively. As consumers become increasingly empowered and vocal about their experiences, the normalization of online complaints has become more prevalent. More individuals feel encouraged to share their dissatisfaction, leading to higher frequency rates (Bozyigit *et al.*, 2022; Von Janda *et al.*, 2021; Morgeson III *et al.*, 2020).

Research indicates that approximately 50% of consumers are likely to share their complaints online following a negative experience. This statistic highlights the shift from private grievances to public outcry (Tucker *et al.*, 2023). Specific platforms experience higher complaint frequencies. For example, social media platforms often experience spikes in activity during high-profile customer service failures or product recalls, as consumers flock to these channels to express their frustrations. Consequently, the rise of smartphones has made it easier for consumers to complain on the go, contributing to an increase in the frequency of online complaints (Bazzan *et al.*, 2023; Sangpikul, 2022; Krishna *et al.*, 2019).

As a result, the frequency of online complaints is on the rise, driven by the increasing accessibility of digital platforms and evolving consumer expectations. As consumers become increasingly empowered and vocal about their experiences, the normalization of online complaints has become more prevalent. More individuals feel encouraged to share their dissatisfaction, leading to higher frequency rates. As more customers choose to voice their grievances online, businesses must prioritize responsiveness and engagement. Embracing this trend is essential for success in today's competitive market.

Another possible consideration for online complaint behavior is the severity of the issue being complained about. Complaint severity refers to the degree of impact or urgency associated with a consumer's grievance (Singh *et al.*, 2023). It can range from minor issues, such as delayed shipments, to serious concerns, including safety violations or product defects. Higher-severity complaints often have a more significant impact on a brand's reputation and customer trust than lower-severity issues (Nazifi *et al.*, 2021; Awa *et al.*, 2021; Abdul Rahim *et al.*, 2019).

The emotional intensity behind a complaint can amplify its perceived severity. Consumers who feel wronged or betrayed may express their grievances more forcefully,

which can impact how others perceive the issue (Jin and Aletras, 2021). Also, complaints made on public platforms often garner more attention, leading to increased scrutiny and potential backlash for the company involved. Additionally, the context in which a complaint arises can influence its severity. For instance, a complaint during a peak shopping season may carry more weight due to heightened consumer expectations (Koc *et al.*, 2023; Nguyen *et al.*, 2021; Joe and Choi, 2019).

In conclusion, the severity of online complaints is a critical factor for businesses to consider in their customer service strategies. By understanding the different levels of complaint severity and the factors that influence them, companies can prioritize their responses effectively, protect their reputations, and foster stronger relationships with their customers. In an era where consumer voices are amplified online, addressing complaints—especially severe ones—proactively and empathetically is essential for long-term success.

The tone and approach of the complaint should also be considered as indicators of online complaint behavior. In the realm of customer service, the tone and approach used in addressing complaints are crucial factors that can significantly influence the outcome of the interaction (Shin and Larson, 2020). Whether responding to a customer's grievance or voicing a complaint themselves, how communication occurs can determine the effectiveness of resolution efforts, customer satisfaction, and the overall relationship between the business and its customers (Van Mulken, 2024; Awa *et al.*, 2021; Decock *et al.*, 2021).

The tone can shape how messages are received and interpreted. A positive tone can foster cooperation, while a negative tone can escalate tensions. A warm, empathetic tone combined with a collaborative approach can lead to higher customer satisfaction (Van Herck *et al.*, 2021). Customers who feel heard and valued are more likely to remain loyal and recommend the business to others. Conversely, a defensive tone or confrontational approach can result in frustration and dissatisfaction. Negative experiences can lead to public complaints, damaging the brand's reputation (Rita *et al.*, 2022; Pol *et al.*, 2020; Barcelos *et al.*, 2019).

The tone and approach used in managing complaints are critical components of effective customer service. By adopting an empathetic tone and a collaborative approach, businesses can enhance customer satisfaction and foster stronger relationships with their consumers. Training staff, standardizing response protocols, and actively seeking feedback are essential steps in fostering a culture of effective communication. In an increasingly competitive marketplace, how businesses handle complaints can significantly influence their reputation and long-term success.

Another possible factor for online complaint behavior is the expectation of response. In the service industry, the expectation of response time has evolved dramatically in recent years (Ashfaq *et al.*, 2019). With the rise of digital communication and social media, customers now anticipate quicker responses to their inquiries and complaints than ever before. The advent of social media, chatbots, and instant messaging has fundamentally changed how customers interact with service providers. Customers

expect immediate acknowledgement of their queries and swift resolutions to their issues. As businesses expand their online presence, customers now expect round-the-clock access to support. This trend is particularly pronounced in sectors like e-commerce, hospitality, and telecommunications (Kaviyani-Charati *et al.*, 2022; Suri, 2020; Biswas *et al.*, 2019).

In many cases, customers seek quick answers to urgent issues. For example, a traveler may need immediate assistance regarding flight changes or cancellations. With numerous options available, customers are more likely to choose service providers that offer faster responses (Goodman, 2019). A slow reply can lead to lost business and damaged customer loyalty. The modern consumer is more informed and empowered than ever. Access to information enables customers to easily compare services, thereby raising their expectations for prompt communication. Online reviews and testimonials often emphasize the importance of quick responses. Customers are influenced by the experiences of others, leading to heightened expectations (Agnihotri *et al.*, 2022; Lee *et al.*, 2019; Dong and Wu, 2019).

In the service industry, the expectation of prompt responses is a critical factor in customer satisfaction and loyalty. As consumer behavior continues to evolve alongside technological advancements, businesses must prioritize swift communication to meet and exceed these expectations. By setting clear response time goals, investing in technology, training staff, and continuously monitoring performance, service providers can enhance the customer experience and build lasting relationships. In a competitive landscape, effective response management is not just an operational necessity; it is a strategic advantage.

Complaint outcome satisfaction may be considered an indicator of online complaint behavior. Complaint outcome satisfaction refers to the level of contentment a customer feels after a business has addressed their complaint. This concept is crucial for understanding customer loyalty, brand reputation, and overall business success (Van Dael *et al.*, 2020). In today's competitive landscape, effectively managing complaints and ensuring positive outcomes can significantly influence customer retention and word-of-mouth marketing (Kozinets *et al.*, 2021; Lee and Hur, 2019; Ndiege, 2019).

Quick resolutions are typically associated with higher satisfaction. Customers appreciate when their complaints are addressed promptly, as it shows that their concerns are taken seriously. The relevance and fairness of the resolution also play a critical role (Ducange *et al.*, 2019). Customers want solutions that adequately address their issues and meet their expectations. Furthermore, transparent and honest communication about the complaint process, potential outcomes, and any delays can significantly improve customer perceptions, even if the resolution is not what they had hoped for (Heriyanto *et al.*, 2022; Creelman, 2022; Khedkar and Shinde, 2020).

In essence, complaint outcome satisfaction is a vital component of customer experience in the service industry. Understanding the factors that influence this satisfaction can help businesses enhance their complaint resolution processes, leading to increased customer loyalty and positive brand reputation. By focusing on effective

training, streamlined processes, continuous feedback, and fostering a customer-centric culture, organizations can turn complaints into opportunities for growth and improvement. In a competitive market, prioritizing customer satisfaction with complaint outcomes is essential for long-term success and customer retention.

Another possible factor for online complaint behavior is consumer empowerment and influence. Consumer empowerment refers to the process by which individuals gain the ability and confidence to make informed choices regarding products and services (Xie *et al.*, 2020). Technological advancements, social media, and the increasing availability of information have significantly amplified this empowerment. As consumers become more informed and connected, their influence over businesses and the marketplace grows (Cambra-Fierro *et al.*, 2021; Mohammad, 2020; Auh *et al.*, 2019).

Consumer empowerment involves providing customers with the tools, resources, and information they need to make confident decisions. It encompasses their ability to voice opinions, influence brands, and demand accountability (Tien *et al.*, 2019). Empowerment can manifest through various channels, including social media, online reviews, and direct communication with brands. Consumers now have a platform to express their needs and preferences, resulting in increased engagement. The internet has democratized access to information, enabling consumers to research products, read reviews, and compare prices effortlessly. This wealth of information empowers consumers to make more informed choices (Ilyas *et al.*, 2021; Nur, 2021; Jiang *et al.*, 2019). Consumer empowerment is reshaping the marketplace, placing greater influence in the hands of individuals. As consumers become more informed and connected, businesses must adapt to meet their evolving expectations. By enhancing communication, fostering a customer-centric culture, embracing transparency, and leveraging technology, brands can navigate this new landscape effectively. Ultimately, recognizing and respecting the power of consumers not only enhances customer satisfaction but also drives long-term success and loyalty in a competitive environment.

