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Justice (is not the same) for all: The role of relationship activity for post-recovery outcomes

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ABSTRACT

Despite the widespread adoption of the justice framework in service recovery literature, research findings vary as to what dimension - distributive, interactional, procedural - is most important. This paper contributes to this debate by considering how an easily accessible variable like relationship activity (i.e., the frequency of visiting and purchasing from a company) moderates the impact of the justice dimensions on post-recovery customer outcomes. Findings show that distributive justice is the only dimension impacting word-of-mouth (WOM) and repurchase behavior for low- and medium-relationship-activity customer segments. For a high-relationship-activity segment, all justice dimensions have a positive and balanced impact on WOM and/or repurchase behavior. This research demonstrates the potential of a segmented approach for recovery, while also providing managers with valuable insights into how they can use readily available information to adapt their service recovery efforts.

1. Introduction

Service failures remain a challenge for all actors involved in service provision, including customers and service companies. This is confirmed by the 2020 National Customer Rage Survey, which shows that 66 percent of US households experienced at least one unfavorable incident with a company in the 12 months preceding the study – risking US$494 billion in business for the companies involved (Customer Care Measurement and Consulting [CCMC], 2020). Research also shows that negative incidents have a substantial effect on customers' future behavior in terms of word-of-mouth (WOM), loyalty, and repurchase intentions (Tronvoll, 2012). Given the large number of involved customers and the scope of business being jeopardized, there is a need to develop a deeper understanding of how different types of customers respond to service failures (Van Vaerenbergh, Varga, De Keyser, & Orsingher, 2019).

Central to recovery efforts is the restoration of the customer's perceived overall justice (Orsingher, Valentini, & de Angelis, 2010), which entails distributive (i.e., fairness of the redress outcome), procedural (i.e., fairness of the redress procedure), and interactional (i.e., fairness of the interpersonal treatment) dimensions, with distinct service recovery actions being best in terms of restoring the different justice dimensions (Van Vaerenbergh et al., 2019). While the meta-analyses of Orsingher et al. (2010) and Gelbrich and Roschk (2011) provide general insights into the relative importance of the justice dimensions for customer outcomes, less is known about how the importance of the justice dimensions varies according to the type of customer experiencing the company's service recovery efforts. Orsingher et al. (2010, p. 184) meta-analysis raises the question of whether customer segments exist for recovery actions: "Are there customer segments? Do customers respond equally to service recovery efforts? Should companies segment complaining customers?"

If so, this would have significant managerial implications, as different customer segments would require different sets of service recovery actions to restore the customer after the failure (Gelbrich & Roschk, 2011; Van Vaerenbergh et al., 2019). This call for research is in line with two recent recovery overview papers (Arsenovic, Edvardsson, & Tronvoll, 2019; and Van Vaerenbergh et al., 2019) that explicitly urge recovery researchers to account for customer heterogeneity in service recovery research.

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One important dimension that reflects customer heterogeneity is relationship activity (Orsingher et al., 2010). In the context of the present paper, relationship activity is reflective of a customer's visiting and purchasing frequency with a company.[1] While service recovery research has established that customers differ in their responses to service recovery actions depending on the quality of their relationship with the service company (Fisher & Grégoire, 2006; Grégoire & Fisher, 2006; Hogreve, Bilstein, & Mandl, 2017), we have little insight into how various levels of relationship activity drive the relative importance of the various justice dimensions, including their subsequent impact on core service recovery outcomes, such as customer loyalty and WOM (Ha & Jang, 2009). This is surprising as research has shown that frequency metrics impact recovery outcomes (e.g., Yagil & Luria, 2016) and given the importance of frequency metrics in customer relationship management (CRM) literature for segmentation and predicting future customer behaviors (Chen, Chiu, & Chang, 2005). Therefore, insights into what types of justice matter the most for customers with differing relationship activity levels could enhance recovery strategies (Gelbrich & Roschk, 2011).

Accordingly, the present study set out to address the above-mentioned shortcomings in the literature by helping to explain the variability in the relative strength of the effects of the respective justice dimensions on service recovery outcomes (as called for by Orsingher et al., 2010). We do this by measuring relationship activity in a real-life retail setting with a set of behavioral (i.e., visit and purchase frequency offline and online) variables, and contrasting the impact of the three justice dimensions on WOM and repurchase behavior across three segments, composed of customers with low, medium, and high levels of relationship activity. In so doing, we contribute to the ongoing debate regarding the role of relationship variables on customers' reactions to service recovery (Béal, Sabadie, & Grégoire, 2019). Moreover, the present study provides managers with insights into how they can segment their customer base, based on customers' relationship activity levels (as called for by Van Vaerenbergh et al., 2019), to better adapt their service recovery efforts. This can be established by means of easily measurable and available variables, giving this study direct and actionable managerial relevance. Finally, we make use of latent class clusters analysis to analyze our real-life data, thus answering the call of Grégoire & Mattila (2020) to bring more advanced analytics into the service failure and recovery field.

2. Theoretical framework

2.1. The relative importance of the justice dimensions

There is agreement in the service recovery literature that justice is a key component in customers' evaluation of service recovery efforts (Van Vaerenbergh & Orsingher, 2016). Essentially, justice perceptions reflect customers' individual subjective assessments of a service company's recovery actions (Smith, Bolton, & Wagner, 1999), with a fair perception being necessary to trigger post-recovery customer outcomes, such as satisfaction, positive WOM, and loyalty (Gelbrich & Roschk, 2011). Three justice dimensions are typically distinguished: distributive justice, interactional justice, and procedural justice (Tax, Brown, & Chandrashekaran, 1998). Distributive justice refers to perceived fairness of the benefits (e.g., the appropriateness of the service recovery outcome) assigned to the customer to rectify the service failure. Interactional justice refers to the perceived fairness of how customers are treated (e.g., interpersonal behaviors such as attentiveness and friendliness). Procedural justice refers to the perceived fairness of the methods and means used by the service company to resolve the failure (e.g., the speed of service recovery and flexibility).

