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Coping, rumination, and electronic word-of-mouth: Segmenting consumer responses to service failure via fuzzy clustering

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ABSTRACT

This study deploys a novel clustering algorithm to identify distinct segments of consumers based on the strategies they use to 'cope' with service failure. Drawing from different anger prototypes and felt intensity therein, it identifies how consumer segments employ a diverse range of rumination behaviours following service failure, with this used to predict manifestations of eWOM thereafter. Individuals with experience of service failure within the Iranian hotel industry context were surveyed, with findings identifying four discrete consumer segments underpinned by varied combinations of active, expressive, and denial-based post-failure coping behaviours. Each distinct segment activated different rumination behaviours. Further, logit models demonstrate that three eWOM archetypes are driven by different predictors, suggesting that consumers' online behaviours following service failure are heterogeneous and shaped by the coping strategy employed.

1. Introduction

Driven by increased awareness of the importance of customer retention, engagement, and satisfaction in shaping service evaluations, scholars and practitioners alike have sought to understand how negative emotions (e.g., betrayal, frustration, anger) influence consumer responses to service failure (Strizhakova, Tsarenko, & Ruth, 2012). As a result, underpinned by a desire to meet expectations throughout the customer journey (Harmeling et al., 2017), many firms recognise that deeper understanding of consumer coping strategies can provide the foundations from which to 'make things better' when service provision inevitably 'falls short' (Choi & La, 2013).

Yet, consumer responses to service failure are not homogeneous nor manifest in isolation, with Lazarus and Folkman (1984) proposing a stress-and-coping appraisal-based model which argues that a combination of personality and situational factors combine to shape how individuals 'cope' with suboptimal experiences (e.g., service failure). This 'coping' relates to both the 'experience' and 'treatment' of any resultant emotional distress, with literature distinguishing between problem-focused and emotion-focused coping strategies therein (Folkman & Moskowitz, 2004). For affected individuals, problem-focused coping strategies minimize stress through modifying oneself or the environment, whereas emotion-focused coping utilizes cognitive techniques to reframe stressful events, reducing their post-fact emotional impact (Martin & Dahlen, 2005).

Academic attention often prioritizes when-and-how an individual uses cognitive coping strategies to regulate and process stressful events (Folkman & Moskowitz, 2004). However, having experienced service failure, consumer coping strategies are *diverse*, with this including rumination, self-blame, denial, blaming others, avoidance, and positive reappraisal (Sengupta et al., 2015; Tsarenko & Strizhakova, 2013). Yet, existing studies fail to thoroughly investigate whether a) different consumer segments show greater inclination towards particular coping strategies and b) whether different consumer anger prototypes (and their felt intensity) typically stimulate different coping strategies.

Further, coping strategies influence the nature and extent to which consumers ruminate on negative events (e.g., service failure) which, in-turn, can impact on their propensity to share (negative) WOM (Strizhakova et al., 2012). This is intensified by the post-service empowerment afforded to the contemporary consumer, where dissatisfaction can

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rapidly mutate into negative Word-of-Mouth (WOM), enacted both in-person and online (eWOM) (Surachartkumtonkun et al., 2013). This is particularly potent when consumer anger is triggered by service providers failing to deliver on promises; when service failure exists across multiple levels; or when a firm's behaviour is considered notably egregious (Harrison-Walker, 2012). Nevertheless, despite its potential influence over ongoing firm success and its established role as a post-consumption outcome (Dedeoğlu et al., 2020), extant studies do not adequately investigate the psychological drivers of negative eWOM following service failure.

Yet, some argue that coping predicated on anger and rumination can directly stimulate post-experience (negative) eWOM thanks to the indelible reach and ubiquity of online platforms (Wakefield & Wakefield, 2018). With this in mind, Moschis (2007) suggests that attention should be paid to empirically investigating the *consequences* of service failure. In response, this study aims to illustrate the interactions between different coping behaviours to identify meaningful segments of consumers based on the post-failure coping strategies they adopt. To do so, we adopt a novel segmentation method underpinned by a fuzzy clustering algorithm for fuzzy data (Fuzzy *C*-medoids for Fuzzy Data (FCM-FD)). Unlike traditional clustering methods, this fuzzy clustering algorithm is advantageous as it allows consumers to belong to different clusters simultaneously (D'Urso et al., 2016). This fuzzy clustering method differs from that deployed in previous studies (e.g., Souiden et al., 2013; Rogers et al., 2017; Zhou et al., 2017; Tohidi et al., 2023) across marketing scholarship, which typically employ Fuzzy C-Means (Table 1). Further, when conducting segment profiling for consumer characteristics, anger prototypes, and rumination strategies, we employ a fractional multinomial logit (FML) model (Papke & Wooldridge, 1996), which has similarly received scant consideration across psychological marketing literature.

The contribution of this study is therefore threefold. First, the findings reveal distinct consumer segments based on the combination of coping strategies they employ in response to service failure. Unlike previous studies (e.g., Sengupta et al., 2015), we demonstrate that different consumer groups use a diverse combination of coping strategies, with these sometimes appearing inconsistent at first glance. Second, the findings demonstrate how each distinct segment differs with regards to characteristics, anger prototypes, and felt intensity therein, alongside the diverse role rumination can play following service failure. Doing so, we extend previous studies investigating consumer rumination following service failure (e.g., Hur & Jang, 2019; Sajtos & Chong, 2018) by demonstrating that diverse anger prototypes affect consumer coping strategies in different ways for different segments.

Third, we demonstrate how the above can stimulate different forms of eWOM (spreading eWOM; denigrating service provider(s) online; warning others not to use the service provider), specific to our newly-identified (segmented) consumer clusters. Doing so, our findings extend extant literature on the outcomes of consumer coping strategies following service failure. We move beyond research concerned with consumer satisfaction and intentions to complain (Sengupta et al., 2015; Tsarenko & Strizhakova, 2013) by instead identifying how different types of eWOM emerge as discrete outcomes of service failure, the nature of which differs depending on the combined coping strategy adopted by the affected consumer segment therein. From a methodological perspective, we therefore also highlight the utility of combining FCM-FD with FML models in furthering our understanding of service failures, complementing other – more common - fuzzy clustering approaches adopted across extant marketing studies (e.g., Lim et al., 2013; Baray & Pelé, 2020; Tohidi et al., 2013).

This paper continues by first discussing the primary consumer coping strategies commonly identified across literature, underpinned by Lazarus and Folkman's (1984) Coping Theory. Thereafter, literature on a range of relevant concepts is reviewed, where different anger porotypes, rumination, and eWOM are discussed. From here, the research design is presented, with emphasis placed on describing the novel clustering algorithm adopted and the methodological contribution of this study within the context of service failure. Results are then presented and discussed, with study limitations offered by way of conclusion.

2. Literature review

2.1. Theoretical background: coping theory, service failure, and consumer coping strategies

Coping Theory suggests that, when faced with adversity, individuals deploy a range of approaches (i.e., coping strategies) to reduce stress and reframe their experiences (Lazarus & Folkman, 1984). Within service settings, consumers thus typically employ such coping strategies when faced with suboptimal service and/or service failures to rationalise (and subsequently deal with) *negative* experiences (Gannon et al., 2022). Consumer coping strategies are therefore inherently emotional, underpinned by an individual's experience, understanding, processing, and response to less than desirable circumstances.

Yet, while the gamut of potential consumer responses to service failure is wide, Folkman et al. (1986) contend that they can be condensed into two broad categories: a) trait-oriented coping or b) process-oriented coping, with both contingent upon psychological and environmental context. For the former (trait-oriented), individual characteristics and the nature of the 'stressful event' are of limited importance. Instead, coping emerges as a reaction to the *psychological* and *environmental stimuli* central to the incident itself. However, this deviates from that which is commonly identified across service failure literature, which often contends that consumer characteristics shape the nature of individual coping behaviours (Cambra-Fierro & Melero-Polo, 2017).

Folkman et al. (1986, p.993) note that this process-oriented coping focuses "on what the person actually thinks during specific stressful encounters, and how this evolves as the encounter unfolds". To this end, Lazarus and Folkman's (1984) stress-and-coping appraisal-based model argues that personality *and* situational factors combine to shape post-event coping processes. Coping Theory thus proposes that, following negative incidents, individuals first assess whether they believe that the experience was stressful (primary appraisal). They then consider whether they need to 'cope' with the stressful situation and the direction in which blame should be attributed (secondary appraisal). Finally, individuals generate a strategy to cope with the stressful situation (coping). Lazarus and Folkman (1984) suggest two dimensions of coping therein: emotion-focused (i.e., thoughts and actions focused on regulating emotions) and problem-focused (i.e., developing strategies to resolve a situation). However, this dichotomy oversimplifies the complexity of post-failure coping behaviours; Nielsen and Knardahl (2014) argue that these two dimensions act neither in conflict nor isolation. Instead, they contend that both emotion-focused and problem-focused coping work in concert, emerging simultaneously in the ruminative period following stressful events (e.g., service failure).