3. Material and Methods

3.1 Study Participants

This study employed a sequential-exploratory mixed methods research design, which combines both quantitative and qualitative research approaches. In the qualitative phase, the researcher conducted in-depth interviews (IDIs) with eight respondents. These individuals can be potential informants for the researcher to identify the dimensions of online customer complaint behavior. Marshall and Rossman (2014) suggest that a sample size of 6 to 10 participants is ideal for focus groups. This size is already sufficient to capture various perspectives while ensuring that each participant has the opportunity to contribute meaningfully to the discussion.

Meanwhile, the researcher conducted two rounds of surveys with the respondents as part of the quantitative phase of this study. The first round was conducted for the researcher to identify various dimensions of online complaint behavior. In choosing the

survey participants, purposive sampling was used. The first round of the survey consisted of 36 items, determined by the identified constructs. Twenty survey items were retained for the second round, having met the minimum threshold of a factor loading coefficient of +0.50 (Hair *et al.*, 2019).

Various criteria were considered in selecting the study's participants. These include being a Filipino regardless of residency in the country, at least 18 years old, those who have installed and have been using any of the online shopping or purchase platforms (Shopee Lazada, Amazon, Shein, Temu, among others), and have either lobbied an online complaint or not in various forms (chat, ticket, email, or customer service call). They should have been using the app for at least six months. Users of mobile food delivery services were excluded from the survey, including those who had just installed the shopping or purchase platform, as well as those who were unable to consent and did not pay for their purchases. Those who qualify can also withdraw from the online survey without penalty or any repercussion for non-participation.

3.2 Materials and Instruments

To generate the data necessary for the study, the researcher employed both structured and semi-structured data collection instruments. A semi-structured interview guide was used to identify the factors that may influence online complaint behavior. The data from the key informants were then the basis for the researcher in developing the final item statements of the survey questionnaire.

Additionally, two phases of the survey were conducted during the second stage of data collection. This comprised a structured survey questionnaire using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Statements extracted from the qualitative phase were included in the EFA. Validity and reliability were established using psychometric measures. Refined statements from EFA were then used for Confirmatory Factor Analysis. Furthermore, a five-point Likert Scale Response Framework was utilized to respond to the given statements. The researcher ensured that ethical considerations were strictly observed and followed in this study. The survey questionnaire was reviewed and approved by the University of Mindanao Ethics Review Committee (UMERC) before distributing it to the research respondents in Region XII.

3.3 Design and Procedure

The initial stage of this research involved the researcher reviewing existing literature and studies on online customer complaint behavior. Before submitting the outline defense, the researcher submitted the draft manuscript, comprising the Introduction and Methods, to the research adviser and the members of the Dissertation Advisory Committee for their suggestions and comments. After the approval of the research proposal, the researcher sent a letter of request, along with the informed consent form, to the key informants who were the subjects of the in-depth Interviews. The participants' responses were then processed and validated by experts. The comments, suggestions,

and recommendations of the Adviser and Thesis Advisory Committee were followed to enhance the survey questionnaire.

Letters of request for approval were sent before the execution of the study. After obtaining approval, the researcher immediately conducted the first phase of data gathering to explore the dimensions of complaint behavior within a web environment. The researcher allotted at least two weeks for the distribution and retrieval of the survey questionnaire.

Exploratory Factor Analysis (EFA) was used in the first round of the survey. The Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity were utilized to determine sampling adequacy. Additionally, Principal Component Analysis (PCA) was applied to extract and identify the reliability and dimensionality of the constructs. Confirmatory Factor Analysis was used in the second phase of the survey to confirm or validate the factors identified in the first phase. The following figure illustrates the procedure implemented by the researcher in this study.

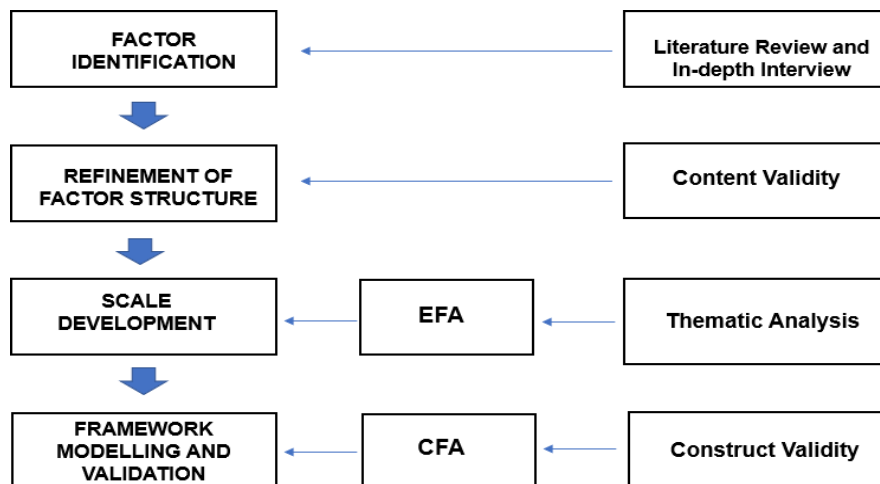


Figure 2: The Scale Development and Validation Process

3.3.1 Qualitative Phase

The initial phase of this study involved performing a comprehensive literature review focused on complaint behavior within the online environment, as illustrated in Figure 2. This was subsequently followed by in-depth interviews with the selected IDI participants. Their responses were analyzed through coding techniques to identify key themes that would guide the creation of the item statement pool. The item statements generated were subsequently evaluated by ten subject matter experts with expertise in scale development and validation. This validation process confirms that the item statements are necessary or essential, allowing them to move forward to Exploratory Factor Analysis. The content validity of the items in the initial scale was assessed quantitatively using both the Item-Level Content Validity Index (I-CVI) and the Scale-Level Content Validity Index calculated via the Average Method (S CVI/Ave).

A binary scoring system was implemented, where a score of 1 was given if an expert deemed the item as "essential." Conversely, a score of 0 was assigned if the expert considered the item to be "useful but not essential" or "not necessary." This process highlights the crucial role of subject matter experts in evaluating the scale to determine the reliability of items, as emphasized by Jelendres *et al.* (2023). A minimum agreement score of 0.80 is essential for validating each item, according to expert consensus. Items that fall below this threshold may either be eliminated or revised (Lawshe, 1975).

Initially, the proposed scale comprised 36 items designed to capture a range of motivations for online complaints, developed through comprehensive interviews. After careful review by subject matter experts, 20 critical items were identified for factor analysis, while 16 items were discarded due to their perceived lack of relevance. Additionally, some items were removed because they exhibited issues with cross-loading or failed to load appropriately, resulting in 17 remaining items.

3.3.2 Quantitative Phase

EFA and CFA were employed in the quantitative phase of this study to uncover the underlying dimensions of online complaint behavior among Filipino e-commerce users in Region XII. Before proceeding with EFA, a variety of statistical tools were used to assess the appropriateness of the dataset for factor extraction (Statistics Solutions, 2022). This process included evaluating sampling adequacy and the presence of sufficient intercorrelations among variables (Kaiser, 1974; Hair *et al.*, 2019). Specifically, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were utilized as preliminary diagnostics. According to Kaiser (1974) and Hair *et al.* (2019), a KMO value of at least 0.50 is considered acceptable for factor analysis, though some researchers suggest aiming for a value of 0.60 before moving forward with the analysis.

Additionally, Bartlett's Test of Sphericity was performed to determine the appropriateness of the data for factor analysis, necessitating a significance value of 0.05 (Hair *et al.*, 2019). To define the scale's dimensionality, principal component analysis (PCA) was utilized with maximum likelihood extraction and VARIMAX orthogonal rotation. This method was selected to reveal the underlying structure of the dataset while improving the interpretability and clarity of the resulting factors (Henson & Roberts, 2006; Beavers *et al.*, 2013). Following best practices in scale development, a more stringent factor loading threshold of ± 0.50 was employed to retain only those items that demonstrated strong contributions to their respective factors. This standard surpasses the usual minimum of 0.40, thereby enhancing the construct validity of the dimensional solution.

The item reduction process aimed to retain only the most relevant components for the final scale, focusing on removing items with low relevance (Boateng, 2018). The validation phase of the newly developed online complaint behavior scale involved applying various statistical analyses to identify its underlying dimensions. Confirmatory Factor Analysis (CFA) was used to assess the model's effectiveness and data suitability. Model fit was evaluated in three areas: absolute fit, incremental fit, and parsimonious fit.

Absolute fit checked how well the model replicated the observed data, using metrics such as chi-square (χ^2) with a p-value over 0.05, RMSEA less than 0.08, and GFI above 0.95. Incremental fit measured improvement over a baseline model with indices like AGFI, CFI, TLI, and NFI, all acceptable above 0.95. Parsimonious fit evaluated model complexity with the χ^2/df ratio, where values under 3.0 are deemed acceptable. These indices provided a thorough assessment of the model's adequacy (Hair *et al.*, 2019).