While there is agreement on the significance of all three dimensions, there is some debate as to their relative importance in driving recovery outcomes (Van Vaerenbergh & Orsingher, 2016). A meta-analysis by Orsingher et al. (2010) shows that distributive justice is the most important dimension driving recovery satisfaction, followed by interactional justice and procedural justice. Further, a meta-analysis by Gelbrich and Roschk (2011) finds that distributive justice has a significant impact on recovery satisfaction, while interactional and procedural justice only have a negligible impact. In contrast, when looking at individual studies, we see differing results in terms of which dimension matters most for post-recovery customer outcomes. While most studies find that distributive justice is the dominant justice dimension (e.g., Homburg & Fürst, 2005; Smith et al., 1999), others find interactional (e.g., Smith & Bolton, 2002; Tax et al., 1998) or procedural (e.g., Maxham & Netemeyer, 2003) justice as the strongest driver of post-recovery customer outcomes. In light of this ongoing debate, more research looking into the relative importance of the three justice dimensions is necessary in order to understand what drives this variability.

Building on Orsingher et al. (2010) call to investigate whether accounting for customer heterogeneity can help shed light on these discrepancies, we consider how a customer's relationship activity level with the service company affects the relative importance of the justice dimensions in driving post-recovery outcomes (see conceptual framework in Fig. 1). Not only do all service companies deal with customers who have different levels of relationship activity, ranging from customers who are new to customers who have a long-standing history with the service company (Kumar & Reinartz, 2016); many companies also invest strongly in building enduring relationships where they frequently interact with their customers (Hogreve et al., 2017). Moreover, relationship activity is an easily captured variable in practice and is therefore usable for a wide variety of companies to segment their customer base, while front-line employees may also uncover this information with ease and act upon it when dealing with customers in real time.

2.2. The impact of relationship activity

Previous service failure and recovery research has considered the impact of customers' relationship with a company in a variety of ways, which can largely be classified into an attitudinal-behavioral dichotomy (see Web Appendix A for a table summarizing the use of the relationship concept in failure and recovery research). To date, research has strongly focused on the attitudinal relationship quality concept; that is, the strength of the customer–company relationship, driven by customers' satisfaction, commitment, and trust (Grégoire & Fisher, 2008). Here, some studies indicate a "love is blind" effect (e.g., Grégoire & Fisher, 2006) with relationship quality acting as a buffer to protect against service failure episodes. Other studies find a "loves becomes hate" effect (e.g., Grégoire & Fisher, 2008; Grégoire, Tripp, & Legoux, 2009) where relationship quality enhances customers' negative reactions after poor recoveries.

The behavioral research stream also finds customer reactions to differ according to relationship length and frequency (e.g., Béal et al., 2019; Gelbrich, Gäthke, & Grégoire, 2016; Hess, Ganesan, & Klein, 2003). Béal et al. (2019), for instance, find that successful recovery is more crucial at the beginning of a relationship, with long-term customers being better protected against poor recovery and seeking to continue business as usual. However, to our best knowledge, no service recovery research has looked into how such frequency metrics may provide a strong basis to establish customer segments for recovery purposes, thereby answering the question: do distinct segments based on frequency metrics value the three justice dimensions differently and

[1] We consider visiting frequency to be as important as purchasing frequency as a metric for companies to gauge. While not every visit may be linked to an actual purchase, it does expose customers to the service process of the company, its products, the servicescape, company practices, and more, and may impact the long-term relation between the company and the customer. This makes relationship activity a broader variable than the typical purchase frequency metric.

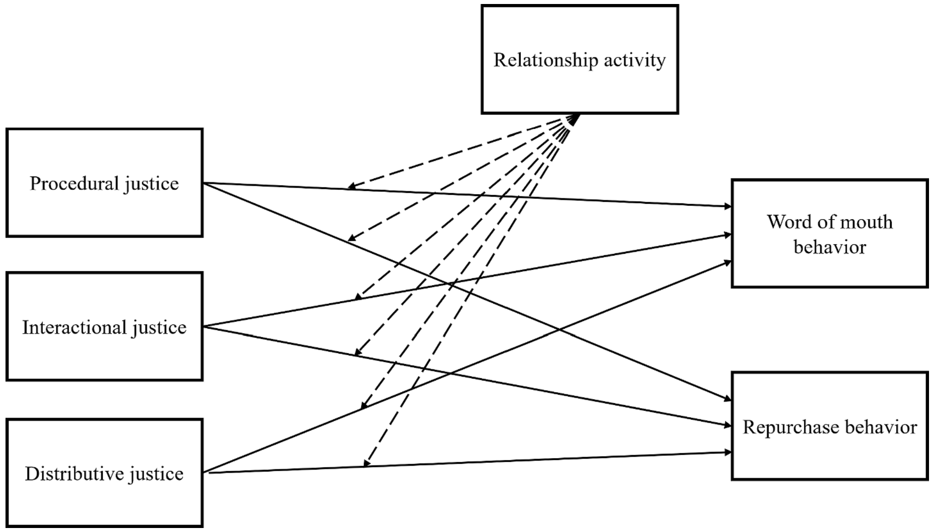

Fig. 1. Conceptual model. Solid lines denote the direct relationship. Dashed lines denote the moderating effect.

require a different approach? This lack of prior research is surprising given that frequency metrics have great value for segmenting customers and predicting future behaviors such as repurchase or churn (Chen et al., 2005), thus playing an important role in CRM (Kumar & Reinartz, 2016). Therefore, it may be equally valuable for service recovery research to consider the impact and usefulness of the relationship activity metric in this research (i.e., a customer's visiting and purchasing frequency with a company). Consequently, the present study aims at extending the dominant attitudinal research stream and contributing to the ongoing debate regarding the role of relationship variables in customers' reactions to service recovery (Béal et al., 2019). In particular, the study investigates the role of varying relationship activity levels (low, medium, high) in moderating the relationship between the three justice dimensions and key customer outcomes such as WOM and repurchase behaviors, thereby evaluating its potential to segment the customer base for recovery purposes.

Previous research shows that regular customers (i.e., high relationship activity) tend to have more defined service recovery expectations (Kelley & Davis, 1994) as they have better insights into how the company operates and what they can expect (Karande, Magnini, & Tam, 2007). Therefore, one may anticipate such customers to have stronger fairness expectations for all justice dimensions (i.e., the equal importance of distributive, interactional, and procedural justice). These customers may expect the company to excel at all aspects of service recovery. By contrast, customers with less established relationships have less defined expectations and focus more on redressing the core service (i.e., distributive justice as the dominant dimension). These customers have not developed relationships with employees and may be less aware or unaware of standard practices used by the service company to deal with service failures (Karande et al., 2007). The most direct and easily observable evidence to judge the encounter at that point is the compensation (i.e., distributive justice) that the company offers to the customer.