Yet, recent years have given rise to competing models aimed at providing both understanding and categorisation of individual coping behaviours. This extends into the domain of consumer behaviour literature, with emphasis placed on investigating the coping strategies adopted by those faced with suboptimal consumption experiences (Han et al., 2015; Weijo et al., 2019; Yi & Baumgartner, 2004). However, prominent coping models typically follow similar principals, focussing on known aspects of coping behaviour. For example, recognizing that when consumers experience negative emotions, they typically seek emotional support and information Duhachek (2005) identified three dimensions of consumer coping: expressive (i.e., emotional venting and support), active (i.e., rational, positive thinking) and denial (i.e., repudiation and avoidance).

In operationalising Duhachek's (2005) consumer coping framework, recent marketing literature typically contends that consumers blame

Table 1
Summary of existing studies on a) service failures and coping, rumination, anger and eWOM b) Segmentation studies using Fuzzy clustering.

Author/Year	*Coping style*	*Rumination*	*Anger*	*eWOM*	*Other topics*	*Data Analysis (segmentation or other methods)*	*Main Findings*	*Limitations*
a) Coping and rumination studies								
Bougie et al. (2003)	X	X	✓	X		-Structural Equations Modelling (SEM)	-Anger mediates the relationship between service encounter dissatisfaction and customers' behavioural responses-Examines negative WOM as an outcome	-Does not consider three of the four main constructs in our study- Does not employ a segmentation approach
Duhachek (2005)	✓	X	✓	X		-Exploratory Factor Analysis (EFA)-Confirmatory Factor Analysis (CFA)-Correlation and multi-group analysis (MGA)	-Develops a multi-dimensional scale to measure consumer coping-Establish links between coping dimensions and discrete emotions-Anger activates different coping styles	-Does not consider two of the four main constructs in our study- Does not employ a segmentation approach
Duhachek & Iacobucci (2005)	✓	X	X	X		- SEM	-Personality traits of consumers interact with cognitive appraisals to influence consumers' choice of coping strategies	-Does not consider three of the four main constructs in our study-Does not employ a segmentation approach
Bodey & Grace (2006)	X	X	X	X		-Multivariate analysis of Variance (MANOVA)-Discriminant analysis	-Attitude toward complaining, perceived control and self-monitoring were significant discriminating variables between "complainers" and "non-complainers".	-Employs a segmentation approach that does not involve clustering but rather the use of MANOVA and discriminant analysis to ascertain segments-Does not consider any of the variables in our study
Bonifield & Cole (2007)	X	X	✓	X		-Analysis of Variance (ANOVA) and MANOVA-Mediation analysis and Analysis of Co-variance (ANCOVA)	-Anger has a role in explaining retaliatory behaviours- Both anger and regret account for the effect of appraisals on conciliatory behaviours.-Recovery efforts that reduce anger decrease retaliatory behaviours-Examines WOM as part of post-purchase behaviours	- Does not consider three of the four main variables in our study-Employs an experimental design rather than a segmentation approach
Duhachek & Kelting (2009)	✓	X	X	X		-CFA-Cluster analysis-EFA and correlation-ANOVA	-Establishes a coping repertoire and this is an important determinant of consumers' coping confidence appraisals-The coping repertoire is also empirically distinguishable from coping efficacy and correlate well with self-complexity-The coping repertoire is different from coping flexibility	- Does not consider three of the four main variables in our study-Employs cluster analysis to identify segments of coping flexibility rather than coping strategies
Gelbrich (2010)	✓	X	✓	X		-ANOVA-Partial Least Square Structural Equations Modelling (PLS-SEM)	-The coincidence of anger (frustration) and high levels of helplessness enhances vindictive nWOM (support-seeking nWOM)-The coincidence of anger (frustration) and low levels of helplessness enhances vindictive complaining (problem-solving complaining)-A retrospective explanation mitigates anger, whereas a prospective explanation mitigates helplessness	-Examines only confrontative coping and support seeking-coping-Rather than eWOM the study examines nWOM-Does not employ a segmentation approach
Gabbott et al. (2011)	✓	X	X	X		- SEM-Hierarchical moderated regression analysis	- The results show that the level of emotional intelligence does predict consumer responses to service failure in terms of customer satisfaction and behavioural intention-Examines WOM as part behavioural intentions	-Does not consider three of the four main variables in our study-Does not employ a segmentation approach

(*continued on next page*)

Table 1 (*continued*)

Author/Year	*Coping style*	*Rumination*	*Anger*	*eWOM*	*Other topics*	*Data Analysis (segmentation or other methods)*	*Main Findings*	*Limitations*
Strizhakova et al. (2012)	✓	✓	✓	✓		- SEM-Mediation analysis	-In more and less conventional service channels, rumination decreases positive behavioural intentions and increases negative word-of-mouth intentions.- Customer coping strategies mediate effects of anger on rumination. Specifically, while expressive coping mediates effects of anger on rumination, active coping mediates these effects in more conventional service channels, whereas denial mediates these effects in less conventional channels.- Customer tendency to ruminate moderates effects in less conventional channels.- Examines both traditional WOM and eWOM	-Does not employ a segmentation approach for coping strategies
Tsarenko & Strizhakova (2013)	✓	X	X	X		-SEM	-Emotional intelligence has a positive association with active and expressive coping strategies but a negative relationship with denial.- Expressive coping leads to greater complaining, whereas denial decreases it.-Consumer self-efficacy mediates the relationship between emotional intelligence and active coping strategy. In contrast, the effect of self-efficacy on expressive strategy is negative	-Does not consider three of the four main variables in our study-Does not employ a segmentation approach
He & Harris (2014)	X	X	✓	X		-ANOVA and ANCOVA-Regression	-People with higher moral identity centrality are less likely to moral disengagement of vindictive negative WOM, when their moralawareness of the behaviour is higher.- Individuals may engage in moral disengagement of vindictive negative WOM, if they have higher anger toward the service failure, and when their moral awareness is lower.-Examines negative WOM	-Does not consider three of the four main variables in our study-Considers only vindictive negative and support-seeking negative WOM-Does not employ a segmentation approach
Fliess & Volkers (2019)	✓	X	✓	X		- qualitative analysis	-Four categories of factors that caused customers to endure a negative event were identified-Customers either experienced inner turmoil (if they perceived having the option to stay or leave) or felt captive; both impacted their well-being and coping strategies in different ways.	-Does not consider two of the four main variables in our study-Touches on rumination but does not identify the different types-Does not employ a segmentation approach
Hur & Jang (2019)	X	✓	X	X		- EFA and SEM	-Self-focused rumination and distraction increase consumer forgiveness-Provocation-focused rumination increases the negative effects of service failure severity on consumer forgiveness	-Does not consider three of the four main variables in our study-Does not employ a segmentation approach
b) Segmentation studies using Fuzzy clustering								
Tohidi et al. (2023)	X	X	X	X	Organic food	-Crisp and fuzzy clustering (K-means, K-medoids, fuzzy C-means and Gath-Geva fuzzy clustering)	- Psychological factors more important than demographic factors in segmentation of organic food market	-Does not consider any of the four variables in the current study

(*continued on next page*)

Table 1 (*continued*)

Author/Year	*Coping style*	*Rumination*	*Anger*	*eWOM*	*Other topics*	*Data Analysis (segmentation or other methods)*	*Main Findings*	*Limitations*
Baray & Pelé (2020)	X	X	X	X	Second car market	-Factorial analysis and fuzzy clustering	-Identifies geographic areas that are typical of a certain supply and specifies the optimal prices. Also, utilizes the types of vehicles for sale in these areas as part of segmentation to inform marketing strategy	-Does not consider any of the four variables in the current study
Zhou et al. (2017)	X	X	X	X	Household electricity consumption	-Fuzzy C-means clustering	-Different electricity consumption patterns of different households identified and the effectiveness of the clustering-based model demonstrated.-The results support the development of personalized and targeted marketing strategies for the improvement of energy consumption	-Does not consider any of the four variables in the current study
Rogers et al. (2017)	X	X	X	X	The presence of double jeopardy and negative double jeopardy in a product category on Twitter	-Fuzzy C-means clustering	-There is a negative double jeopardy with original tweets-Larger brands suffer more by an increased negativity due to a larger proportion of tweets associated with them	-Does not consider any of the four variables in the current study
Safari et al. (2016)	X	X	X	X	Customer lifetime value	-Fuzzy C-means clustering and fuzzy analytic hierarchy process (AHP)	-Improved capability for a company to evaluate its customers by dividing them into nine ranked segments	-Does not consider any of the four variables in the current study
Lim et al. (2013)	X	X	X	X	Luxe bargain shoppers	-Fuzzy clustering	-Identifies four distinct segments: deal hunters, sale-prone shoppers, active luxe-bargain shoppers, and royal shoppers-Consumer segment exhibits differences in consumer characteristics, demographics, and behavioural tendencies	-Does not consider any of the four variables in the current study
Souiden et al. (2013)	X	X	X	X	Nutrition labelling	-Fuzzy C-means clustering	-Identifies three segments that are different in their understanding and use of nutrition labels, knowledge of nutrition and manipulation of quantitative information on nutrition.	-Does not consider any of the four variables in the current study
Current study	✓	✓	✓	✓		- Fuzzy *C*-medoids for fuzzy data (FCM-FD) clustering	-Different segments of coping styles following service failure- Segments differ on rumination and anger levels-Segments differ on propensity to express different types of eWOM	

service providers following sub-optimal (or failed) service encounters, with this likely to stimulate negative emotional responses (active coping). Yet, under such circumstances, consumers also often seek expressive support in order "to marshal social resources to improve [their] emotional and/or mental state" (Duhachek, 2005, p.45). Further, some consumers share their experience of sub-optimal service after-the-fact with those they trust and respect as a way of regulating their emotions and feelings (expressive coping). However, consumer responses to service failure are not always active or immediately discernible; some consumers cope with service failure in a passive manner in an attempt "to completely close off oneself mentally from a source of stress" (Duhachek, 2005, p.46). As such, despite widespread adoption, Duhachek's framework remains limited as a) it focuses on self-efficacy as a situational determinant of coping, disregarding situational control and, b) it conflates consumers' enduring coping preferences with the influence of dispositional personalities. Nevertheless, this three-dimensional approach remains the most common way for scholars to capture and categorise consumer coping mechanisms following service failure.