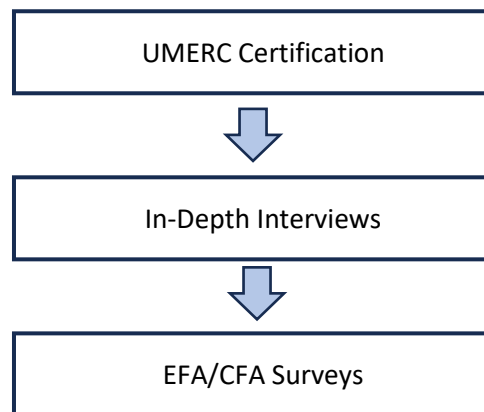


Figure 3: Data Gathering Procedure

Figure 3 outlines the methodical approach the researcher employed to gather essential data from the participants. Initially, prior to initiating the data collection, the researcher secured the required permissions from the University of Mindanao Ethics Review Committee (UMERC), under Protocol Number UMERC-2025-169. Once the UMERC approval was granted, letters were sent to the participants selected for the In-Depth Interviews to inform them about the study.

In-depth interviews with key participants were conducted after obtaining the necessary informed consent. Each interview lasted around 30 minutes. Two separate sets of surveys were conducted, with 250 participants each for Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The surveys were carried out through in-person interactions. Prior to taking part, participants were provided with clear explanations regarding the study's goals, methods, and any potential risks. Ethical considerations were rigorously adhered to, ensuring that the anonymity of all respondents was maintained in accordance with the country's Data Privacy Act of 2012, which governs the appropriate handling of data.

4. Results and Discussion

The subsequent discussions focus on the initial phase of the scale development process, which pertains to generating an item statement pool that reflects online complaint behavior. These discussions primarily focus on generating item statement pools from in-depth interviews, establishing the content validity, dimensionality, and sampling adequacy of the items based on the initial survey conducted in the study.

4.1 Generation of Item Pool from In-Depth Interviews

In-depth interview data were systematically converted into formalized item statements for scale development, reflecting customers' online complaint behavior. A total of 36 hypothetical but contextually grounded interview excerpts were gathered from eight identified interviewees (coded as IDI 1 to IDI 8), representing a diverse linguistic mix of English, Tagalog, and Bisaya. These responses were then translated and thematically aligned with the emerging domains of online complaint behavior.

The development process followed established best practices in qualitative-to-quantitative scale design (Boateng *et al.*, 2018), beginning with open coding of raw narrative data. Verbatim responses were carefully evaluated to preserve the authenticity and contextual nuances of participant perspectives. To ensure semantic clarity and psychological accessibility for future respondents, each raw statement was transformed into a declarative item statement using formal and behaviorally anchored language.

4.2 Content Validity

The content validity of the 36-item scale was quantitatively evaluated using both the Item-Level Content Validity Index (I-CVI) and the Scale-Level Content Validity Index based on the Average Method (S CVI/Ave). A binary scoring system was applied, wherein a score of 1 indicated that an expert rated the item as "essential." In contrast, a score of 0 was assigned if the expert rated the item as either "useful but not essential" or "not necessary." A panel of 10 subject matter experts participated in the evaluation.

Table 1: Item-Content Validity Ratio (I-CVR) with
Ten (10) Expert Panel for the Initial 36-Item Scale

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	CVR
Item 1	1	1	1	1	1	1	1	1	1	1	1.00
Item 2	1	1	1	1	1	1	1	1	1	1	1.00
Item 3	1	0	1	1	1	1	1	1	1	1	0.80
Item 4	1	1	1	1	1	1	0	1	1	1	0.80
Item 5	0	0	1	1	0	1	1	1	1	1	0.40
Item 6	0	0	1	0	0	0	0	1	1	1	-0.20
Item 7	0	0	1	0	0	0	0	1	1	1	-0.20
Item 8	0	0	1	1	0	1	1	1	0	1	0.20
Item 9	1	1	0	1	1	1	1	1	1	1	0.80
Item 10	0	1	0	0	0	1	1	1	0	1	0.00
Item 11	1	1	1	1	1	1	1	1	0	1	0.80
Item 12	1	1	1	0	0	1	0	1	1	1	0.40
Item 13	1	1	1	0	1	1	1	1	1	1	0.80
Item 14	1	1	1	1	1	1	1	1	1	1	1.00
Item 15	0	0	1	0	0	1	0	1	1	1	0.20
Item 16	0	1	1	0	0	1	0	1	1	1	0.20
Item 17	0	1	1	0	0	1	0	1	0	1	0.00
Item 18	0	1	1	0	1	1	0	1	0	1	0.20
Item 19	1	0	1	0	1	0	0	0	0	1	-0.20
Item 20	0	1	1	1	1	1	1	1	1	1	0.80
Item 21	0	1	1	0	1	1	1	0	1	1	0.40
Item 22	1	1	1	1	1	1	1	1	1	1	1.00
Item 23	0	0	1	1	1	0	1	1	0	1	0.20
Item 24	1	1	1	1	1	1	1	0	1	1	0.80
Item 25	0	1	1	0	0	1	1	1	0	1	0.20
Item 26	0	1	1	0	0	0	0	1	1	1	0.00
Item 27	1	0	1	1	1	1	1	1	1	1	0.80
Item 28	1	1	1	1	1	1	1	1	1	1	1.00
Item 29	1	1	1	1	1	1	1	1	1	1	1.00
Item 30	0	1	0	0	1	1	0	1	1	1	0.20
Item 31	1	1	1	0	1	1	1	1	1	1	0.80
Item 32	1	1	1	1	1	1	1	1	1	1	1.00
Item 33	1	1	1	1	1	1	1	1	1	1	1.00
Item 34	1	1	1	1	1	1	1	1	1	1	0.80
Item 35	1	1	1	1	1	1	1	1	1	1	1.00
Item 36	1	1	1	1	1	1	1	1	1	1	1.00
CVR(Critical) for a panel size (N) of 10 is 0.8.											0.556

As seen in Table 1, the I-CVI results revealed that 20 out of 36 items achieved scores equal to or greater than 0.80, indicating a high degree of agreement among experts regarding their essentiality. These items, therefore, met the recommended threshold and were deemed to possess acceptable content validity. In contrast, 16 items fell below the 0.80 threshold (specifically Items 5, 6, 7, 8, 10, 12, 15, 16, 17, 18, 19, 21, 23, 25, 26, and 30), suggesting insufficient consensus regarding their relevance. Of these, Items 10, 17, 19, and 26 received a CVI of 0.00, indicating that few experts considered them essential. Items 5, 6, 7, 8, 12, 15, 16, 18, 21, 23, 25, and 30 also demonstrated particularly weak ratings (CVI = 0.40 or lower), and thus, are recommended for deletion or substantial revision.

The computed S-CVI/Ave of 0.556 indicates that the overall content validity of the scale is poor. This suggests that less than 60% of the items were rated as relevant by the panel of experts, implying that the instrument may not adequately represent the construct it aims to measure. A low S-CVI/Ave value such as this raises concerns about the clarity, relevance, and appropriateness of the items included in the scale. Therefore, it is recommended to review and revise the items based on expert feedback to improve the content validity of the instrument. Further evaluation may be necessary after revisions to ensure that the revised scale better reflects the intended construct.

Table 2: Assumption of sampling adequacy and multidimensionality in factor analysis

Test		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.933
Bartlett's Test of Sphericity	Approx. Chi-Square	2679
	Degree of Freedom	190
	Significance	$p < 0.01$

4.3 Sampling Adequacy

Prior to conducting exploratory factor analysis (EFA), statistical assumptions were tested to evaluate the suitability of the dataset for factor extraction. These assumptions included assessments of sampling adequacy and the presence of sufficient intercorrelations among variables. Specifically, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were utilized as preliminary diagnostics.

As shown in Table 2, the KMO index yielded a value of 0.933, which exceeds the commonly accepted threshold of 0.60 for adequate sampling (Kaiser & Rice, 1974). Values closer to 1.00 indicate a higher degree of shared variance among items, suggesting that factor analysis is likely to yield reliable factors. The result of 0.933 is considered "marvelous" based on the interpretive guidelines provided by Kaiser (1974), and strongly supports the factorability of the correlation matrix.

Furthermore, Bartlett's Test of Sphericity was conducted to assess the suitability of the data for factor analysis. The test yielded a chi-square value of $\chi^2(190) = 2679$, with a significance level of $p < .001$. This significant result indicates that the correlation matrix is not an identity matrix, meaning that the variables are sufficiently correlated to justify

the application of factor analysis. Therefore, the data meet one of the key assumptions required for conducting exploratory factor analysis. Taken together, these findings confirm that the dataset meets the necessary likelihood extraction and VARIMAX rotation. The sample size and inter-item correlations are deemed adequate to support the extraction of latent constructs underlying the scale items.