In addition, as customers with established relations are acclimated with a company and its service level, they typically expect the regular level of performance to continue in the future and generally hold higher expectations of relationship continuity (Hess et al., 2003). Thus, customers with a highly developed relationship can be considered to be more interested in establishing equitable personal interactions (i.e., interactional justice), treating each other fairly (i.e., procedural justice), and having a balanced compensation (i.e., distributive justice) to be able to continue the relationship. By contrast, customers without a (yet) established relationship are likely to value the relationship less and be more interested in direct compensation (i.e., distributive justice) and care less about other aspects (i.e., interactional and procedural justice). This seems to be confirmed by Hogreve et al. (2017), who find that customers with a weak relationship (i.e., first-time buyers) are more calculative and oriented towards faster and higher monetary compensation following service failure than those with a strong relationship (i.e., regular buyers) customers.

Taken together, we may assume that as customers develop an established and frequent relationship with a service company, they are more likely to attach importance to all three justice dimensions in the restoration of the customer–company relationship and in ensuring relationship continuity. Conversely, customers with a less established and frequent relationship are more likely to focus on distributive justice, as they are typically more short-term-outcome-oriented (Bolton & Mattila, 2015; Hur & Jang, 2016). Hence, one may expect a strong moderating effect of the relationship activity metric on the relationship between the justice dimensions and customer outcomes, like WOM and repurchase behavior. Thus, for a segment composed of high-relationship-activity customers (i.e., those with high visiting and purchasing frequency), all justice dimensions matter, whereas only distributive justice will matter for the segment of low-relationship-activity customers (i.e., those with low visiting and purchasing frequency). For customers in the middle – those who have a somewhat developed relationship, but not too strong – the impact of relationship activity seems less evident. However, while it could be that all justice dimensions matter relatively early on, they may only matter for customers with a strong company relationship. Therefore, we refrain from positing any expectation as to how the different justice dimensions matter for a medium relationship activity segment. To conclude, we expect the following:

H1a: *For customers with high levels of relationship activity, all three justice dimensions – distributive, procedural, interactional – will exert a balanced influence on recovery outcomes (WOM and repurchase behavior).*

H1b: *For customers with low relationship activity, distributive justice is the only justice dimension impacting recovery outcomes (WOM and repurchase behavior).*

3. Data collection and measures

A survey design was initiated in collaboration with an international furniture and home accessories company. To reassure measurement accuracy, a pre-test was conducted (Hulland, Baumgartner, & Smith, 2018). The pre-test was distributed to undergraduate students from Sweden and the United Kingdom (n = 143). This pre-test enabled us to address any unclear areas in the final survey design based on student feedback. The survey for the main study was published on the company's website (see Table 1 for sample description).

To ensure that respondents had experienced a service failure and engaged in a service recovery process with the service company, the respondents had to state whether or not they had had an unfavorable experience during the six months preceding the survey and, if so, whether they chose to share that experience with the service company. This retrospective approach is common in recovery research (Grégoire & Fisher, 2006; Tax et al., 1998) and is particularly suitable for memorable events that customers can recall (East & Uncles, 2008). The six-month time interval was selected because it is often used in service recovery research and ensures customers can recall events in enough detail (Voorhees, Brady, & Horowitz, 2006; Andreassen, 2000). The final sample included a total of 2,163 customers who had experienced a service failure. Of these customers, 13.3 percent (n = 289) also filed complaints with the service company, a number which is within the range commonly cited in prior studies (e.g., Huppertz, 2007; Mittal, Huppertz, & Khare, 2008). The recovery process of the company predominantly occurs offline, given its setting.

To establish customers' relationship activity levels, we combined absolute and relative measures of a customer's visiting and purchase frequency. The absolute items were adapted from the service company's prior customer surveys and reflected how many times a customer has visited and respectively made purchases with the service company in the last year. These items were expressed as "During the last year, I have purchased a product at *Company X*"; "During the last year, I have visited a *Company X* store"; "During the last year, I have purchased product in the *Company X* online store"; "During the last year, I have visited the *Company X* online store" and used the response format 0, 1, 2–3, 4–6, up to 7 + times including N/A. The absolute items also included both online and offline visits and purchases, as the service company involved is active on both ends. The frequency with which a customer makes purchases has been widely used in earlier service recovery research as an indicator of relationship strength (Hess et al., 2003; Knox & Van Oest, 2014; Tax et al., 1998).

Mirroring the rationale from the absolute relationship activity measures, the relative items reflect how the customers relate to other customers in their visiting and purchasing frequency online and offline. The items were expressed as follows: "Compared to others, I consider myself to be a frequent visitor to *Company X* stores"; "I think I buy products at *Company X* stores more frequently than other people I know"; "Compared to others, I consider myself to be a frequent visitor of the *Company X* online store"; "I think I buy products at the *Company X* online store more frequently than other people I know"; all were measured on a seven-point scale anchored with 1 (strongly disagree) and 7 (strongly agree). The addition of relative metrics to measure the relationship activity level corresponds to the growing call to incorporate relative metrics into marketing/service research (Aksoy, Hogreve, Lariviere, Ordanini, & Orsingher, 2015; Keiningham et al., 2015). These metrics allow the capturing of customers' perceived relationships with the service company compared to other customers, thus adding an additional layer of information to customers' actual purchase behaviors and their perceived relationship with the company.

Interactional justice was measured using a three-item scale adapted from Yi and Gong (2013). Distributive justice was measured using a three-item scale built on Patterson, Cowley, and Prasongsukarn (2006). The items were altered to fit the context and scope of the study and had to be approved by the company. Procedural justice was measured using a three-item scale adapted from Chebat and Slusarczyk (2005) and Bitner (1995). Outcomes included service company-specific items related to WOM (items resembling the ones from Brown, Barry, Dacin, & Gunst, 2005) and, following Bergkvist and Rossiter (2007) recommendation, a concrete and company specific single-item was used for post-recovery purchase behavior ("Since my last complaint handling experience with *Company X* , I have purchased more than I did before that experience"). The involved service company considers these metrics to be a key indicator of its success in recovery of business. All items were measured on a seven-point scale (ranging from 1 = strongly disagree to 7 = strongly agree). Table 2 reports the individual items and item loadings.

Table 1
Demographic overview of the full sample.*

Demographics	Total = 2,163
Gender	
Male	34.2%
Female	65.8%
Age	
Under 20	2.2%
20–29	18.1%
30–39	29%
40–49	23.2%
50–59	17.9%
60+	9.6%
Voicing behavior	13.4%
Loyalty club member	55.5%

[*] To check the representativeness and validity of the sample, the management of the company involved in this study was asked to review the data in terms of customer characteristics and confirm its mirroring of the general customer database.