Accordingly, applied coping studies reveal that the stress-and-coping model can stimulate diverse behavioural and emotional outcomes (Albrecht, Walsh, & Beatty, 2017). For example, Strizhakova et al. (2012) found that rumination was crucial in developing an understanding of how consumers cope with service failure, highlighting ways in which rumination can stimulate negative eWoM. Further, Tsarenko and Strizhakova (2013) identified links between emotional intelligence and both active and expressive coping strategies. Mattila and Patterson (2004) found that Western consumers are more likely to adopt direct coping behaviour(s), while non-confrontational approaches are typically adopted by Eastern consumers. Further, historical perspectives on consumer coping suggest that such strategies directly impact upon emotions and subsequently influence behaviour with regards to service

evaluation and decision-making by offsetting distressed emotional states (Williams, 2014). Thus, following service failure, consumers in highly-negative emotional states are likely to engage in different coping strategies (Duhachek, 2005; Tsarenko & Strizhakova, 2013). Yet, while prior research focuses on establishing direct relationships between coping strategies and negative emotions in the event of service failure (e.g., Albrecht et al., 2017; Tao, Karande, & Arndt, 2016; Yi & Baumgartner, 2004), *how* different coping strategies are enacted remains overlooked. This is surprising given the established view that negative consumer emotions (e.g., anger) shape behavioural outcomes.

2.2. Consumer rumination and anger

While its role in shaping individual responses to negative stimuli is established, there remains little consensus on the definition of rumination (Thomsen, 2006). Within the context of consumer coping strategies, rumination denotes the "repetitive thoughts and behaviours related to symptoms of distress and the potential causes and consequences of these symptoms" (Liu, He, & Li, 2019, p.1355). Yet, broader psychology literature connects rumination to different negative effects, including discrepancies between events and goals, or as an associative antecedent to more obvious emotional outcomes, such as anger and/or anxiety (Thomsen, 2006). For example, following the goal process theory of renunciation (Martin & Tesser, 2006), Bui et al. (2011, p.1071) suggest that "rumination on a particular topic helps consumers progress toward their ideal goal until discrepancies between actual and ideal goals becomes non-existent". Thus, rumination may shape the duration, intensity, or frequency of a negative 'affect' (Thomsen, 2006).

In this study, we focus on anger as a negative 'affect'. In the service failure context, anger is "a common and morally-relevant emotional reaction" (He & Harris, 2014, p.140) that occurs "when people attribute a goal incongruent event to external sources" (Gelbrich, 2010, p.568). Anger emerges when an individual perceives a negative outcome as being caused by others (Funches, 2011), and it is typically characterised in two ways: vengeful anger and problem-focused anger (Antonetti, 2016). While vengeful anger stimulates a desire to 'hurt' the 'offending' party (i.e., service provider, employee, etc.), problem-focused anger focuses attention on a specific outcome: feelings of frustration (Antonetti, 2016). Consistent with the study's objective to investigate negative eWOM as an outcome of service failure, we place primary focus on vengeful anger. Yet, there is no reliable scale to measure vengeful anger and several anger prototypes exist across literature: anxiety, frustration, and annoyance are commonly used to conceptualize this negative emotion (Antonetti, 2016). Anger has also been linked to rumination (Martin & Dahlen, 2005), with vengeful anger most likely to encourage consumers to ruminate on prior incidents and/or stimulate a desire to hurt service providers (Antonetti, 2016). However, whether different anger prototypes activate such behaviours has yet to be comprehensively identified.

Anger in the service failure context can be elicited from perceptions of broken promises, unfair treatment, and hostility from service providers (Funches, 2011). When consumers reach the negative emotional state common post-failure, levels of rumination may increase, with emphasis placed on seeking revenge and/or emotional support, alongside a desire to spread negative WOM (Nolen-Hoeksema et al., 2008; Strizhakova et al., 2012). Yet, rumination is not the only coping strategy consumers activate following service failure (Strizhakova et al., 2012). Those who encounter service failures are likely to engage in expressive and active coping and are less likely to distract themselves from the sub-optimal situation at hand (Strizhakova et al., 2012). Psychology literature confirms that different coping behaviours are highly correlated because each tap into different facets of emotion-focused coping (Carver & Connor-Smith, 2010; van der Kaap-Deeder et al., 2016). This implies that different coping behaviours can prove congruous, but more importantly, that coping behaviours predict rumination (Strizhakova et al., 2012). For example, consumers who engage strongly in rumination following service failure are more likely to demonstrate escapist behaviours, with coping strategies designed to release and realise their self-directed thoughts (Liu et al., 2019; Strizhakova et al., 2012).

To this end, Lu and Sinha (2017, p.411) highlight that "rumination may deplete mental resources, exacerbate depression, reduce self-control, increase impulsive and aggressive responses to provocations, and cause negative thinking, binge eating and drinking, and poor problem solving". Following service failure, consumers may exhibit high levels of rumination underpinned by unresolved emotional anguish, with coping mechanisms often enacted in a tangible manner. This can include actively engaging in behaviour harmful to firms, such as switching service providers or spreading negative WOM (Liu et al., 2019; Lu & Sinha, 2017; Moe & Trusov, 2011). Literature thus contends that different coping strategies may stimulate different levels of rumination, with this contingent upon the level of consumer anger manifest following service failure (Strizhakova et al., 2012; Porath, MacInnis, & Folkes, 2010).

2.3. eWOM

With the growth of the internet and social media, marketers are increasingly interested in the effects, influence, and antecedents of eWOM (Liu, Steenkamp, & Zhang, 2018). It is well-established that service failure can lead to unfavourable eWOM (Au, Buhalis, & Law, 2014). However, service failure does not always do so. For example, post-failure, consumers typically consider whether the service provider correctly dealt with the incident, whether appropriate solutions were provided to resolve the failure, and whether communication was apposite throughout. Yet, this process is complicated by the increasingly open and social nature of eWOM platforms. As consumer eWOM and service provider replies are often publicly available online, other consumers can gain insights into the intricacies of this two-way communication (VanNoort & Willemsen, 2012). Further, per Wakefield and Wakefield (2018), non-economic failures (e.g., poor customer service) receive greater scrutiny when compared to economic failures (e.g., faulty products), yet both can motivate negative eWOM. To this end, Liang and Scammon (2011) suggest that eWOM facilitates communication by enabling both problem-focused and emotion-focused coping strategies.

Yet, the nature of the relationship between consumers and service providers can temper negative WOM post-failure (DeWitt & Brady, 2003). Similarly, sharing eWOM can encourage rumination following both positive and negative events and consumption experiences (Berger, 2014). Accordingly, studies argue that the emotions elicited following service failure (and the coping strategies enacted by consumers thereafter) can stimulate negative WOM (Thomas et al., 2017; Yi & Baumgartner, 2004), with consumer eWOM triggered by negative emotions (e.g., anger) and rumination varying across consumer groups (Bushman, 2002). To this end, demographic variables (e.g., age) can moderate the relationship between service recovery, coping strategies, emotions, and eWOM (Kim et al., 2018; Moliner-Velázquez et al., 2015).

As such, in capturing the review of existing studies into service failure and related concepts outlined throughout this section, Table 1 (below) highlights that while consumer coping strategies are commonly examined (Duhachek, 2005; Gelbrich, 2010; Fliess & Volkers, 2020), their emergence is rarely linked to rumination and anger. Indeed, only Strizhakova et al. (2012) examine consumer coping styles alongside rumination and anger as combined antecedents of both traditional and online word-of-mouth outcomes. However, in contrast with this study, Strizhakova et al. (2012) do not segment customers based on their coping style and do not use demographics as an explanatory variable for their results.