4.4 Latent Roots Criterion

Table 3: Latent roots criterion

Factor	SS Loadings	% of Variance	Cumulative %
1	3.70	18.5	18.5
2	3.65	18.2	36.7
3	3.28	16.4	53.1

To establish the dimensionality of the scale, principal component analysis (PCA) was conducted using maximum likelihood extraction and VARIMAX orthogonal rotation. This approach was chosen to uncover the underlying structure of the dataset while enhancing interpretability and content clarity of the emerging factors (Henson & Roberts, 2006; Beavers *et al.*, 2013). In line with best practices in scale development, a stricter factor loading threshold of ± 0.50 was applied to retain only items with strong contributions to their respective components. This threshold exceeds the commonly accepted minimum of 0.40, thereby ensuring stronger construct validity in the dimensional solution.

Results of the latent roots criterion are presented in Table 3. According to Kaiser's rule, factors with eigenvalues greater than 1.0 are considered significant and retained for interpretation. The analysis revealed a three-factor solution. Factor 1 yielded a sum of squared loadings (SS) of 3.70 and accounted for 18.5% of the total variance. Similarly, Factor 2 also produced an SS of 3.65, explaining an additional 18.2% of the variance. Factor 3 also produced an SS of 3.28, explaining an additional 16.4% of the variance. Together, these three factors accounted for a cumulative 53.1% of the total variance, which exceeds the minimum variance threshold typically recommended for exploratory factor analysis in behavioral and social sciences (Hair *et al.*, 2010).

This three-dimensional structure, derived from the refined pool of items that loaded at or above ± 0.50 , indicates a meaningful clustering of constructs within the scale. It supports the emerging theoretical framework underlying online complaint behavior of consumers. The substantial proportion of variance explained and the strong loadings of retained items reflect both conceptual coherence and statistical robustness of the derived dimensions. These results provide a sound empirical foundation for subsequent confirmatory factor analysis and scale validation efforts.

4.5 Exploratory Factor Analysis

An exploratory factor analysis (EFA) was conducted to examine the underlying structure of a scale measuring online complaint behavior of consumers. Table 4 shows the rotated component matrix, further showing the items that clustered in the identified dimensions. The analysis utilized maximum likelihood estimation with VARIMAX rotation, and factor retention was determined via parallel analysis. The results yielded a three-factor solution, explaining a cumulative variance of 53.1% (Factor 1 = 18.5%, Factor 2 = 18.2%, Factor 3 = 16.4%), suggesting that the three extracted dimensions capture a substantial portion of the variability in responses.

Table 4: Rotated component matrix showing factor loadings of items in extracted dimensions via VARIMAX rotation

	Factor 1	Factor 2	Factor 3	Uniqueness
5. I frequently complain online when I experience poor service or product quality.	0.997			0.437
4. I use online complaints as a way to vent my frustrations about a bad service experience.	0.993			0.590
3. I express dissatisfaction online to inform other consumers about my negative experience.	0.784			0.555
6. I only complain online if my issue remains unresolved after several attempts to contact the company.	0.587			0.546
7. I complain online more when the problem affects my safety or well-being.	0.572			0.791
1. I complain online when I feel that a company's service has been unfair or unjust.	0.559			0.582
15. I tend to continue complaining if I am dissatisfied with the initial response.	0.554	0.523		0.672
8. I feel compelled to complain when the financial loss caused by the issue is significant.	0.519	0.540		0.613
18. My intention is to hold companies accountable by sharing my negative experiences publicly.		0.871		0.655
19. I aim to raise awareness about a company's poor practices through my online complaints.		0.708		0.599
10. I expect a prompt response when I post a complaint on a company's social media page.		0.652		0.716
17. I feel empowered when my online complaint prompts a company to take action.		0.616		0.636
16. I believe my complaints can influence other consumers' perceptions of a brand.		0.611		0.460
9. I prefer to provide detailed explanations rather than brief complaints.		0.544		0.562
14. I feel satisfied when my complaint is resolved efficiently and promptly.			0.814	0.233
13. I am content when the company provides an apology or explanation for the issue.			0.684	0.496
12. I am satisfied if my complaint results in a refund or compensation.			0.648	0.498
20. I believe that my complaints contribute to improving the quality of services or products.			0.580	0.414
11. I feel dissatisfied if my online complaint goes unnoticed by the company.			0.560	0.569
2. I am motivated to complain when I believe it will result in compensation or a solution.				0.739

Note: Items with no factor loadings did not pass the ± 0.50 factor loadings required in the analysis and are therefore eliminated

Factor loadings and uniqueness values for all items are presented in Table 4. Items with high factor loadings and low uniqueness values indicate strong representation within the extracted dimensions. Factor 1, which we label as “Emotionally Driven Complaining,” includes items that focus on the customer’s emotional expression, personal frustration, and perceived injustice if a poor product or service occurs. The

highest-loading items in Factor 1 include " I frequently complain online when I experience poor service or product quality." ($\lambda = 0.997$, uniqueness = 0.437) and " I use online complaints as a way to vent my frustrations about a bad service experience." ($\lambda = 0.993$, uniqueness = 0.590). These items imply that companies must recognize that online complaints are often driven not just by rational problem-solving motives but by consumers' emotional need to vent frustration and seek validation after negative experiences. This result aligns with Tronvoll's (2011) findings, which indicate that negative emotional frustration is the strongest predictor of complaint behavior directed at service providers.

Furthermore, it suggests that many complaints arise primarily as a form of emotional coping rather than purely to obtain redress or influence others. This means businesses should prioritize swift, empathetic, and human-centered responses that acknowledge customers' feelings and provide reassurance, as such approaches are likely to be more effective in de-escalating dissatisfaction and preserving trust than generic or purely procedural replies.

Additionally, "I express dissatisfaction online to inform other consumers about my negative experience" ($\lambda = 0.784$, uniqueness = 0.555) underscores the communicative intent behind online complaints, particularly the role of consumer advocacy. This item reflects the proactive nature of sharing negative experiences, not just as a personal outlet, but as a warning or guidance to others. The relatively low uniqueness value suggests that this item is well-explained by the underlying factor, which captures consumer-driven motivations for public complaint behavior. Individuals scoring high on this factor are likely to view online platforms as tools for influence, using them to shape perceptions, demand accountability, and potentially drive change in service quality. This aligns with Zheng's (2024) findings, emphasizing that individuals often engage in online complaint behavior to alert others about product or service failures.

On the other hand, Factor 2, which we label as "Empowered and Advocacy-Based Complaining," includes items that reflect a proactive, empowered attitude, the consumer believes their complaints can make a difference, raise awareness, and influence outcomes. The highest-loading item in factor 2, "My intention is to hold companies accountable by sharing my negative experiences publicly" ($\lambda = 0.871$, uniqueness = 0.655), emphasizes the consumer's desire to use public platforms as a means of enforcing corporate accountability. This statement reflects a strategic and purpose-driven approach to online complaint behavior, where expressing dissatisfaction is not only personal but also a form of social responsibility. The high factor loading indicates a strong association with the underlying construct, while the moderate uniqueness value suggests that a significant portion of the item's variance is explained by this factor. Consumers who score high on this dimension are likely to view public feedback as a tool for promoting transparency, influencing company practices, and protecting fellow consumers. This supports the conclusions drawn by Thackeray and Hunter (2010), highlighting the important role that technology plays in lodging their negative experience as a means of raising awareness among others.

Furthermore, "I aim to raise awareness about a company's poor practices through my online complaints" ($\lambda = 0.708$, uniqueness = 0.599) reflects the advocacy-oriented motivation behind public expressions of dissatisfaction, where consumers seek to inform others and influence corporate behavior. Another notable item, "I expect a prompt response when I post a complaint on a company's social media page" ($\lambda = 0.652$, uniqueness = 0.716), highlights the expectation of immediate engagement and accountability from companies in digital spaces.

These findings suggest that Factor 2 captures a form of socially engaged and feedback-driven complaint behavior, where consumers not only express grievances but also anticipate responsiveness and transparency from organizations. The combination of high loadings and thematically aligned content points to a consumer mindset that values both awareness-raising and timely resolution in online complaint contexts. The results align with Istanbuluoglu's (2017) analysis, showing that both a faster initial response and a prompt resolution contribute to greater satisfaction with how complaints are managed. This study indicates that a swift response enhances satisfaction, regardless of the consumers' goals.

Lastly, Factor 3, which we label as "Complaint Resolution Expectations," includes items that center on expectations of resolution, desire for compensation, and satisfaction with responses, which primarily focus on the results of the complaint. The highest-loading item in factor 3, "I feel satisfied when my complaint is resolved efficiently and promptly" ($\lambda = 0.814$, uniqueness = 0.233), underscores the importance of resolution speed and efficiency in shaping customer satisfaction. Its high loading and low uniqueness indicate that this item is strongly representative of the underlying factor.