Table 2
Overview of survey constructs, factor loadings and reliability.

Measures[a]	Factor loadings	α	CR	AVE
Distributive justice (adapted from Patterson et al., 2006)		0.97	0.98	0.95
Overall, I am positive about how *Company X* handled the problem.	0.97			
"Organization" solved the problem appropriately.	0.98			
Overall, I found the responses from *Company X* to be in line with what I wanted.	0.97			
Interactional justice (adapted from Yi & Gong, 2013)		0.93	0.95	0.87
We were friendly to each other during the complaint handling process.	0.91			
We listened to what each other had to say during the complaint handling process.	0.95			
We were respectful to each other during the complaint handling process.	0.94			
Procedural justice (adapted from Chebat & Slusarczyk, 2005)		0.88	0.92	0.80
I received fast responses throughout the complaint handling process.	0.90			
The complaint handling process did not take more time than was promised.	0.88			
Promises *Company X* made during the complaint handling process were kept.	0.91			
Word-of-mouth behavior (adapted from Brown et al., 2005)		0.97	0.98	0.95
Since my last complaint handling experience with *Company X* , I have recommended *Company X* to close personal friends.	0.98			
Since my last complaint handling experience with *Company X* , I have recommended *Company X* to acquaintances.	0.98			
Since my last complaint handling experience with *Company X* , I have recommended *Company X* to other people.	0.96			
Repurchase behavior[b]		–	–	–
Since my last complaint handling experience with *company X* , I have purchased more than I did before that experience.	–			

Note: CR = composite reliability, AVE = average variance extracted.
[a] All items were measured using a seven-point Likert scale (1 = strongly agree; 7 = strongly disagree).
[b] Single-item measure, determined by the company under investigation.

4. Analysis and results

Based on our exploratory aim, the analysis is divided into two parts. In the first part, the objective is to discern customer clusters based on the level of relationship activity. To obtain relationship activity clusters, we employed a latent class cluster analysis (LCCA) across all customers (that is, the full sample, n = 2,163) who experienced a service failure based on the two dimensions of relative and absolute relationship activity. This approach matches earlier marketing literature that looked at clusters through an LCCA approach (e.g., De Keyser, Schepers, & Konuş, 2015; Konuş, Verhoef, & Neslin, 2008).

In a second part, this clustering serves as an input to investigate the impact of relationship activity on the relationship between the various justice dimensions and the customer recovery outcomes. Specifically, we examined whether customers with different levels of relationship activity (that is, different LCCA clusters) attach different levels of importance to the different dimensions of justice. To this end, the second part of our analysis focused solely on the voicing customers (that is, the voicing subsample – 13.4 percent of the total sample, n = 289), as those customers experienced a service recovery encounter. This part of the analysis follows a three-step approach. First, due to the exploratory nature of our study and to examine the predictive power of our theoretical model (Hair, Risher, Sarstedt, & Ringle, 2019), we employed a partial least square structural equation modeling (PLS-SEM) technique and checked its psychometric properties. Second, to validate our findings, we conducted a PLS predict analysis that allowed us to test the quality of our model by examining its predictive power and, as such, ensure its usefulness (Shmueli, Ray, Estrada, & Chatla, 2016). Lastly, we performed a multi-group analysis using the PLS-MGA technique to examine whether customers belonging to the a priori defined clusters respond differently to the different dimensions of justice.

4.1. LCCA procedure and model specification

To discern customer clusters based on relationship quality level, we employed an LCCA model using Latent GOLD (version 5.1.0.18212). We clustered the customers based on the eight items measuring relationship activity. This method is common in the marketing field (e.g., De Keyser et al., 2015; Herhausen, Kleinlercher, Verhoef, Emrich, & Randolph, 2019; Konuş et al., 2008). In this phase, the total sample of 2,163 customers facing service failure were able to state their level of relationship activity. Age, gender, voicing (yes/no), and loyalty program membership (yes/no) were used as covariates in the analysis to predict class membership, and this also enabled us to validate our sample in relation to prior research. We used the following probability specification for the LCCA model:

$$f(y_i|z_i^{\text{cov}}) = \sum_{x=1}^{K} P(x|z_i^{\text{cov}}) \prod_{h=1}^{H} f(y_{ih}|x, z_i^{\text{cov}})$$

The model specifications $f(\boldsymbol{y}_i|\boldsymbol{z}_i^{cov})$ follow a general mixture model specification, in which $\boldsymbol{y}_i$ is the vector for the sum of ordinal variables and z_i^{cov} is the vector for the sum of nominal covariates used for the latent factor. The first part of the model, $\sum_{x=1}^{K} \mathrm{P}(\mathrm{x}|\mathbf{z}_i^{\text{cov}})$, specifies the probability of the number of K-classes. We assumed one latent factor, theorized as relationship activity (x), on which the number of K-classes is not set a priori, but is determined by the model fit and capability for interpretation (Vermunt & Magidson, 2015). The second part of the model formulation, $\prod_{h=1}^{H} f(\boldsymbol{y}_i|x, z_i^{cov})$, describes that $\boldsymbol{y}_i$ variables belonging to different sets are assumed to be mutually independent given the latent and exogenous variables, but are allowed to correlate within the classes (Vermunt & Magidson, 2015). As in the first part of the probability model, $x$denotes the single nominal latent variable, and z_i^{cov} is the vector for the sum of covariates affecting the latent factor relationship activity$x$.

4.2. LCCA results

We estimated our model for solution from one to six clusters, and we have applied the AIC3 criterion for model selection (Vermunt & Magidson, 2015). In addition, classification error and cluster interpretability were used as supplementary selection criteria (Ngobo, 2017). In combination, this yields a three-class solution, and a 2,000-bootstrap procedure was used to ensure the significance criteria were met ($p > 0.05$) (Vermunt & Magidson, 2015). A summary of the covariates for each cluster is reported in Table 3.

To illustrate the relationship between the absolute and relative metrics used to predict the level of relationship, a scatter plot based on the three-class posterior classification is shown in Fig. 2. In the scatter plot, we combined the four items reflecting the absolute and the four items reflecting the relative relationship activity measures. The visual illustration uses green, blue, and orange to discern the customer clusters and specifies class association. The X-axis represents the level of relative relationship activity, and the Y-axis represents the level of absolute relationship activity. In addition, the size of the plots denotes the frequency of different participants' responses. The scatter plot retains some opacity to make it possible to distinguish when different clusters are overlapping. As we used an unconstrained model specification for our class identification that builds on a predefined clustering algorithm, the overlapping of clusters is unavoidable (Adam & Blockeel, 2017).