3. Methodology

3.1. Data collection procedure

Data was primarily collected via a quantitative survey. However, following Gerbing and Anderson (1988), the questionnaire instrument was developed from insight gleaned from semi-structured interviews with hotel employees and customers (n = 30), alongside an extensive literature review. Pre-survey interviews helped identify factors capable of influencing consumer emotions, coping strategies, and issues specific to service failure within the hotel context. This process can minimise Common Method Variance (CMV) (Podsakoff et al., 2003). Interviews ranged from short intercept-style conversations to longer in-depth discussions lasting 45-minutes. Participants were asked to be precise about: their feelings related to a previously-experienced service failure and/or critical incident; the reasons/rationalization underpinning such feelings; and how they reacted to the service failure and evaluated the 'offending' firm . The qualitative sample size was controlled by the principle of saturation, with thematic analysis used to identify patterns therein (Creswell & Creswell, 2018). This process was fluid, with codes revised as ideas developed. As service failure is a sensitive topic, anonymity and confidentiality were assured. Ultimately, the qualitative phase was crucial in identifying the constructs deployed in the main quantitative stage of the inquiry.

A professional research company with experience of operating within Iran were trained and informed about the nature of study, with questionnaires distributed to hotel customers during 'check-out' via purposeful sampling. Despite a burgeoning domestic consumer services sector, the Iranian context remains largely overlooked with regards to service failure and recovery processes therein, with only a handful of studies published in this area in recent years (e.g., Gannon et al., 2022). Using a self-administrated face-to-face approach, we identified a random sample of hotel guests who had stayed for at least one night at four- and five-star hotels within a major Iranian city during 2018. This city is a leading destination in Iran for both domestic and international visitors. At the request of the hotels *and* participants, all identifiable information has been anonymized. For local customers, the questionnaire was translated into Farsi and back-translated into English to verify item-meanings.

Additionally, the confidentiality of survey responses was guaranteed. Harman's single-factor approach was used to evaluate CMV by adding all constructs into an exploratory factor analysis. Findings revealed 6 factors with Eigenvalues < 1, accounting for 68.51% of total variance, with the first factor reporting only 31% of total variance (i.e., >50% which did not explain most of the variance). Coelho et al.'s (2021) unmeasured method factor was also used. We measured the average variance of items and the method factor. Findings revealed that the average variance linked to items was 58%, while the average method-based variance was 1.4% (41:1). Hence, CMV did not shape our findings.

Overall, 1000 guests were surveyed. Following identification, participants were screened to ensure that they had experienced service failure during their stay and that the main purpose of their stay was 'leisure and tourism' to achieve consistency across the dataset. 885 useable questionnaires were returned, constituting an 85% response rate, which is highly satisfactory and representative of the population (Fowler, 2002). There is no rule of thumb determining sample size for segmentation studies using fuzzy algorithms (Khoo-Lattimore et al., 2019); however, the sample size herein exceeds the 600 required for convenience sampling (95% confidence interval, ±5% margin error, and 0.5 proportion).

3.2. Measures

To ensure content validity, questionnaire constructs were adapted from extant literature. All measures were anchored at 1= 'strongly disagree' and 5= 'strongly agree'. Three dimensions capturing consumer coping strategies (expressive (7-items), active (7-items) and denial (3-items)) were borrowed from Strizhakova et al. (2012) and Duhachek (2005). Consistent with Shaver et al. (1987) and Strizhakova et al. (2012), 5 items were used to measure consumer anger. For consumer rumination, 5 items were used to capture the extent to which service failure incidents lingered in participants' minds (adapted from Strizhakova et al., 2012; Wade et al., 2008). Finally, the eWOM measure included 6 items adapted from Gelbrich (2010) and Strizhakova et al. (2012).

3.3. Data analysis

Likert-scales (and ordinal data therein) are the most popular way of segmenting consumer response data. This type of data coverts judgements into linguistic expressions that are then transformed into numbers for analytical purposes; increasing uncertainty and decreasing the precision of data captured through subjective judgements (Davidov et al., 2014; Disegna et al., 2018; Biasetton et al., 2023). Thus, to obtain trustworthy, accurate segments based on clustering that can correctly inform practitioners, it is essential to address the uncertainty embedded in such data. One way of addressing such issues a-posteriori is to transform Likert-scale data into 'fuzzy numbers', which can then be used as inputs for clustering algorithms (D'Urso et al., 2016). We used Coppi et al.'s (2012) procedure to convert Likert-scale data into fuzzy numbers (a detailed overview of this procedure can be found in Khoo-Lattimore et al., 2019).

As segmentation variables are fuzzy data, a suitable clustering algorithm for fuzzy data must be adopted. In this study, we suggest the fuzzy *C*-medoids for fuzzy data (FCM-FD) algorithm as the most suitable approach for segmenting consumers based on various coping strategies. Several justifications guided the choice of this unsupervised clustering algorithm (Hwang et al., 2007). First, fuzzy clustering algorithms (when compared to hard clustering algorithms such as hierarchical clustering with Ward linkage and *k*-means) allow the assignment of units to different clusters simultaneously rather than restricting each to a single cluster. This implies that the result of a fuzzy clustering is a membership degree matrix in which each element describes how much a unit belongs to a cluster and the sum of the membership degrees related to a unit equals 1 (D'Urso & Massari, 2013; McBratney & Moore, 1985). This allows for a more realistic multidimensional description of the data, which can thus better satisfy managerial requirements (Zhang et al., 2013).

Second, fuzzy clustering algorithms are computationally more efficient than hard clustering algorithms because dramatic changes in the cluster's membership are less likely (D'Urso 2007; Heiser & Groenen, 1997). Third, Heiser and Groenen (1997) demonstrated that fuzzy clustering algorithms are less affected by local optima problems as they avoid the creation of undesired final clusters. Fourth, the membership degrees computed per respondent and cluster allow the verification of whether a 'second-best cluster' (i.e., one almost as good as the best cluster) per respondent exists; a result which hard clustering algorithms cannot reveal (Everitt et al., 2001).

Our choice of using fuzzy *C*-medoids instead of fuzzy *C*-means (i.e., the two most common fuzzy clustering algorithms for fuzzy data) was based on two factors. First, an important difference between fuzzy *C*-means and fuzzy *C*-medoids algorithms stems from the latter's ability to represent final clusters as actual observed units ('medoids') rather than 'virtual' units ('prototypes') computed as the weighted means of units belonging to the same cluster (Kaufman & Rousseeuw, 2005; Khoo-Lattimore et al., 2019). Second, the fuzzy *C*-means algorithm for fuzzy data is inappropriate for our analysis given the nature of our collected data. We use Likert-type ordinal scale data for which the distance between scale points cannot be defined nor presumed equal (Jamieson, 2004; Dolnicar, 2020). As such, the computation of the mean is an inappropriate measure to deploy herein. To simplify this, Jamieson (2004) highlights that the average value between "good" and "fair" is

not "fair- and-a-half" for Likert-scale data. Nevertheless, scholarly discussion on whether researchers should compute the distance between scale points remains ongoing (Harpe, 2015). However, herein, we adopt the position that Likert-type scales are neither continuous nor interval but instead should be treated as ordinal data (Biasetton et al., 2023).

We followed Khoo-Lattimore et al.'s (2019) five-step clustering procedure to generate the final clusters. In Step 1, Likert-scale data were recoded into triangular fuzzy numbers, the most common among the Left and Right (LR)-type fuzzy numbers (Hung & Yang, 2005). Let x_{ik} the k-th Likert-type variable ($k = 1,\ldots,K$) observed for the i-th unit ($I = 1,\ldots, n$). The triangular fuzzy variable is generally denoted by $\widetilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_T$ where m_{ik} is the centre while l_{ik} and r_{ik} are the left and right spreads that express the uncertainty of data (l_{ik} and r_{ik} can assume any real value between 0 and 1 inclusive). The following triangular membership function describes the link between the Likert-type variable and the fuzzy one:

$$\mu_{\widetilde{x}_{ik}}(x_{ik}) = \begin{cases} 1 - \dfrac{m_{ik} - x_{ik}}{l_{ik}} for x_{ik} \leq m_{ik} \\ 1 - \dfrac{x_{ik} - m_{ik}}{r_{ik}} for x_{ik} \geq m_{ik} \end{cases}$$

Following Hung and Yang (2005), the fuzzy recoding used in this study is displayed in Fig. 1. For more details on both fuzzy numbers and the fuzzification procedure for Likert-type data, please see Biasetton et al. (2023).

The fuzzy C-medoids for fuzzy data (FCM-FD) algorithm was then applied (Step 2 & 3) to the 17 coping items [for technical details please see Khoo-Lattimore et al. (2019) and D'Urso and De Giovanni (2014)]. Please note that the FCM-FD algorithm used in this research adopts the distance for fuzzy numbers suggested by Coppi et al. (2012), instead of a more traditional distance, such as the Euclidean distance, as the latter is not suitable for finding similarities between units characterised by fuzzy data. Thus, the FCM-FD algorithm used in this paper is a generalisation of the more traditional fuzzy C-medoids algorithm, also known as the Partition Around Medoids algorithm (Kaufman & Rousseeuw, 2005).