Narayan *et al.* (2021) emphasize the significance of effectively resolving complaints, suggesting that it plays a crucial role in ensuring customer retention. Similarly, "I am content when the company provides an apology or explanation for the issue" ($\lambda = 0.684$, uniqueness = 0.496) highlights the value consumers place on acknowledgment and transparency during the complaint resolution process. Together, these items suggest that Factor 3 reflects satisfaction-driven expectations, where efficient handling and meaningful communication are key to restoring trust and achieving resolution.

This factor appears to capture outcome-focused complaint behavior, emphasizing both prompt action and relational repair. Notably, uniqueness values in Factor 3 are relatively moderate to low (ranging from 0.233 to 0.739), further reinforcing that this dimension effectively explains variance in satisfaction-oriented complaint resolution, emphasizing the importance of timely responses, clear communication, and customer reassurance. These findings align with those of Odoom and Hinson (2020) and Sengupta (2018), emphasizing the significance of recovery strategies, like issuing an apology to affected customers during service failures, on customer perception and satisfaction.

4.6 Confirmatory Factor Analysis

The subsequent discussions focus on the final phase of the scale development process, which pertains to the validation through confirmatory factor analysis of the generated item statements reflecting online complaint behavior.

Table 5: Factor loadings for CFA Model 1

Factor	Indicator	Std. Loading	SE	Z	p-value
Factor 1	Item3	0.587	0.0528	9.25	< .001
	Item6	0.654	0.0447	10.57	< .001
	Item7	0.542	0.0430	8.42	< .001
	Item4	0.605	0.0519	9.64	< .001
	Item1	0.580	0.0478	9.10	< .001
	Item5	0.568	0.0511	8.91	< .001
Factor 2	Item16	0.521	0.0464	8.21	< .001
	Item9	0.486	0.0457	7.57	< .001
	Item17	0.545	0.0440	8.61	< .001
	Item10	0.631	0.0471	10.38	< .001
	Item19	0.638	0.0460	10.48	< .001
	Item18	0.595	0.0477	9.56	< .001
Factor 3	Item20	0.350	0.0496	5.03	< .001
	Item14	0.512	0.0560	7.63	< .001
	Item13	0.616	0.0493	9.38	< .001
	Item12	0.606	0.0500	9.25	< .001
	Item11	0.659	0.0482	10.38	< .001

As shown in Table 5, the results of CFA Model 1 confirmed a three-factor structure consisting of 17 retained items, each loading significantly on its designated latent construct. The first factor, labeled Emotionally Driven Complaining, is composed of 6 items (Items 3, 6, 7, 4, 1, 5). These items demonstrated moderate standardized loadings, ranging from 0.568 to 0.654, all statistically significant ($p < .001$). The highest loading was observed for Item 6 (“I only complain online if my issue remains unresolved after several attempts to contact the company”), suggesting that consumers, particularly those in younger demographics, view online complaints as a secondary or last-resort strategy. This behavior reflects a sense of fairness and patience, where individuals exhaust direct channels before resorting to public platforms.

The item's strong loading implies that the underlying factor captures escalation-based complaint behavior, characterized by a structured approach to resolving issues—first privately, then publicly if necessary. This underscores the importance of effective and timely customer service in preventing dissatisfaction from becoming publicly visible. Items related to advocacy, emotional expression, fairness, and personal impact (e.g., Items 3, 7, 4, 1, and 5) further reinforce the strategic and emotionally driven foundations of this factor. These items highlight how online complaints serve not only as a response to poor service but also as tools for advocacy, emotional release, and calls for accountability.

The second factor, labeled Empowered and Advocacy-Based Complaining, comprises 6 items (Items 16, 9, 17, 10, 19, 18). These items similarly exhibited moderate standardized loadings, ranging from 0.486 to 0.638, all of which were statistically

significant at the $p < .001$ level. The highest loading in this factor was Item 19 (“I aim to raise awareness about a company’s poor practices through my online complaints”), underscoring the centrality of social responsibility and public advocacy in the online complaint behaviors valued by the respondents. This highlights a tendency to use digital platforms not just for personal resolution, but to influence broader awareness and accountability.

Other items reflect a focus on social influence (Item 16: “I believe my complaints can influence other consumers’ perceptions of a brand”), expressive communication (Item 9: “I prefer to provide detailed explanations rather than brief complaints”), empowerment (Item 17: “I feel empowered when my online complaint prompts a company to take action”), responsiveness (Item 10: “I expect a prompt response when I post a complaint on a company’s social media page”), and accountability (Item 18: “My intention is to hold companies accountable by sharing my negative experiences publicly”). Collectively, these items suggest that respondents associate effective online complaint behavior with transparency, influence, and timely corporate engagement—reflecting a strategic, emotionally aware, and socially conscious approach to digital consumer activism.

The third factor, labeled Complaint Resolution Expectations, comprises of 5 items (Items 20, 14, 13, 12, 11). These items similarly exhibited low to moderate standardized loadings, ranging from 0.350 to 0.659, all of which were statistically significant at the $p < .001$ level. The highest loading in this factor was Item 11 (“I feel dissatisfied if my online complaint goes unnoticed by the company”), underscoring the importance of recognition and corporate engagement in shaping consumer satisfaction. This highlights a growing expectation among digital consumers for acknowledgment and responsiveness from companies when issues are raised online. Rather than viewing complaints solely as expressions of dissatisfaction, respondents appear to see them as part of a dialogue—one in which company silence signals neglect, while acknowledgment affirms the consumer’s voice and value. This orientation is further supported by related items that reflect dissatisfaction when companies fail to respond, indicating that acknowledgment and engagement are essential components of what respondents perceive as responsible and impactful consumer action.

Other items emphasize outcome-oriented motivations and emotional resolution in online complaint behavior. Item 20 (“I believe that my complaints contribute to improving the quality of services or products”) reflects a proactive, improvement-driven mindset, where consumers see themselves as partners in quality enhancement. Item 14 (“I feel satisfied when my complaint is resolved efficiently and promptly”) highlights the importance of timeliness and procedural efficiency in shaping consumer satisfaction. Emotional closure is evident in Item 13 (“I am content when the company provides an apology or explanation for the issue”), suggesting that acknowledgment and communication are critical to restoring trust. Finally, Item 12 (“I am satisfied if my complaint results in a refund or compensation”) illustrates the role of tangible restitution in fulfilling complainants’ expectations. Together, these items point to a pragmatic,

resolution-focused approach to online complaining, where effectiveness, responsiveness, and fairness drive consumer engagement and satisfaction.

Table 6: Factor covariances – model 1

Factors	Std. Covariance	SE	Z	p-value
Factor 1 – Factor 2	0.890	0.0393	22.70	< .001
Factor 1 – Factor 3	0.644	0.0625	10.30	< .001
Factor 2 – Factor 3	0.862	0.0477	18.10	< .001

To further establish the robustness of the three-factor structure in CFA Model 1, the analysis proceeded to estimate inter-factor covariances, as shown in Table 6. These estimates help assess the distinctiveness and relational dynamics of the latent constructs. The estimated covariances were 0.890 (SE = 0.0393, $z = 22.70$, $p < .001$) for factor 1-2, 0.644 (SE = 0.0625, $z = 10.30$, $p < .001$) for factor 1-3, 0.862 (SE = 0.0477, $z = 18.10$, $p < .001$) for factor 2-3. This statistically significant and moderately strong positive covariance indicates that the two factors are interrelated but conceptually distinct. Collectively, these results support the theoretical coherence and empirical distinctiveness of the three-factor model. The adequate variance within each factor, coupled with their moderate correlation, reflects a well-defined measurement structure suitable for assessing online complaint behavior.

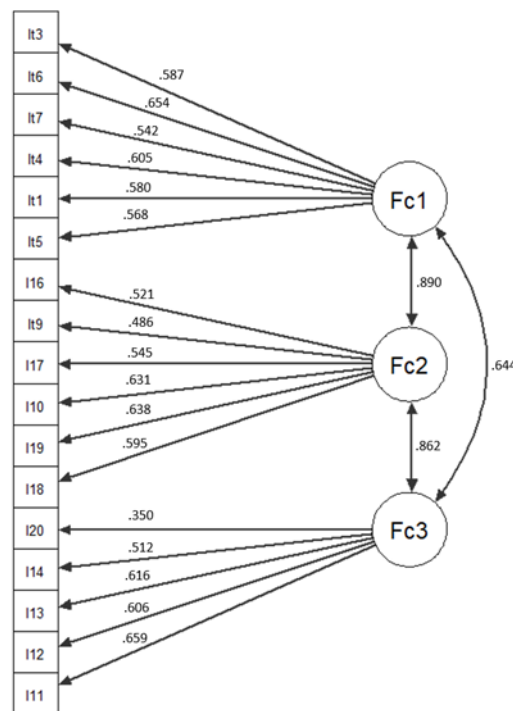


Figure 4: CFA baseline model diagram

The diagram for the measurement model in Figure 4 represents the baseline measurement model (CFA Model 1). Each latent factor is associated with six and five observed items, respectively, all of which show standardized factor loadings ranging

from 0.350 to 0.659. These loadings indicate strong and statistically significant relationships between the latent variables and their respective indicators, thereby affirming the internal consistency and convergent validity of the scale at this stage.