Our findings show that 36.5 percent of the customers in the total sample have a high level of relationship activity (orange group) and 19.2 percent have a low level of relationship activity (green group). The remaining 44.3 percent fall in between (blue group) and have a medium level of relationship activity. Our findings show that customers in the high-relationship-activity cluster (orange group) are significantly less likely to voice their complaints, which corroborates prior findings (e.g., Umashankar, Ward, & Dahl, 2017). Additionally, our LCCA model shows that customers with high levels of relationship activity are more likely to be loyalty program members than those with low and medium levels.

Table 3
LCCA results.

Covariates	High relationship activity n = 782 (36.5%)	Medium relationship activity n = 967 (44.3%)	Low relationship activity n = 414 (19.2%)
Gender^{ns}			
Male	33.9%	32.2%	39.4%
Female	66.1%	67.8%	60.6%
Age^{ns}			
Under 20	1.8%	1.8%	3.5%
20–29	19.8%	16.7%	18.1%
30–39	31.9%	27.3%	27.5%
40–49	22%	25.1%	20.9%
50–59	17.1%	18.3%	19%
60+	7.5%	10.7%	11%
Voicing behavior	11.5%	13.4%	16.7%
Loyalty membership	73.2%	47.4%	40.6%

Note: Results show that the three classes are significantly different ($p > 0.05$). Voicing behavior and loyalty membership are different across the clusters ($p < 0.05$). Age and gender are not significantly different ($p > 0.05$).

4.3. PLS-SEM procedure and psychometric properties

In the second part of our analysis, examining whether customers

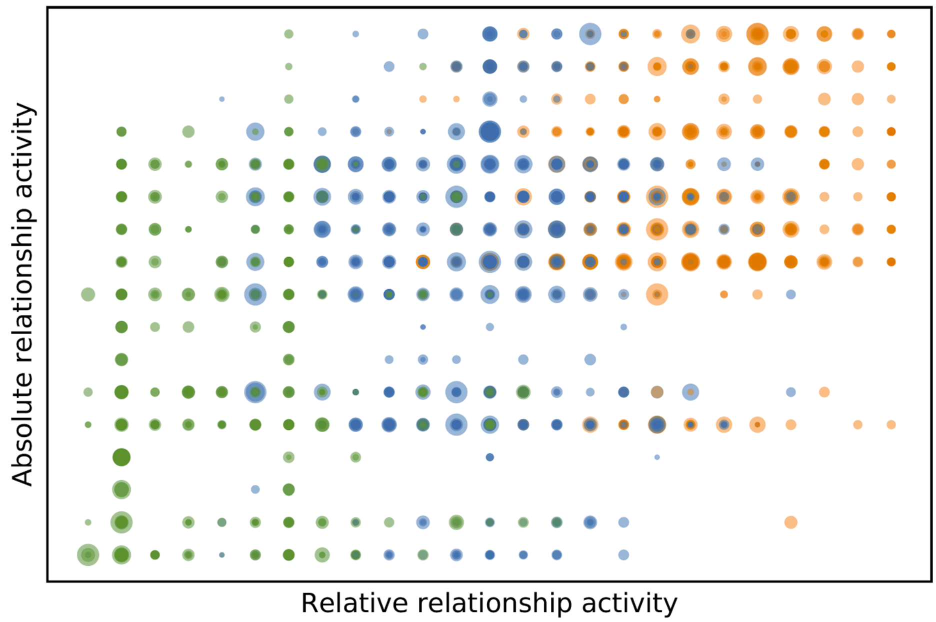

Fig. 2. Visual illustration of the posterior classification in relation to the customer's absolute and relative relationship activity. **Notes:** *Green = low relationship activity (19.2 percent), blue = medium relationship activity (44.3 percent)*, and *orange = high relationship activity (36.5 percent).*

involved in service recovery encounters attach different levels of importance to the justice dimensions, we zoomed in on customers who voiced a complaint (n = 289).[2] Using this sample, we assessed our model by examining the psychometric properties using PLS-SEM through SmartPLS version 3.3.2. (Ringle, Wende, & Becker, 2015), with a BCa 5,000-bootstrap procedure (Hair, Hult, Ringle, & Sarstedt, 2016). The PLS-SEM analysis was chosen over covariance-based structural equation modeling (CB-SEM) due to the exploratory and predictive potential made possible with the PLS-SEM (Hair et al., 2019). In addition, as our clustering technique splits the sample into smaller groups, PLS-SEM enabled us to examine the moderating effect of relationship activity based on the LCCA clusters despite using smaller sample sizes (Hair et al., 2019; Sarstedt, Ringle, & Hair, 2017).

We tested our complete model (considering the total sample of voicing customers n = 289), including the separate models for the three-class posterior classification (*high*, *medium*, and *low* relationship activity) obtained from the prior LCCA. The psychometric properties for the complete model, including the three separate models (*high, medium,* and *low* relationship activity), meet the criteria for convergent validity of all outer loadings > 0.70, and as such exhibit a sufficient level of reliability (Hair et al., 2019). Internal consistency reliability for the multi-item constructs (distributive, interactional, and procedural justice), including the multi-item construct WOM behavior, was above the threshold (composite reliability > 0.70), and the average variance extracted was > 0.50, indicating satisfactory convergent validity. The heterotrait-monotrait (HTMT) ratio was below the conservative threshold of < 0.85, which indicates satisfactory discriminant validity across the models (Sarstedt et al., 2017), and the adjusted R^2 for the endogenous constructs. WOM behavior and repurchase behavior (hereafter REP) suggested a moderate and, respectively, a weak explanatory power (Hair et al., 2019). In detail, for the complete model WOM indicated a moderate explanatory power (R^2 adjusted = 0.51p < 0.001) and REP reported a weak explanatory power (R^2 adjusted = 0.30, p < 0.001). The R^2 adjusted was largely consistent across the three a priori identified relationship activity clusters: the medium-relationship-activity cluster (WOM: R^2 adjusted = 0.46, p < 0.001; REP: R^2 adjusted = 0.26, p = 0.001), the high-relationship-activity cluster (WOM: R^2 adjusted = 0.51, p < 0.001; REP: R^2 adjusted = 0.36, p < 0.001), and the low-relationship-activity cluster (WOM: R^2 adjusted = 0.61, p < 0.001; REP: R^2 adjusted = 0.25, p = 0.033). Table 4 provides descriptive statistics related to the customer classification clusters of relationship activity.