In Step 4, the best fuzzy partition was identified using internal validity measures (D'Urso et al., 2016). Fuzzy Silhouette (FS), Xie and Beni (XB), and Fukuyama and Sugeno (FuS) cluster validity index for fuzzy clustering algorithms, suitably adapted to fuzzy data, were deployed for partition identification. FS and XB both showed that partitions between either 2 or 4 would achieve strongest internal validity (Fig. 2). FuS index decreases as the number of clusters increase indicating that clusters are not well separated (i.e., there are clusters that are too similar to each other) (Chong et al., 2002). Accordingly, the 4-cluster solution was chosen for interpretation as this solution identifies greater nuance in consumer coping strategies.

The final phase (Step 5) comprised the profiling of the clusters on consumer characteristics, anger prototypes (and their felt intensity), rumination strategies, and eWOM. Membership degrees for each cluster were used as weights during this process (D'Urso et al., 2016), with the

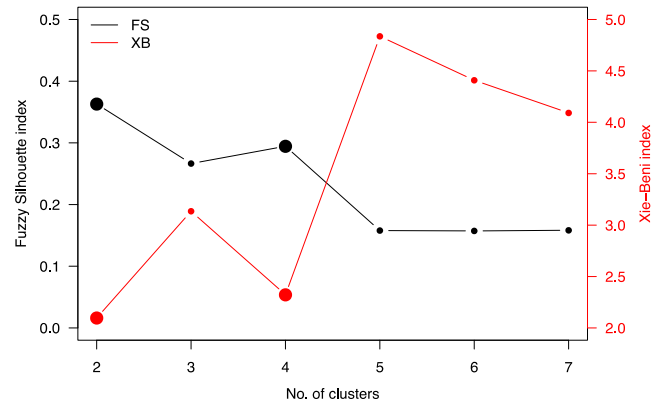

Fig. 2. Fuzzy Silhouette (FS) and Xie and Beni (XB) cluster validity index values for each cluster partition C from 2 to 7.

fractional multinomial logit (FML) model (Papke & Wooldridge, 1996) used to further profile the clusters (Khoo-Lattimore et al., 2019).

Unlike crisp clustering algorithms such as k-means, which generate a binary matrix of a respondent either belonging or not belonging to a cluster, the result of a fuzzy clustering algorithm is stored in a matrix of membership degrees ranging from 0 to 1. This implies that each respondent belongs to each cluster with a certain membership degree in a way that the sum of the membership degree by respondent is 1. Responding to service failure, customers do not use a singular coping mechanism (Tsarenko & Strizhakova, 2013); they can belong to different clusters simultaneously. Thus, the medoid (which captures the membership degree to any one cluster) will be 0 for all clusters and 1 for the cluster that it represents. Due to the nature of fuzzy clustering algorithm results, we estimated fractional multinomial logit consistent with Khoo-Lattimore et al. (2019) and Disegna et al. (2018), in which the vector of membership degrees is set as the dependent variable to further profile the clusters. This allows us to describe the final clusters by means of variables that have not been used to create the clusters. The fractional multinomial logit model allows us to obtain more detailed cluster profiling, enabling us to identify more informative practical and managerial implications.

3.4. Findings

3.4.1. Sample profile

Table 2 outlines the demographic profile of the sample and the proportion of respondents in each newly-identified cluster. The sample polled more males (60.8%) than females (39.2%), with representation across age groups (Table 2). The sample comprised mainly consumers from Iran (domestic visitors to hotels) (70.2%), with predominantly well-educated individuals therein (82% held at least a college degree). Cluster 1 (CL1) was the largest with 25.7% of respondents, followed by

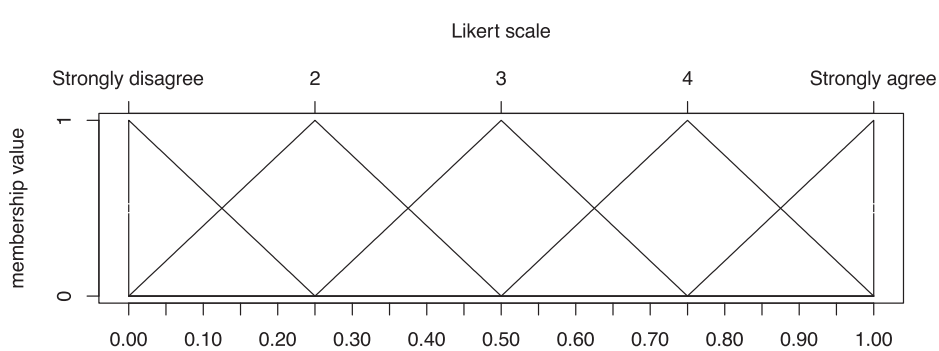

Fig. 1. Likert-type scale terms recoded into fuzzy numbers.

Table2
Demographic information (percentage).

Category	Sample	CL1	CL2	CL3	CL4
Weighted size		25.65%	24.86%	25.33%	24.16%
Gender					
Male	60.80%	58.25%	60.21%	62.35%	58.73%
Female	39.20%	41.75%	39.79%	37.65%	41.27%
Age					
18–25 years old	11.80%	10.87%	11.65%	11.92%	12.21%
26–35 years old	39.30%	39.33%	37.23%	39.93%	37.92%
36–45 years old	30.80%	30.66%	32.86%	32.17%	31.71%
46–55 years old	12.20%	12.09%	12.82%	11.51%	12.94%
56 years old or older	5.90%	7.05%	5.44%	4.47%	5.22%
Education					
Basic	2.80%	2.68%	2.72%	2.99%	3.00%
Secondary school	5.20%	7.64%	5.74%	4.31%	5.02%
High school	10.10%	11.15%	10.45%	9.00%	9.47%
College degree	35.30%	36.41%	34.20%	33.83%	34.26%
Bachelor degree	29.30%	28.75%	28.04%	27.42%	29.09%
Master degree/PhD	17.40%	13.36%	18.85%	22.45%	19.16%
Nationality					
Locals(Iran)	70.20%	70.38%	70.83%	71.77%	70.48%
Asia	6.60%	6.98%	6.50%	6.37%	6.70%
Middle East	5.20%	4.53%	5.73%	5.65%	5.81%
Europe	18.10%	18.11%	16.95%	16.21%	17.01%

Note: Sample size is 885 while the sample used for the segmentation (and therefore for the regressions) is 738 due to missing values.

Cluster 3 (CL3) with 25.3%.

3.4.2. Segmenting coping strategies

Table 3 reports the medoids (i.e., the typical respondents who represent the final clusters). The four clusters were overlapping (i.e., all medoids strongly agree) regarding some types of expressive coping (COE2-COE4). Medoid 1 represents a cluster that agrees or strongly agrees with almost all 17 coping items. The main difference between medoid 1 and the others is that it shows strong agreement with COA5, while all other medoids show strong disagreement with COA5. Medoid 2 disagrees with COE7 and COA1-COA3. Medoid 3 and 4 are similar as both strongly disagree with COA4 and COA5 while they differ for COE6, COE7 and COA2 (for which medoid 4 strongly agrees), and COA3 and COD3 (for which medoid 3 strongly agrees).

The weighted percentage distribution of respondents for each of the four identified clusters under each coping item is shown in Fig. 3. Cluster 1 (CL1) held a high percentage of customers that use all 17 coping items following service failure. Cluster 2 (CL2) contained respondents that generally deployed expressive and denial-based coping strategies, while being either 'neutral' or disagreeing with the adoption of active coping strategies post-failure. Cluster 3 (CL3) comprised a high percentage of respondents who either strongly agreed (COE1, COE2, COE3) or agreed with using expressive coping when faced with service failure, while also avoiding active coping strategies therein. These respondents do, however, use denial as a coping strategy. Cluster 4 (CL4) held a high percentage of respondents who use some forms of expressive coping (COE1-COE5) but avoid others (COE6 and COE7). These respondents use denial to a lesser extent but do employ active coping as a mechanism to deal with service failure. Overall, the results suggest that expressive coping and denial combine as mechanisms to deal with service failure across all four clusters, with no consensus on the role of active coping strategies.

3.4.3. Relationship between coping clusters, consumer anger, and rumination

The interdependency between cluster membership and a) consumer characteristics, b) anger prototypes, and c) rumination strategies was analysed using a stepwise FML model. This allows for proportion estimation assuming the degree of membership to each cluster are negatively correlated (i.e., a respondent belongs 'more' to one cluster but 'less' to the other three) (Khoo-Lattimore et al., 2019). As the sum of

Table 3
Coping items value by medoids.