Moreover, the covariance across the three factors is moderately positive (0.890, 0.644, 0.862), suggesting that while factor 1, factor 2, and factor 3 are conceptually distinct, they are moderately interrelated, which is theoretically consistent with the integrated nature of online complaint behavior.

Crucially, the model includes multiple non-zero error covariances, as shown by the dashed bidirectional arrows connecting certain item residuals. These correlated error terms indicate localized misfit, suggesting that some items may share overlapping content or semantic redundancy not accounted for by the latent constructs alone. While allowing these error covariances may improve model fit from a statistical standpoint, their presence highlights the need for theoretical scrutiny and potential item refinement. Given these results, CFA Model 1 serves as a plausible but not optimal representation of the hypothesized measurement structure. The inclusion of several residual covariances and high standardized loadings without full error independence suggests that the model may benefit from further re-specification. Guided by modification indices and grounded in theoretical justification, the next step involves refining the model through item pruning or reallocation to enhance both its parsimony and empirical fit.

Table 7: Factor loadings for CFA model 2

Factor	Item	Std. Loading	SE	Z	p-value
Factor 1	Item3	0.553	0.0538	8.55	< .001
	Item6	0.668	0.0447	10.77	< .001
	Item7	0.553	0.0430	8.59	< .001
	Item4	0.608	0.0520	9.66	< .001
	Item1	0.545	0.0487	8.40	< .001
	Item5	0.570	0.0513	8.90	< .001
Factor 2	Item16	0.505	0.0467	7.90	< .001
	Item9	0.460	0.0461	7.12	< .001
	Item17	0.509	0.0443	7.95	< .001
	Item10	0.623	0.0468	10.31	< .001
	Item19	0.625	0.0470	10.06	< .001
	Item18	0.567	0.0484	9.00	< .001
Factor 3	Item20	0.346	0.0496	4.96	< .001
	Item14	0.513	0.0560	7.63	< .001
	Item13	0.616	0.0493	9.37	< .001
	Item12	0.609	0.0500	9.27	< .001
	Item11	0.659	0.0483	10.35	< .001

Table 7 presents the standardized factor loadings for Model 2, which reflects a modified three-factor solution implemented following the evaluation of Model 1 (Table 6). While the initial model demonstrated an acceptable factor structure, Model 2 was specified to improve model fit based on empirical indicators such as modification indices and theoretical considerations, consistent with best practices in confirmatory factor analysis (Brown, 2015).

The refined model retained the original three-factor structure, representing Factor 1: Emotionally Driven Complaining, Factor 2: Empowered and Advocacy-Based

Complaining, and Factor 3: Complaint Resolution Expectations, while likely incorporating minor adjustments such as error covariances between specific item pairs. All items remained assigned to their original factors, and all standardized loadings in Model 2 were statistically significant ($p < .001$), demonstrating consistent contributions of each item to its corresponding latent construct.

In Factor 1, loadings ranged from 0.545 to 0.668, reflecting moderate to strong associations. Notably, Item 6 and Item 4 showed slight increases in loadings (e.g., Item 6 increased from 0.654 to 0.668), suggesting a moderate improvement in the measurement precision for those items. In contrast, Factor 2 loadings ranged from 0.460 to 0.625, representing a slight decrease overall compared to Model 1, which may indicate subtle shifts in the underlying latent structure due to the model refinement process. Factor 3 showed high stability across both models, with loadings in Model 2 ranging from 0.346 to 0.659, nearly identical to Model 1. This consistency supports the robustness of Factor 3 and its indicators.

Overall, the modest differences in loadings between Model 1 and Model 2 suggest that the modifications contributed to a refined estimation of item–factor relationships without compromising the theoretical integrity of the model. These revisions underscore the importance of iterative model testing and theory-driven adjustments to address areas of local misfit and enhance overall model parsimony (Kline, 2016).

Table 8: Factor covariances for the modified three-factor solution (CFA Model 2)

Factors	Std. Covariance	SE	Z	p-value
Factor 1 – Factor 2	0.932	0.0423	22.00	< .001
Factor 1 – Factor 3	0.643	0.0636	10.10	< .001
Factor 2 – Factor 3	0.885	0.0506	17.50	< .001

Table 8 further supports the internal coherence and structural validity of the revised three-factor model through an analysis of factor covariances. The correlation between Factor 1 and Factor 2 was estimated at 0.932 ($SE = 0.0423$, $z = 22.00$, $p < .001$), indicating a strong and statistically significant relationship between these two latent constructs. Similarly, the covariances between Factor 1 and Factor 3 (0.643, $SE = 0.0636$, $z = 10.10$, $p < .001$) and between Factor 2 and Factor 3 (0.885, $SE = 0.0506$, $z = 17.50$, $p < .001$) were both positive and significant.

These findings suggest that while the three factors are conceptually distinguishable, they are also highly interrelated, reflecting a shared underlying structure among the measured constructs. The robust relationship between Factor 1 and Factor 2 may imply overlapping dimensions of the broader latent domain, while the slightly lower covariance with Factor 3 supports its relative distinctiveness within the model.

Table 9: Residual Covariances for Covaried Error in CFA Model 2

		Estimate	SE	Z	p	Stand. Estimate
Item3	Item3	0.4803	0.0481	9.99	< .001	0.694
	Item1	0.0989	0.0323	3.06	0.002	0.227
Item6	Item6	0.2888	0.0320	9.03	< .001	0.554
Item7	Item7	0.3102	0.0309	10.04	< .001	0.694
Item4	Item4	0.4305	0.0443	9.71	< .001	0.631
Item1	Item1	0.3962	0.0395	10.04	< .001	0.703
Item5	Item5	0.4344	0.0437	9.94	< .001	0.675
Item16	Item16	0.3984	0.0380	10.49	< .001	0.745
	Item17	0.0545	0.0251	2.17	0.030	0.145
Item9	Item9	0.4012	0.0377	10.65	< .001	0.788
	Item10	0.0906	0.0273	3.32	< .001	0.236
Item17	Item17	0.3538	0.0333	10.63	< .001	0.741
	Item18	0.0747	0.0263	2.84	0.005	0.199
Item10	Item10	0.3669	0.0363	10.11	< .001	0.612
Item19	Item19	0.3482	0.0361	9.65	< .001	0.609
Item18	Item18	0.3991	0.0394	10.14	< .001	0.678
Item20	Item20	0.4467	0.0416	10.73	< .001	0.880
Item14	Item14	0.5121	0.0513	9.99	< .001	0.737
Item13	Item13	0.3491	0.0387	9.02	< .001	0.620
Item12	Item12	0.3656	0.0399	9.16	< .001	0.630
Item11	Item11	0.3248	0.0371	8.76	< .001	0.566

Table 9 provides an overview of the residual covariances in Model 2, offering further insight into item-level measurement precision and areas of potential localized misfit. As expected in a well-specified model, the majority of residual variances were statistically significant ($p < .001$), reflecting the unique variance in each observed variable not accounted for by the latent factor structure.

Standardized residual variances ranged from 0.554 (Item 6) to 0.880 (Item 20), indicating generally moderate to high proportions of item-specific variance. For instance, Item 20 exhibited the highest standardized residual (0.880), suggesting a substantial amount of unexplained variance despite its relatively low factor loading. In contrast, Item 6 had the lowest residual (0.554), reflecting a more efficient representation of its underlying latent construct.

In addition to residual variances, several residual covariances between item pairs were also statistically significant. For example, the residual covariance between Item 3 and Item 1 was estimated at 0.227 ($SE = 0.0323$, $Z = 3.06$, $p = .002$), while Item 9 and Item 10 shared a residual covariance of 0.236 ($SE = 0.0273$, $Z = 3.32$, $p < .001$). These localized correlations suggest shared variance beyond what is captured by the factor model—possibly due to overlapping item content, similar phrasing, or common response tendencies. Additional residual associations were observed between Item 16 and Item17 (0.145, $p = .030$) and Item 17 and Item 18 (0.199, $p = .005$), potentially reflecting conceptual or semantic proximity among items within the same factor.

Overall, the pattern of residual variances and covariances supports the adequacy of the model's structure, while also highlighting specific item pairs that may benefit from refinement in future model iterations. These findings underscore the importance of

evaluating residual diagnostics as part of the confirmatory factor analysis process to ensure a parsimonious and well-fitting model (Brown, 2015; Kline, 2023).