Table 4
Descriptive statistics.

			Correlations				
	M	SD	1.	2.	3.	4.	5.
Combined model							
1. Distributive justice	3.1	2.2	1				
2. Interactional justice	5.1	1.7	0.52	1			
3. Procedural justice	3.7	2.0	0.71	0.57	1		
4. WOM behavior	3.3	1.9	0.68	0.53	0.56	1	
5. Repurchase behavior	2.7	1.6	0.54	0.37	0.42	0.66	1
High relationship activity							
1. Distributive justice	3.2	2.3	1				
2. Interactional justice	5.3	1.5	0.43	1			
3. Procedural justice	3.9	2.0	0.73	0.53	1		
4. WOM behavior	3.8	2.1	0.62	0.59	0.62	1	
5. Repurchase behavior	3.1	1.8	0.54	0.44	0.57	0.66	1
Medium relationship activity							
1. Distributive justice	3.3	2.2	1				
2. Procedural justice	5.3	1.5	0.53	1			
3. Interactional justice	3.8	1.9	0.68	0.54	1		
4. WOM behavior	3.5	1.8	0.68	0.42	0.48	1	
5. Repurchase behavior	2.9	1.5	0.52	0.22	0.32	0.62	1
High relationship activity							
1. Distributive justice	2.5	2.0	1				
2. Procedural justice	4.3	1. 9	0.59	1			
3. Interactional justice	3.1	2. 0	0.70	0.62	1		
4. WOM behavior	2.4	1.9	0.79	0.49	0.57	1	
5. Repurchase behavior	1.9	1.4	0.52	0.33	0.31	0.62	1

Notes: Values below diagonals represent correlation within the posterior classification of customers based on their relationship activity.

[2] Customers within the high relationship activity clusters were less likely to voice their complaints. As such, zooming in on the customers who chose to voice their complaints decreased the proportion of customers with a high relationship activity from 36.5 percent to 30.1 percent (n = 87). The number of customers in the sample with medium relationship activity increased from 44.3 percent to 46 percent (n = 133), and the number of customers with low relationship activity increased from 19.2 percent to 23.9 percent (n = 69).

4.4. PLSpredict analysis

In order to validate our findings, a PLSpredict analysis was utilized to analyze the prediction quality of our model. Prediction modeling is an underused, but important way for researchers to test a model's predictive power and ensure its theoretical and practical usefulness (Shmueli, 2010, Shmueli & Koppius, 2011; Shmueli et al., 2016). We assessed the model using the guidelines suggested by Shmueli et al. (2019). Consequently, to ensure that our training samples met the minimum sample criteria, we utilized the minimum R^2 method that is commonly used in service and marketing research to determine the minimal sample size (Hair et al., 2019; Hair et al., 2016). The inherent simplicity of our model (a maximum of three paths directed towards the latent variables), and a decided significance level of 0.05 including a minimum $R^2 = 0.25$, enabled us to follow the convention for PLSpredict for the complete model (Shmueli et al., 2019). When conducting the analysis, K-folds was set to 10 and the number of repetitions r was set to 10. First, we assessed the PLS-SEM Q^2_{Predict} values for all the indicators in the measurement model. The PLS-SEM Q^2_{Predict} measures all reported > 0, confirming that the endogenous constructs outperformed the naïve benchmark. Second, the prediction-error distribution for both endogenous constructs visually followed a bell-curved shape, which we interpreted as symmetrical.[3] Mirroring Shmueli et al. (2019) approach, we chose to examine whether the root mean squared error (RMSE) results in the PLS-SEM scored lower than the linear regression model (LM) RMSE on the individual indicators (see Table 5). All indicators scored lower on the RMSE in the PLS-SEM than the LM. This confirms that our model has high predictive power (Shmueli et al., 2019).[4]

4.5. PLS-SEM and multigroup analysis

To examine whether the three justice dimensions impact recovery outcomes differently for customers with different levels of relationship activity, the LCCA clusters were used to input into the PLS-SEM. Making meaningful clusters/segments is a long-standing call in service recovery research (Orsingher et al., 2010), and the LCCA approach allows us to combine various relationship metrics to distinguish meaningful clusters, rather than using continuous variables to test our assumption. We ran both a combined model and individual models for all three LCCA clusters (see Table 6).

First, in line with H1a, results show that for high relationship activity customers there is a relatively balanced influence of the three justice dimensions on customer outcomes, WOM and repurchase behavior (see column High RA in Table 6).

Table 5
PLS predict results.

Item	PLS-SEM RMSE	Q^2_{Predict}	LM RMSE	PLS-SEM RMSE - LM RMSE
Purchase behavior (single-item)	1,371	0,287	1,388	−0,017
Word-of-mouth (friends)	1,479	0,451	1,503	−0,024
Word-of-mouth (acquaintances)	1,43	0,514	1,441	−0,011
Word-of-mouth (others)	1,47	0,441	1,494	−0,024

Second, the analysis shows that distributive justice is most important in driving recovery outcomes in the combined model (WOM: $\beta = 0.52$, $p < 0.001$; REP: $\beta = 0.45$, $p < 0.001$). This finding is largely consistent with prior studies (e.g., Homburg & Fürst, 2005; Orsingher et al., 2010; Smith et al., 1999). Considering the three cluster-related models, our findings show that distributive justice is the most important justice dimension for the vast majority of customers. In particular, distributive justice is shown to have a strong positive and significant impact on post-recovery WOM behavior for all three clusters (low: $\beta = 0.76$, $p < 0.001$; medium: $\beta = 0.62$, $p < 0.001$; high: $\beta = 0.31$, $p = 0.017$). However, while distributive justice is the most important dimension for the low ($\beta = 0.58$, $p < 0.001$) (in line with H1b) and medium ($\beta = 0.59$, $p < 0.001$) relationship activity customers in driving repurchase behavior, it is not significantly linked ($\beta = 0.24$, $p = 0.089$) to customers' repurchase behavior if they belong to the high-relationship-activity cluster.