Medoid	COE1	COE2	COE3	COE4	COE5	COE6	COE7	COA1	COA2	COA3	COA4	COA5	COA6	COA7	COD1	COD2	COD3
medoid1	4	5	5	5	3	4	4	5	4	3	4	5	4	4	3	4	3
medoid2	5	5	5	5	5	4	2	1	2	2	3	1	5	4	4	5	5
medoid3	5	5	5	5	5	4	4	4	4	5	1	1	5	5	5	5	5
medoid4	5	5	5	5	5	5	5	4	5	4	1	1	5	5	5	5	4

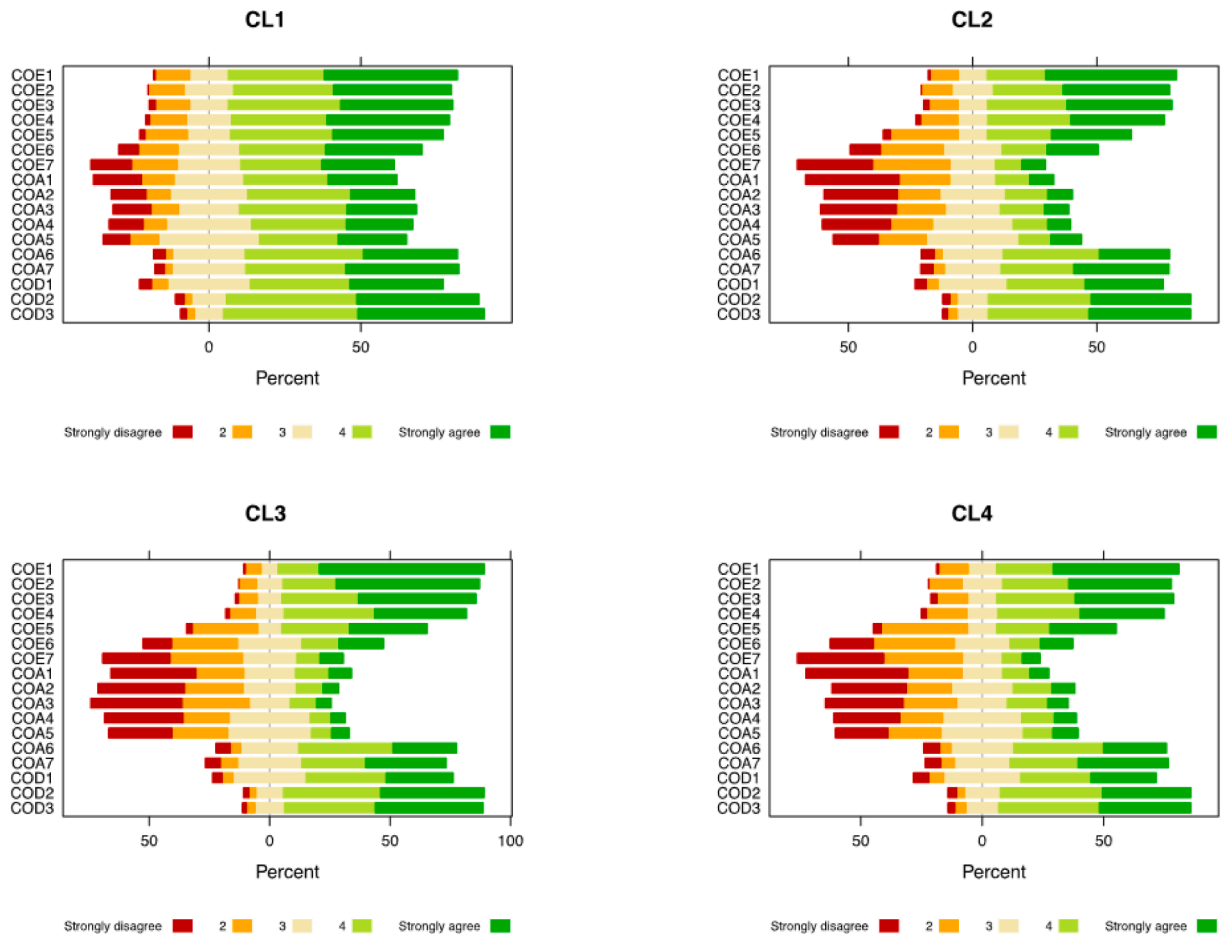

Fig. 3. Weighted percentage distribution of coping items (expressive, active, denial) by cluster.

membership degrees for all clusters are equal to one per each observed unit, one cluster serves as the reference group (herein CL1) for profiling purposes. Table 4 shows estimated coefficients obtained via stepwise estimation.

Results show that when compared to Cluster 1 (CL1), Clusters 2, 3, and 4 (CL2, CL3, CL4) held higher proportions of respondents with education above college level (i.e., Bachelor, Masters, PhD). Cluster 3 (CL3) had a lower proportion of respondents aged 45 + compared to Cluster 1 (CL1). Regarding anger prototypes, Clusters 3 and 4 (CL3 and CL4) held higher proportions of respondents who felt anger following service failure compared to Cluster 1 (CL1). Cluster 3 (CL3) contained respondents who felt greater annoyance and distress in comparison to those in Cluster 1 (CL1). With regards to rumination, results show that Clusters 2, 3 and 4 (CL2, CL3, CL4) had higher proportions of respondents who were less likely to use RUM1 as a coping mechanism ("*I know the incident will linger in my mind for a long time*") in comparison to Cluster 1 (CL1). Clusters 2 and 3 (CL2 and CL3) had higher proportions of respondents who were more likely to use RUM3 ("*Thinking about the incident at the hotel will spoil the rest of my evening and trip*") as a coping mechanism in contrast to Cluster 1 (CL1). Clusters 1 and 4 (CL1 and CL4) had higher proportions of respondents who were less like to use RUM5 ("*I find myself replaying the incident at the hotel over-and-over in my mind*") as a coping mechanism compared to Cluster 1 (CL1).

3.4.4. Relationship between eWOM, coping clusters, consumer anger and rumination

For each of the three items measuring eWOM, a logit model (with consumer characteristics, anger prototypes, cluster membership, and rumination strategies as predictors) was estimated, using the original 5-

Table 4
Fractional Multinomial Logit stepwise estimations for the membership degrees of the coping clusters.

Independent variables	CL2	CL3	CL4
Male	0.064 (0.07)	0.139 (0.09)	0.010 (0.08)
More than 45 years old	−0.079 (0.09)	−0.250 (0.11) **	−0.065 (0.11)
Iranian (local)	0.013 (0.08)	0.042 (0.09)	−0.003 (0.09)
Bachelor, Master or PhD	0.145 (0.07)**	0.184 (0.09)**	0.215 (0.08) ***
Consumer Anger (Agree or Strongly agree)			
anger	0.164 (0.11)	0.316 (0.14)**	0.225 (0.13)*
frustration	−0.085 (0.12)	−0.105 (0.16)	−0.126 (0.14)
irritation	−0.053 (0.11)	0.031 (0.13)	−0.186 (0.13)
annoyance	0.085 (0.1)	0.225 (0.13)*	0.081 (0.11)
distress	−0.016 (0.1)	0.264 (0.13)**	0.040 (0.11)
Rumination strategies (Agree or Strongly agree)			
RUM1 (linger in mind)	−0.416 (0.08) ***	−0.636 (0.1) ***	−0.463 (0.09) ***
RUM2 (lasting effect on rest of stay)	0.058 (0.09)	0.140 (0.11)	−0.099 (0.1)
RUM3 (spoil rest of evening)	0.235 (0.08) ***	0.328 (0.1)***	0.121 (0.1)
RUM4 (not be far from my mind)	−0.112 (0.09)	−0.168 (0.11)	−0.102 (0.1)
RUM5 (replaying the incident)	−0.216 (0.1) **	−0.074 (0.11)	−0.265 (0.11) **
constant	0.133 (0.14)	−0.494 (0.19) ***	0.425 (0.16) ***

Note: Coefficients interpreted relative to omitted category of Cluster 1. Test results are not significant unless indicated otherwise. Robust standard errors are in parentheses. N = 738; Wald $\chi^2(42) = 316.79$; $p > \chi^2 = 0$. ***Significant at $p \leq 0.01$, **significant at $p \leq 0.05$, *significant at $p \leq 0.1$.

point Likert scale variable. Table 5 shows that better-educated consumers (Bachelor, Masters, PhD) were less likely to spread eWOM ($\beta = -0.315$). Those who felt greater anger were less likely to spread eWOM ($\beta = -0.471$) but were more likely to engage in this type of behaviour if they felt irritated ($\beta = 0.892$). Likewise, consumers who used 4 (of 5) rumination strategies were more likely to spread eWOM (Table 5). Yet, those belonging to Cluster 4 (CL4) were less likely to spread negative eWOM about the hotel and service failure therein.

Following the procedure outlined prior, a logit model was estimated with the second item for eWOM ("*denigrate the hotel online*") as the dependent variable and the same variables listed in Table 3 as independent variables. Results (Table 6) suggest that no demographic factor explained the variance in eWOM, while consumers who felt anger were less likely to denigrate the hotel online ($\beta = -0.532$) but more likely to do so if they felt irritated ($\beta = 0.790$) and distressed ($\beta = 0.719$). Consumers were also more likely to denigrate the hotel online if they used two of the five rumination strategies (RUM4 and 5). As with the previous model (Table 4), consumers were less likely to denigrate the hotel if they belonged to Cluster 4 (CL4).