Table 10: Factor loadings for CFA Model 3

Factor	Item	Std. Loading	SE	Z	p-value
Factor 1	Item3	0.556	0.0537	8.60	< .001
	Item6	0.667	0.0447	10.75	< .001
	Item7	0.553	0.0430	8.58	< .001
	Item4	0.610	0.0519	9.71	< .001
	Item1	0.546	0.0487	8.41	< .001
	Item5	0.566	0.0514	8.82	< .001
Factor 2	Item16	0.482	0.0466	7.57	< .001
	Item9	0.457	0.0465	7.01	< .001
	Item17	0.491	0.0445	7.65	< .001
	Item10	0.629	0.0467	10.44	< .001
	Item19	0.609	0.0482	9.55	< .001
	Item18	0.547	0.0483	8.69	< .001
Factor 3	Item20	0.356	0.0497	5.10	< .001
	Item13	0.533	0.0517	7.74	< .001
	Item12	0.537	0.0530	7.72	< .001
	Item11	0.660	0.0516	9.69	< .001

Table 10 presents the standardized factor loadings for Model 3, representing a further refinement of the three-factor solution previously examined. This version was developed following additional model diagnostics and fit evaluation, with the aim of improving parsimony and construct clarity without altering the theoretical foundation of the measurement model. As with previous models, Model 3 preserves the original factor structure, maintaining three distinct but related latent variables.

All item loadings remained statistically significant ($p < .001$), confirming the continued relevance of each item in representing its corresponding latent factor. In Factor 1, standardized loadings ranged from 0.546 (Item 1) to 0.667 (Item 6), reflecting stable and moderately strong relationships across items. The consistency in loading values suggests that Factor 1 continues to be reliably measured, with minimal deviation from previous models.

Factor 2 showed loadings between 0.457 (Item 9) and 0.629 (Item 10), slightly lower overall than in earlier versions of the model. These values indicate moderate associations between items and the latent construct, and may reflect ongoing refinement in capturing the conceptual focus of this factor. Notably, Item 10 and Item 19 retained strong loadings (0.629 and 0.609, respectively), anchoring the factor's structure.

For Factor 3, item loadings ranged from 0.356 (Item 20) to 0.660 (Item 11). The loading for Item 20 remained low but statistically significant, consistent with earlier observations, suggesting that this item contributes uniquely but less strongly to the factor. Other items within Factor 3 demonstrated moderately strong loadings (e.g., Item 11 = 0.660), supporting the construct's internal consistency.

Overall, Model 3 preserves the conceptual integrity of the factor structure established in earlier models, while introducing modest adjustments to improve model fit and measurement efficiency. The significance and magnitude of the standardized

loadings confirm the robustness of the latent constructs and underscore the model's alignment with theoretical expectations.

Table 11: Factor covariances for the modified three-factor solution (CFA model 3)

Factors	Std. Covariance	SE	Z	p-value
Factor 1 – Factor 2	0.950	0.0444	21.40	< .001
Factor 1 – Factor 3	0.731	0.0694	10.50	< .001
Factor 2 – Factor 3	0.986	0.0627	15.70	< .001

Table 11 presents the factor covariances for Model 3, further illustrating the relationships among the three latent constructs. The covariance between Factor 1 and Factor 2 was estimated at 0.950 (SE = 0.0444, Z = 21.40, $p < .001$), indicating a very strong and statistically significant association between these two factors. Similarly, Factor 2 and Factor 3 demonstrated an exceptionally high covariance of 0.986 (SE = 0.0627, Z = 15.70, $p < .001$), suggesting substantial conceptual overlap. The covariance between Factor 1 and

Factor 3 was also strong, estimated at 0.731 (SE = 0.0694, Z = 10.50, $p < .001$).

These results suggest that while the three factors are theoretically distinct, they are highly interrelated in practice, particularly Factor 2 and Factor 3, which approach near collinearity. This pattern may reflect an underlying shared dimension or functional similarity among constructs within the broader theoretical framework. The elevated inter-factor correlations underscore the need to interpret the factors not as isolated domains but as interconnected components of a larger psychological or behavioral system. While strong correlations can enhance structural coherence, such high values also warrant consideration of potential redundancy and could inform future model adjustments (e.g., second-order factor models or construct re-specification) if theoretical justification allows (Brown, 2015; Kline, 2016).

Table 12 summarizes the residual variances and covariances for Model 3, offering further insight into item-level uniqueness and potential sources of localized misfit. As in prior models, all residual variances were statistically significant ($p < .001$), indicating that each item retains a proportion of unexplained variance after accounting for its respective latent factor. Standardized residual variances ranged from 0.556 (Item 6) to 0.873 (Item 20), which reflects a range of moderate to high item-specific variance. Consistent with earlier models, Item 20 continued to exhibit the highest residual variance (0.873), suggesting that although it remains a statistically significant indicator of Factor 3, it may capture additional variance not fully explained by the latent structure.

Table 12: Residual covariances for covaried error in CFA model 3

		Estimate	SE	Z	p	Stand. Estimate
Item3	Item3	0.4784	0.0479	9.98	< .001	0.691
	Item1	0.0977	0.0322	3.04	0.002	0.225
Item6	Item6	0.2896	0.0320	9.05	< .001	0.556
Item7	Item7	0.3104	0.0309	10.05	< .001	0.695
Item4	Item4	0.4286	0.0442	9.70	< .001	0.628
Item1	Item1	0.3957	0.0395	10.03	< .001	0.702
Item5	Item5	0.4373	0.0439	9.96	< .001	0.680
Item16	Item16	0.4102	0.0385	10.65	< .001	0.768
	Item17	0.0783	0.0267	2.93	0.003	0.202
	Item18	0.0868	0.0288	3.02	0.003	0.211
Item9	Item9	0.4027	0.0380	10.61	< .001	0.791
	Item10	0.0902	0.0276	3.27	0.001	0.236
Item17	Item17	0.3657	0.0347	10.55	< .001	0.759
	Item18	0.0953	0.0276	3.45	< .001	0.245
Item10	Item10	0.3623	0.0359	10.08	< .001	0.604
Item19	Item19	0.3601	0.0378	9.53	< .001	0.630
Item18	Item18	0.4126	0.0399	10.33	< .001	0.701
Item20	Item20	0.4432	0.0414	10.69	< .001	0.873
Item13	Item13	0.4028	0.0421	9.58	< .001	0.716
	Item12	0.1034	0.0328	3.15	0.002	0.254
Item12	Item12	0.4133	0.0438	9.45	< .001	0.712
Item11	Item11	0.3242	0.0413	7.84	< .001	0.564

In addition to residual variances, several statistically significant residual covariances were observed between item pairs, reflecting shared variance not explained by the factor model alone. For example, the residual covariance between Item 3 and Item 1 was estimated at 0.225 ($p = .002$), while Item 9 and Item 10 also shared a residual covariance of 0.236 ($p = .001$), suggesting possible overlap in item content or response tendencies. Similarly, Item 16 demonstrated residual associations with both Item 17 (0.202, $p = .003$) and Item 18 (0.211, $p = .003$), and Item 17 and Item 18 also covaried (0.245, $p < .001$), indicating a small network of interrelated residual effects within Factor 2. Within Factor 3, a residual covariance of 0.254 ($p = .002$) was found between Item 13 and Item 12, again pointing to potential content or contextual overlap between those items.

Overall, the pattern of statistically significant residual variances and localized covariances supports the adequacy of the model's structure, while also identifying specific item pairs that may benefit from refinement in future model iterations. These observations reinforce the value of examining residual diagnostics in CFA to ensure that model improvements do not obscure localized dependencies that could impact interpretability or validity (Brown, 2015; Kline, 2023).

Figure 5 illustrates the validated three latent constructs of the Online Complaint Behavior scale: Factor 1 (Emotionally Driven Complaining), Factor 2 (Empowered and Advocacy-Based Complaining), and Factor 3 (Complaint Resolution Expectations), with observed items It1–It20 reflecting their strength of association.

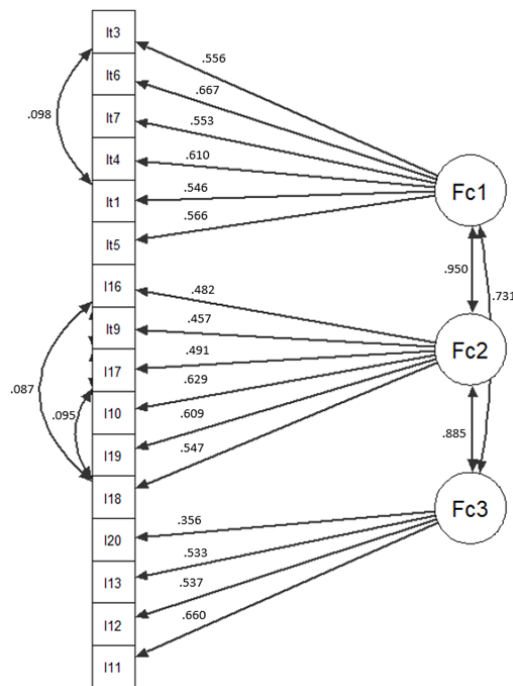


Figure 5: CFA final model diagram

For Factor 1, Emotionally Driven Complaining, loadings range from 0.546 to 0.667, suggesting that items like It3, It6, and It7 effectively capture consumers' emotional motivations for online complaints. Factor 2, Empowered and Advocacy-Based Complaining, shows loadings between 0.457 and 0.629, indicating valid contributions, particularly from It10 (0.629) and It19 (0.609), which reflect consumer empowerment and advocacy. Factor 3, Complaint Resolution Expectations, has loadings from 0.356 to 0.660, with It20 showing the weakest association but still significant. This factor indicates that consumers expect online complaints to lead to corrective actions. High correlations among the factors (0.950 between Factors 1 and 2, 0.885 between Factors 2 and 3) highlight their interconnectedness, though they raise concerns about discriminant validity. Error covariances suggest that some items share variance beyond their latent factors, which in turn improves the model's fit.