To establish whether the differences across the customer clusters are significant, a two-tailed significance test using PLS-MGA (Hair et al., 2019) with a BCa 5,000-bootstrap procedure was employed; see Table 7.[5] A PLS-MGA analysis was selected, as the nature of the sample is unequal in size, which is a critical condition using other group comparison techniques such as a permutation test (Hair, Sarstedt, Ringle, & Gudergan, 2017). Our results show that the positive influence of distributive justice on WOM (medium vs. high: $p = 0.063$; high vs. low: $p = 0.013$) and repurchase behavior (medium vs. high: $p = 0.043$; high vs. low: $p = 0.106$) is not unequivocally lower for the high-relationship-activity cluster compared with the two other clusters. Moreover, no significant differences are found between the low- and medium-relationship-activity clusters. As such, we can conclude that distributive justice matters for all customers, regardless of their level of relationship activity, with a somewhat lower importance for customers with high levels of relationship activity.

Second, in the combined model, interactional justice also has a positive impact on WOM ($\beta = 0.21$, $p < 0.001$) and only a marginally significant positive impact on repurchase behavior ($\beta = 0.10$, $p = 0.052$). Focusing on the separate clusters, our findings reveal that interactional justice does not significantly impact WOM (low: $\beta = 0.03$, $p = 0.657$; medium: $\beta = 0.09$, $p = 0.213$) or repurchase behavior (low: $\beta = 0.07$, $p = 0.425$; medium: $\beta = -0.06$, $p = 0.496$) for low- and medium-relationship-activity customers (in line with H1b). However, interactional justice does have a substantial impact on post-recovery customer outcomes for the high-relationship-activity cluster, especially on WOM (WOM: $\beta = 0.34$, $p < 0.001$; REP: $\beta = 0.18$, $p = 0.054$) with an impact of equal magnitude compared to distributive justice. The PLS-MGA results (Table 7) confirm this. More precisely, the positive impact of interactional justice on WOM for high-relationship-activity customers is significantly higher and different from the other clusters (medium vs. high: $p = 0.025$; high vs. low: $p = 0.007$). Conversely, this difference does not hold for the impact of interactional justice on repurchase behavior (medium vs. high: $p = 0.063$; high vs. low: $p = 0.384$). Again, there are no significant differences between the low- and medium-relationship-activity customers. Taken together, we may conclude that interactional justice drives WOM as a post-recovery customer outcome for the high-relationship-activity cluster and not for the two other groups.

Third, procedural justice does not show a significant impact on either recovery outcome (WOM: $\beta = 0.08$, $p = 0.248$; REP: $\beta = 0.05$, $p = 0.502$) in the combined model. Regarding the separate customer clusters, the

[3] Examining the PLS prediction residuals in more depth, the Shapiro-Wilk test for normality was significant ($p < 0.001$) for both the word-of-mouth behavior and repurchase behavior constructs. Therefore, we also examined the predictive power of the model for non-normal distributed data. This analysis show that a majority of indicators (three out of four indicators) have lower MAE values than the naïve LM benchmark, indicating a medium predictive power.

[4] Employing the same analytical approach for the individual clusters, the findings document high predictive power across all three relationship activity clusters (PLS-SEM < LM on the individual indicators; also holds for RMSE and MAE).

[5] Additional analyses were carried out to reassure the results from the PLS-MGA hold. In particular, a Parametric test and a Welch-Satterthwait test were conducted. The results were consistent using this multi-method approach (Hair et al., 2017). Please refer to Table 7 for additional information.

Table 6
Structural model results.

Relationship	Combined model (n = 289)		High RA (n = 87)		Medium RA (n = 133)		Low RA (n = 69)	
	β	p	β	p	β	p	β	p
DISJUST -> WOM	0.52***	< 0.001	0.31**	0.017	0.62***	< 0.001	0.76***	< 0.001
DISJUST -> REP	0.45***	< 0.001	0.24*	0.089	0.59***	< 0.001	0.58***	< 0.001
INTJUST -> WOM	0.21***	< 0.001	0.34***	< 0.001	0.09	0.213	0.03	0.657
INTJUST->REP	0.10*	0.052	0.18*	0.054	−0.06	0.496	0.07	0.425
PROJUST -> WOM	0.08	0.248	0.21	0.119	0.02	0.815	0.02	0.853
PROJUST -> REP	0.05	0.502	0.30**	0.028	−0.05	0.592	−0.14	0.351

Notes: The results reported are standardized. RA = relationship activity, DISTJUST = distributive justice, INTJUST = interactional justice, PROJUST = procedural justice, WOM = word-of-mouth behavior, REP = repurchase behavior.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 7
Multigroup analysis results.

Relationship[1]	Medium RA vs. High RA		Medium RA vs. Low RA		High RA vs. Low RA	
	Diff in β	p	Diff in β	p	Diff in β	p
DISJUST -> WOM	0.31	0.063	−0.13	0.357	−0.44	0.013* a, b
DISJUST -> REP	0.35	0.043* a, b	0.00	0.997	−0.34	0.106
INTJUST -> WOM	−0.25	0.025* a, b	0.06	0.570	0.31	0.007* a, b
INTJUST->REP	−0.24	0.063	−0.13	0.283	0.11	0.384
PROJUST -> WOM	−0.19	0.239	0.00	0.996	0.19	0.288
PROJUST -> REP	−0.35	0.039* a, b	0.09	0.601	0.44	0.032* a, b

Notes: The results reported are standardized. RA = relationship activity, DISTJUST = distributive justice, INTJUST = interactional justice, PROJUST = procedural justice, WOM = word-of-mouth behavior, REP = repurchase behavior.
[1] The MGA-PLS significance test reports significant difference at the 5% level* (p < 0.05). Additional tests verifying the differences are consistent. [a] Parametric test and [b] Welch-Satterthwait test indicate a significant difference at the p < 0.05 significance level.

results show that procedural justice does not significantly influence WOM (low: β = 0.02, p = 0.853; medium: β = 0.02, p = 0.815) or repurchase behavior (low: β = −0.14, p = 0.351; medium: β = −0.05, p = 0.592) for low- and medium-relationship-activity customers (in line with H1b). For the high-relationship-activity cluster, procedural justice does not have a significant impact on WOM (β = 0.21, p = 0.119), but it does have a significant positive impact on repurchase behavior (β = 0.30, p = 0.028) that is of equal magnitude to that of distributive and procedural justice. The PLS-MGA results further confirm the above findings. More precisely, they show no significant differences between the groups for the procedural justice–WOM relationship. However, the positive impact of procedural justice on repurchase behavior for high-relationship-activity customers is significantly higher and different from the other clusters (medium vs. high: p = 0.039; high vs. low: p = 0.032). Again, we found no differences between the low- and medium-relationship activity customers. We can conclude that procedural justice matters for the high-relationship-activity cluster in driving repurchase behavior, but not for the two other clusters.