For the third eWOM item, using the same independent variables as outlined prior, logit model results (Table 7) show that neither demographics nor consumer anger had any effect on the dependent variable. However, three of the five rumination strategies (RUM1, 4 and 5) could significantly predict eWOM. For example, consumers who typically linger on incidents in their mind for a long time were more likely to warn others not to go to the hotel via online means ($\beta = 0.575$). Similarly, those who play the incident over-and-over in their mind are also more likely to use online means to warn others not to visit the hotel. As with previous models, consumers belonging to Cluster 4 were less likely to engage in this eWOM subtype.

Overall, the results suggest that treating eWOM as a generic post-consumption behaviour that *all* consumers engage in (*in the same way*) is problematic. Instead, the findings contend that different facets of consumer anger and different rumination strategy archetypes predict different aspects of eWOM. Further, the results also reveal that different segments of consumers (with demographic diversity therein) can also influence the emergence of eWOM (alongside the form in which this takes).

Table 5
Determinants of eWOM (spread eWOM about hotel).

Independent variables	β	Odds ratio
Male	0.034 (0.15)	1.034
More than 45 years old	−0.025 (0.19)	0.975
Turkish (local)	−0.126 (0.16)	0.881
Bachelor, Masters or PhD	−0.315 (0.15)**	0.730
Consumer anger (Agree/Strongly agree)		
Anger	−0.471 (0.26)*	0.625
Frustration	0.091 (0.26)	1.095
Irritation	0.892 (0.23)***	2.440
Annoyance	−0.214 (0.21)	0.807
Distress	0.163 (0.23)	1.177
Rumination strategies (Agree/Strongly agree)		
RUM1	1.091 (0.17)***	2.978
RUM2	0.337 (0.19)*	1.401
RUM3	0.090 (0.18)	1.094
RUM4	0.594 (0.21)***	1.812
RUM5	0.950 (0.23)***	2.585
Membership to Cluster		
Belong to cl 2	1.593 (1.15)	4.919
Belong to cl 3	−0.099 (0.53)	0.906
Belong to cl 4	−2.464 (0.76)***	0.085
τ1 = Strongly disagree	−2.274 (0.56)***	
τ2 = Neutral	1.498 (0.49)***	
τ3 = Agree	3.180 (0.50)***	

Notes: Robust standard errors in parentheses. There are only 3 thresholds as the distinction between the "Disagree" and the "Neutral" options was not significant. Number of obs = 737; Wald chi2 (17) = 152.14; Prob > chi2=greater than0.001; Log pseudolikelihood = −778.48642. ***Significant at $p \leq 0.01$, **Significant.

Table 6
Determinants of eWOM (denigrate hotel online).

Independent variables	B	Odds ratio
Male	0.004 (0.16)	1.004
More than 45 years old	0.222 (0.21)	1.248
Turkish (local)	−0.257 (0.17)	0.773
Bachelor, Master or PhD	0.048 (0.16)	1.049
Consumer anger (Agree/Strongly agree)		
anger	−0.532 (0.24)**	0.587
frustration	0.156 (0.25)	1.169
irritation	0.790 (0.26)***	2.203
annoyance	0.126 (0.23)	1.135
distress	0.719 (0.25)***	2.052
Rumination strategies (Agree/Strongly agree)		
RUM1	0.168 (0.18)	1.182
RUM2	0.248 (0.21)	1.282
RUM3	0.056 (0.21)	1.057
RUM4	0.540 (0.21)***	1.716
RUM5	0.909 (0.24)***	2.481
Membership to Cluster		
Belong to cl 2	1.218 (1.12)	3.381
Belong to cl 3	−0.116 (0.58)	0.890
Belong to cl 4	−3.329 (0.81)***	0.036
τ1 = Disagree	−2.090 (0.55)***	
τ2 = Agree	2.388 (0.56)***	

Notes. Robust standard errors in parentheses. There are only 2 thresholds as the distinction among "Disagree", "Neutral" and "Agree" was not significant. Number of obs = 736; Wald chi2 (17) = 88.47; Prob > chi2=greater than0.001; Log pseudolikelihood = −523.66563. ***Significant at $p \leq 0.01$, **Significant at $p \leq 0.05$, *Significant at $p \leq 0.1$.

Table 7
Determinants of eWOM (warn others online not to go to hotel).

Independent variables	B	Odds ratio
Male	−0.015 (0.16)	0.985
More than 45 years old	0.051 (0.21)	1.052
Turkish (local)	0.001 (0.17)	1.000
Bachelor, Master or PhD	0.189 (0.16)	1.208
Consumer anger(Agree/Strongly agree)		
anger	−0.215 (0.23)	0.807
frustration	−0.062 (0.26)	0.940
irritation	−0.029 (0.27)	0.972
annoyance	0.133 (0.23)	1.143
distress	0.381 (0.24)	1.464
Rumination strategies (Agree/Strongly agree)		
RUM1	0.575 (0.18)***	1.778
RUM2	0.329 (0.20)	1.390
RUM3	−0.047 (0.20)	0.954
RUM4	0.603 (0.20)***	1.827
RUM5	1.157 (0.24)***	3.180
Membership to Cluster		
Belong to cl 2	1.491 (1.21)	4.441
Belong to cl 3	−0.616 (0.56)	0.540
Belong to cl 4	−2.732 (0.81)***	0.065
τ1 = Disagree	−1.918 (0.54)***	
τ2 = Agree	2.189 (0.53)***	

Notes: Robust standard errors in parentheses. There are only 2 thresholds since the distinction among "Disagree", "Neutral" and "Agree" was not significant. Number of obs = 736; Wald chi2 (17) = 90.55; Prob > chi2=greater than0.001; Log pseudolikelihood = −544.12679. ***Significant at $p \leq 0.01$, **Significant at $p \leq 0.05$, *Significant at $p \leq 0.1$.

4. Discussion and theoretical implications

This study extends extant understanding of consumer responses to service failure by exploring how coping behaviours relate to the emotional responses and rumination strategies employed by consumers post-failure, with emphasis placed on identifying how these psychological variables influence eWOM. Doing so, the study is the first to

demonstrate that the coping style adopted by customers can trigger different rumination strategies, with this subsequently impacting upon the nature of complaints shared via eWOM. Results herein reveal four discrete consumer segments underpinned by the distinction between active (e.g., apportioning blame), expressive (e.g., demonstrating anger), and denial-based (e.g., disengaging with provider) coping (Strizhakova et al., 2012). Empirically, the fuzzy-clustering algorithm employed demonstrates that customers generally use all three coping styles to varying degrees following service failure.

However, while post-failure consumer responses have been studied extensively (Antonetti, 2016), the consumer subtypes identified herein are distinct, with our segmentation of coping behaviours underpinned by the interactions amongst demographics, anger, and five established rumination strategies. This study thus offers deeper insight into how service failure can negatively affect the psychological welfare of consumers, with anger and rumination post-failure capable of adversely impacting upon consumer well-being and resilience (Hur & Jang, 2019). Yet, in extending Tsarenko and Strizhakova (2013) and Senguptal et al. (2015), our findings not only identify overlapping coping styles for different consumer segments but, in doing so, also support Duhachek's (2005) assertion that consumers cope with negative emotions by blaming the service provider to varying degrees while also seeking the support required to regulate the felt-intensity of any emergent negative emotions.

Further, findings herein demonstrate that different anger prototypes (e.g., anger; frustration; irritation; annoyance; distress) predicate different coping styles. For example, in comparison to Cluster 1, which draws upon all three coping styles, Cluster 4 is more prone to anger than frustration or distress following service failure. Conversely, again compared to Cluster 1, the anger, annoyance, and distress which together typify Cluster 3 demonstrates that such consumers use expressive and denial-based coping over-and-above active coping strategies. The identified differences in anger prototypes across segments extend established studies linking coping behaviours to anger more generally (Hur & Jang, 2019; Tsarenko & Strizhakova, 2013). Specifically, we develop upon Strizhakova et al. (2012) which prioritises anger's role as a determinant of different types of coping behaviours by clarifying the impact different anger prototypes have on the combinations of expressive, active, and denial-based coping exhibited by segments post-failure. Doing so, we empirically confirm Antonetti's (2016) assertion that anger prototypes have varying impacts on psychological constructs and consumer outcomes.

Our findings also demonstrate the importance of rumination to post-failure consumer coping; supporting Strizhakova et al. (2012) in suggesting that consumer anger activates expressive coping and denial, which in-turn increases rumination. However, we extend prior work by showing that expressive, active, and denial-centric coping behaviours shape the nature of rumination in different ways across our identified segments. For example, findings show that service failure typically lingers for consumers in Cluster 4, who replay the incident over-and-over post-failure by way of rumination more than those within Cluster 1. This has negative implications for the psychological variables linked to consumer rumination strategies, such as stress and anxiety (Kemp et al., 2021). Conversely, consumers in Cluster 3, when compared to those in Cluster 1, engage in a more complex mix of short- and medium-term ruminative reflection, simultaneously dissociative and tangible, where sub-optimal service experiences spoil the remainder of their day despite them not replaying the incident in their mind post-failure. Thus, the findings extend existing understanding of post-failure rumination and coping by contending that groups who cope with service failure in a similar manner *can also* engage in diverse post-failure rumination behaviours along the way.