In conclusion, the CFA Final Model Diagram supports a robust three-factor solution for online complaint behavior, illustrating that Filipino consumers' complaints are driven by emotional expression, empowerment, and expectations for resolution.

Table 13 summarizes key fit statistics for Models 1, 2, and 3, providing a comprehensive evaluation of model adequacy and improvement across iterations. All three models demonstrated acceptable fit according to established benchmarks, with relative chi-square (χ^2/df) values below 3.00, and incremental fit indices (CFI, TLI) exceeding the 0.90 threshold. Model 3 exhibited the best overall fit, achieving a relative chi-square of 1.97, which falls below the more stringent "good" cutoff of 2.00, indicating a well-fitting model.

Table 13: Comparison of Model Fit Indices for CFA Models 1–3

Fit Index	Standard Cutoff Criteria	Model 1	Model 2	Model 3
χ^2/df (Relative χ^2)	< 3.00 (acceptable); < 2.00 (good)	2.27	2.10	1.97
CFI (Comparative Fit Index)	≥ 0.90 (acceptable); ≥ 0.95 (excellent)	0.933	0.945	0.954
TLI (Tucker-Lewis Index)	≥ 0.90 (acceptable); ≥ 0.95 (excellent)	0.919	0.933	0.944
RMSEA (Root Mean Square Error of Approximation)	≤ 0.08 (acceptable); ≤ 0.05 (good)	0.065	0.060	0.056
SRMR (Standardized Root Mean Square Residual)	≤ 0.08 (acceptable); ≤ 0.05 (good)	0.061	0.057	0.054
AIC (Akaike Information Criterion)	Lower is better (used for model comparison)	4801.92	4780.43	4761.08
BIC (Bayesian Information Criterion)	Lower is better (used for model comparison)	4923.86	4907.21	4889.14

Incremental fit indices also favored Model 3, with a CFI of 0.954 and TLI of 0.944, approaching the excellent fit range (≥ 0.95). The RMSEA and SRMR for Model 3 were 0.056 and 0.054, respectively, demonstrating improved fit relative to Models 1 and 2 while remaining within acceptable thresholds (≤ 0.08). Notably, Model 3 consistently showed lower Akaike Information Criterion (AIC = 4761.08) and Bayesian Information Criterion (BIC = 4889.14) values compared to earlier models, supporting its superiority in balancing model complexity and explanatory power.

These fit indices collectively indicate a progressive improvement from Model 1 through Model 3, reflecting the effectiveness of iterative model refinements guided by theory and empirical evidence. Model 3's superior fit underscores its appropriateness as the final measurement model, capturing the underlying factor structure with greater precision and parsimony (Schumacker & Lomax, 2016; Hair *et al.*, 2019).

5. Recommendations

This study successfully produced a psychometrically sound and theoretically grounded instrument for measuring online complaint behavior among consumers. The validated scale offers practical utility for academics, digital marketing professionals, and customer experience strategists.

For business practitioners, particularly in customer service and brand management, it is recommended that the validated scale be integrated into customer feedback analysis tools and complaint handling systems. The identified dimensions of online complaint behavior—such as emotionally driven complaining, empowered and advocacy-based complaining, and complaint resolution expectations—can serve as diagnostic indicators to assess consumer sentiment and tailor response strategies accordingly. Brands can enhance service recovery by aligning digital complaint-handling approaches with the specific behavior patterns captured by the scale.

Marketing and customer experience teams are encouraged to use the scale for audience segmentation and persona development. Understanding which dimensions dominate among particular customer groups can inform more personalized

interventions, chatbot scripts, or platform-based responses. The insights gained from the scale can be embedded into training programs for digital community managers, enabling staff to interpret better, de-escalate, and resolve online complaints effectively.

The findings also carry strategic implications for platform and policy design. Organizations should revisit their social media and feedback mechanisms to ensure they support constructive online engagement, allow visibility into issue resolution, and foster consumer empowerment. Transparent complaint tracking, real-time feedback loops, and publicly visible resolution pathways can improve brand trust and reduce escalation of negative sentiment.

Meanwhile, academic institutions offering programs in marketing, communication, or consumer psychology may include the validated scale in coursework to enrich discussions on digital consumer behavior and brand-consumer interaction. It can serve as a basis for case analyses, simulation activities, or applied research projects in online engagement dynamics.

Future research may explore the generalizability of the scale across different industries (e.g., e-commerce, telecommunications, public services) and demographic groups. It is recommended that the scale be subjected to multi-group confirmatory factor analysis (CFA) to assess measurement invariance across age, gender, or digital literacy levels. Additionally, longitudinal studies could investigate how online complaint behavior patterns evolve over time and how they relate to key outcomes such as customer loyalty, advocacy, or brand switching behavior.

6. Conclusion

This study set out to develop and validate a context-specific scale that captures the dimensions of online complaint behavior among consumers. Through a rigorous, multi-phase scale development process—beginning with qualitative input, followed by exploratory factor analysis (EFA), and culminating in confirmatory factor analysis (CFA)—the study produced a psychometrically sound three-factor structure that reflects the complex nature of how consumers express dissatisfaction in digital spaces.

The initial item pool was developed through content analysis of qualitative data and refined using expert validation. Content validity was established with strong CVR values and a satisfactory S-CVI/Ave, ensuring the scale's relevance and representativeness. EFA results revealed a three-factor model that explained a substantial proportion of the variance, suggesting a multidimensional construct of online complaint behavior.

Subsequent CFA procedures confirmed the robustness of this structure. Three CFA models were tested, with Model 3 showing the best overall fit. Key indices—such as CFI, RMSEA, and SRMR met or exceeded conventional thresholds, while reductions in AIC and BIC values supported its parsimony and statistical superiority. Moreover, the model's internal structure was supported by significant and theoretically coherent factor

loadings, factor covariances, and residual diagnostics, which together affirmed the construct validity of the scale.

The final model captures three distinct yet interrelated facets of online complaint behavior: emotionally driven complaining, advocacy-based complaining, and complaint resolution expectations. These findings provide empirical clarity to the nature of digital complaint behaviors, a topic increasingly relevant in today's consumer environment but often overlooked in scale development literature.

By offering a validated and theory-informed measurement tool, this study contributes to the broader understanding of consumer behavior in online contexts. The instrument can be utilized by marketers, platform managers, and researchers aiming to design better response systems, enhance customer experience strategies, and conduct future studies on digital consumer expression.

Acknowledgements

I want to express my sincere gratitude to everyone who contributed to the completion of this study.

First, I would like to thank my research adviser, Dr. Sophremiano B. Antipolo, for his guidance, support, and expertise throughout this process.

I also appreciate Dr. Rosalia Gabronino, Dr. Joel Tan, Dr. Rebecca Maquiling, Dr. Vicente Montaña, Dr. Stilo Floyd Schneider, and Dr. Jomarie Baron for their valuable input in validating the qualitative research instrument. Their evaluations significantly improved the quality of this work.

Thanks to Dr. Exequiel Gono, Dr. Eric Rellon, Dr. Ronie Panes, Dr. Tomas Diquito Jr., Dr. Eva Marie Sam, Dr. John Vianne Murcia, Dr. Darylle Hanna Millanes, Dr. Ronel Dagohoy, Dr. Victoria Ligan, and Dr. Ricardo Jimenez for their insightful assessments and recommendations, which strengthened the quantitative research instrument.

I recognize Dr. John Vianne Murcia for his expert statistical support, assisting with data analysis and interpretation.

My heartfelt appreciation goes to Ma'am Grace Lastimoso Dupio, our dedicated Administrative Officer, for her continuous support, and to Ma'am Amor Irish Lozano, our School President, for her leadership and encouragement throughout this journey.

To my family—especially my wife, Kreselda J. Imba, and my children, Jk-Leen Abigail Imba and John Eli Imba—I am deeply grateful for their love, patience, and understanding during this academic pursuit.

I also thank my friends for their encouragement and kindness, which have been a source of strength along the way.

Finally, I extend my gratitude to Almighty God, whose strength and wisdom have enabled me to accomplish this significant undertaking.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

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