5. Discussion

5.1. Theoretical implications

This paper examines whether the impact of the three justice dimensions (distributive, interactional, and procedural) on post-recovery customer outcomes varies across customers with differing levels of relationship activity. This results in two main contributions.

First, the paper contributes to the long-standing debate in the service recovery literature as to which justice dimension matters the most, as well as to the ongoing debate regarding the role of relationship variables on customers' reactions in recovery settings (Béal et al., 2019). Despite the widespread adoption of the justice framework, research findings vary considerably regarding which dimension is most important. While Orsingher et al. (2010) and Gelbrich and Roschk (2011) meta-analytical studies provide evidence for the dominance of distributive justice in driving post-recovery customer outcomes, several individual papers find that interactional and procedural justice matter more (e.g., Maxham & Netemeyer, 2003; Smith & Bolton, 2002). The current study considers how the level of relationship activity may underlie these standing differences. Existing literature supports the notion that customers with a high level of relationship activity may attach importance to all justice dimensions, as they seek to restore all facets of the relationship (Grégoire & Fisher, 2006) and have well-defined recovery expectations (Karande et al., 2007). Conversely, customers with lower levels of relationship activity may attach most importance to distributive justice, as they are typically more calculative (Hogreve et al., 2017) and have less defined expectations about the totality of the service recovery process (Karande et al., 2007). The compensation given then acts as a simple heuristic to evaluate the recovery and impact post-recovery outcomes.

The findings corroborate this conceptual thinking and show that distributive justice is the only dimension that significantly influences WOM and repurchase behavior for customers with low and medium levels of relationship activity. Neither interactional or procedural justice significantly impact post-recovery customer outcomes for these clusters, which largely confirms the findings of Orsingher et al. (2010) and Gelbrich and Roschk (2011). However, for customers with high relationship activity, all three dimensions of justice matter for either WOM (distributive and interactional justice) or repurchase behavior (distributive and procedural justice). In addition, the size of their impact on these post-recovery customer outcomes is relatively balanced, which means that none of the three dimensions stand out. This is interesting, given that previous meta-analyses have found a clear hierarchy of importance among the three justice dimensions. The level of relationship quality is shown to have a clear impact on the importance of the various subdimensions.

Second, we address Orsingher et al. (2010) long-standing call to examine whether meaningful customer segments exist in service recovery. Our findings confirm that it makes sense to cluster customers based on behavioral variables – in this case, relationship activity – and to adapt service recovery efforts accordingly so that they match customers' sought-after outcomes. In so doing, we also respond to the calls of Arsenovic et al. (2019) and Van Vaerenbergh et al. (2019) to account for customer heterogeneity in service recovery research and show that future research needs to account for relationship activity, as it strongly impacts what customers pay attention to in service recovery efforts. Failure to account for such customer differences may lead to conclusions that are not generalizable across a wide range of customers or customer segments.

5.2. Managerial implications

This research has important implications for practice. Specifically, we show that service companies can benefit from adopting a segment-based approach toward service recovery. Clearly, any company's customer base is inherently heterogeneous, and not only should service managers account for this while setting up their core service processes, but segmentation is also a good practice to support the recovery part of the business. While this recommendation stems from previous research (Van Vaerenbergh et al., 2019; Arsenovic et al., 2019), the present study specifically demonstrates how relationship-activity-based clusters react differently to the recovery process by attaching different levels of importance to the various dimensions of justice, and hence have differing expectations for recovery.

As post-recovery outcomes for customers with low and medium levels of relationship activity are predominantly driven by distributive justice, service managers should focus on providing an appropriate solution to customers, clearly handling and solving the service failure. The nature of the recovery outcome should match the failure (Roschk & Gelbrich, 2014). For high-relationship-activity customers, companies should invest heavily in a good combination of delivering an appropriate solution, favorable employee behavior (such as being friendly, respectful, and attentive), and organizational procedures (recovery time, flexibility, etc.) to match justice expectations on all three levels (Van Vaerenbergh et al., 2019).

Without wishing to suggest that favorable employee behavior and organizational procedures do not matter at all for the other customer clusters, an appropriate service recovery outcome is most critical and should be the central focus of the recovery to allow frequent relationships to develop. If handling/solving the problem is critical for WOM and repurchase behavior for low- and medium-relationship-activity customers, then companies really have to work hard to do the (recovery) job correctly. For this purpose, they need to have people who can handle and ultimately solve the problem. This requires hiring and training the right employees to demonstrate competence, having the right attitude and authority to influence the process, and solutions based on customer expectations in order to optimize the customers' fairness evaluation (Gruber, 2011).

In addition, our research demonstrates that recovery segmentation can easily be done to provide actionable knowledge. The upside of using relationship activity as a key segmentation variable for recovery is that it is typically directly attainable from the customer database (for example, customer purchase frequency and monetary value). Moreover, our findings show that loyalty card membership may act as a proxy for relationship activity if no such metric is available. Hence, companies do not need to set up complex segmentation models. Employees can use readily available customer data to adapt the recovery process to distinct customer segments in real time (such an approach is often promoted in CRM circles, where a traffic light system underlies what type of service is given to different customer types after identification through check-in, reading of loyalty card information, etc.; Zeithaml, Rust, & Lemon, 2001).

5.3. Limitations and directions for future research

Although this study uses survey data that reflect actual events and behavioral data to investigate service recovery encounters of a global service company (i.e., external validity), certain limitations need to be noted. While the retrospective nature of our survey study is common in recovery research, future research could use scenario-based experiments to replicate our findings and to control for additional covariates. Moreover, collaborating with a global service company limited the possibility of including additional moderators/mediators (e.g., fairness perceptions) and other key-marketing metrics linked to service recovery efforts. Future research might replicate our study by further incorporating post-recovery outcomes, such as recovery satisfaction (Orsingher et al., 2010) and trust (Basso & Pizzutti, 2016), and also generalize our findings by replicating the study in settings other than furniture and home accessories.

Furthermore, the present study operationalizes relationship activity as the customer's purchase and visiting frequency over a set period (12 months). Future research might expand this timeframe and account for customers' entire history with the company. Finally, this study does not discuss and discern between various service recovery options that may impact the relative importance of the justice dimensions. Future work could consider adding this additional layer of information (see Van Vaerenbergh et al. (2019) for an overview of the various service recovery options).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2021.05.031.

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