While previous studies contend that coping behaviours serve as a psychological driver of WOM (Vermeer et al., 2019), we demonstrate that coping is also an essential predictor of *eWOM*. Consumer-driven online recommendations are crucial to a range of positive post-consumption outcomes, including repeat purchases and loyalty (Wakefield & Wakefield, 2018). Yet, our findings demonstrate the varied effects of consumer characteristics, enacted coping behaviours, and anger prototypes on different types of eWOM. This distinction is another core contribution of this study, as research which considers eWOM as a singular behaviour cannot accurately discriminate between segments that have demonstrate a propensity to share eWOM of different types. For example, findings herein suggest that better-educated consumers are less likely to spread eWOM, while those who felt irritated following service failure are more likely to engage in such behaviours.

Further, while rumination stimulates consumer eWOM, the findings suggest that this differed across consumer segments based on the form of rumination enacted, further demonstrating the study's contribution to the development of a more nuanced and robust understanding of post-failure consumer coping strategies. For example, consumers who chose to denigrate the hotel online post-failure are primarily driven by feelings of irritation and distress, whereas those who ruminate by replaying failure incidents in their mind tend to warn others accordingly. Yet, the findings ultimately conclude that consumers who use expressive coping are typically more likely to engage in all types of eWOM following service failure. Thus, while this study primarily contributes to existing understanding of consumer coping by revealing complex behaviour-oriented clusters, it also extends extant knowledge of the role of rumination, alongside the way eWOM manifests therein.

4.1. Practical implications

Service failure is an unfortunate by-product of the inherent fluidity and complexity of experiential consumption, where expectations vary at the firm-customer level and across customer groups (Harmeling et al., 2017). While this study investigates the strategies distinct customer segments employ in order to cope with failure, this is not aimed at eliminating the underlying psychological mechanisms therein. Instead, the findings hint at ways service providers can rectify perceived failures, reducing the likelihood of detrimental consumer behaviours in-turn (e.g., negative eWOM, switching) (Liu et al., 2019).

Gaining greater understanding of *how* different coping strategies interact and combine to shape consumer responses to service failure is crucial for marketing managers; forearming them with the requisite knowledge to develop, implement, and adapt service recovery mechanisms capable of speaking to specific customer segments, instead of adopting ineffective one-size-fits-all protocols. Thus, by first understanding *how* different customer segments process service failure, firms can ensure their post-failure actions are consistent with the coping strategy adopted by disaffected customers, increasing effectiveness commensurately. The findings therefore encourage segment-specific scenario-based recovery design and planning; employees should draw upon the most relevant (of multiple divergent recovery process paths) service recovery strategy based on the coping strategy that negatively affected consumer(s) are activating at any given time.

A generalised overview of this is demonstrated in Table 8; for *each* customer coping style identified for *every* cluster, appropriate service recovery strategies are outlined, and corresponding service policies/actions are highlighted. For example, when customers deploy expressive coping styles following service failure, they are emotionally expressive in their communication and exhibit support-seeking behaviours to deal with elicited stress. Thus, service recovery strategies should focus on restoring their well-being by encouraging complaints and providing facilities (e.g., toll-free numbers, online complaint portals) for customers to vent frustrations. Conversely, those engaged in denial-based coping post-failure are unlikely to complain and will dismiss the problem. This encourages proactivity; service experiences must be fail-safe and service design principles should be used to identify problematic touch-points in advance. Customers employing a denial coping style might not repurchase again, and thus, monitoring customer engagement and net promoter scores (NPS) could help identify customer dissatisfaction that

Table 8
Service recovery strategies for each cluster based on coping styles.

Coping strategies	Focus of service recovery strategies	Service policies/actions
Expressive coping (emotional expression, communication and support seeking behaviours) – CL1, CL2, CL3, CL4	Restore emotional wellbeing of customers	• Access to 24/7 Toll-free numbers for customers to express service dissatisfaction • Provision of online complaint service for customers • Acknowledge customer feeling and empathize with customer needs following service failure • Clear communication of service standards and recovery actions for sub-standard service • Track complaints and negative online reviews
Denial coping (passive dismissal of the problem) – CL1, CL2, CL3	Service redesign to achieve fail-safe service	• Identify customer journeys and potential problematic touch points • Use customer relationship management tools to monitor engagement with services and products • Monitor Net Promoter Score (NPS)
Active coping (solving the problem) – CL1, CL4	Solution-focused	• Financial compensation policies (discount on next purchase, vouchers, price incentives) • Complementary access to other services offered by the provider. • Take responsibility of the issue and promptly address the service failure • Follow through after service recovery completed

is otherwise not captured through direct complaints. Finally, for customers employing active coping aimed at problem-solving and resolution, the focus of service recovery should be on timely, effective remedial action; taking responsibility and quick response times attenuate negative feelings. Such service recovery should be supported by comprehensive compensation policies.

As such, while fluid and subjective (e.g., coping mechanisms are internalised within affected individuals and difficult for outsiders to objectively assess), employees must be trained and supported to act with the speed and specificity necessary to stop consumers' initial post-failure reactions from developing into more egregious behaviours (e.g., negative eWOM). This is in many ways contingent upon eliminating the time required for the negative effects of rumination to emerge (Wakefield & Wakefield, 2018). Understanding the diversity of ruminative processes is particularly important due to its role in shaping consumer responses to service situations in which experience does not match expectation; alongside the consequences post-failure rumination can have on consumers' propensity to spread eWoM.

Yet, not all service recovery protocols will be successful; eWOM is likely to remain a pervasive and ongoing concern for even the most recovery-centric service providers (Kim et al., 2018). Accordingly, Vermeer et al. (2019) contend that *webcare* - the "act of engaging in online interactions with (complaining) consumers, by actively searching the web to address consumer feedback (e.g., questions, concerns, and complaints)" (VanNoort & Willemsen, 2012, p.133) should be central to customer relationship management, with this likely to prove most compelling and effective when dealing with those customers identified within this study who a) choose to denigrate service providers online or b) opt to engage in spreading general negative word-of-mouth outside of their real-life networks. Thus, while this study acknowledges that service failures cannot be eradicated completely, the findings offer the insight required to develop a two-pronged approach to recovery; first centred on developing segment-specific recovery protocols to eliminate post-failure rumination at source, and second, to acknowledge the role that early *webcare* could play in diluting negative eWOM.

Further, specific to developing a strategic marketing framework underpinned by STP (segmentation, targeting and positioning), the findings provide the foundations from which to understand the priorities of different consumer segments, allowing for the development of targeted and accurately-positioned service recovery strategies following service failure. By identifying several distinct segments based on diversity in post-failure coping styles, alongside variance therein with regards to a range of demographic characteristics, this study highlights the ongoing utility and relevance of traditional segmentation bases (e.g., psychographic and demographic) in understanding consumer behaviour. As our findings illustrate, the concurrent use of demographic (e.g., age, gender, and education) and psychographic variables (anger, rumination) to understand differences in consumer segments allows for the adoption of more refined targeting strategies to aid service recovery. This is again illustrated in Table 8, where simplified segment specific service recovery strategies are offered. Accordingly, the results offer precise action points for service providers to realign their marketing mix (e.g., processes, services, and staff) to meet customer expectations following service failure.

Additionally, given that different segments also activate different types of eWOM post-failure, promotional activities undertaken via social media platforms should also be reviewed and aligned with customer expectations. Service providers should continue to encourage customers to express their dissatisfaction following service failure via social media, but this should be deployed in a strategic manner as a key component of the firm's service recovery initiatives, where comprehensive, timely, and effective communication therein can go some way to rebuilding customer relationships post-failure. Through actively managing social media as part of their recovery strategy, service providers have an opportunity to strengthen the positioning of their brands and services online as they can address service failures quickly, personalize service recovery, and respond to different forms of service failure in a more bespoke, effective manner.

4.2. Limitations and future research

This study's limitations provide avenues for future research. *First,* while context (Iranian hotel customers) limits generalizability, researchers should investigate whether the distinct customer segments identified across the findings are replicable in other settings. *Second*, the tri-conceptualisation of coping (expressive; active; denial) discussed herein has received criticism, with alternative coping categorisations worthy of consideration (Hur & Jang, 2019). *Third,* this study examines five anger prototypes, with others (e.g., anxiety; contempt; disgust; rage) also of potential scholarly interest. Similarly, this study focused on vengeful anger's implications for eWOM; future studies could prioritise problem-focused anger and its impact upon coping, rumination, and eWOM.

Fourth, a range of negative emotions are activated post-service failure (e.g., guilt; disappointment; shame). Future studies should thus investigate the diversity in consumers' psychological responses to service failure to identify segments therein. *Finally*, given the increased propensity for consumers to share experiences of service failure post-fact via online reviews, text mining and sentiment analysis could be deployed to better understand this specific subset of post-failure rumination. This would complement our approach to segmenting consumer responses to service failures.

CRediT authorship contribution statement

Martin Gannon: Writing – review & editing, Conceptualization. **Babak Taheri:** Writing – review & editing, Supervision, Data curation. **Marta Disegna:** Formal analysis. **Girish Prayag:** Writing – review & editing, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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