Reality cannot be fooled: A text-mining of social media communication between sustainable fashion brands and consumers

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Introduction. Sustainability issues and concerns have emerged as the core topic of the fashion industry because the fashion industry has been identified as the second polluting industry (Choi & Cheng, 2015). Due to increased consumer awareness and concerns about sustainability, fashion brands are pushed to adopt sustainable initiatives (Da Giau et al., 2016). Many companies have launched sustainable fashion products and shared how they transform production processes to be sustainable while protecting workers' well-being. However, existing literature addresses a lack of evidence of the effectiveness of communicating these efforts (Orminski et al., 2021). Consumers still hesitate and distrust companies' sustainable initiatives due to a lack of transparent communication about them (Hussain, 2017). Especially considering the prevalent use of interactive communication channels, such as social media, provides much information, we are interested in exploring how social media messages from sustainable fashion brands are communicated and what message tones attract consumers to respond. In the literature, emotional messages drive positive feelings about the brand/product, creating positive reactions (Goldberg & Gorn, 1987). A recent study by Chae (2022) has evidenced that emotional messages about CSR develop consumers' positive engagement in the message (e.g., likes, Shares). Based on the evidence from the previous literature, the following research questions are suggested: (1) What emotional valence in social media messages published by sustainable fashion brands is communicated? (2) what emotions within social media messages from sustainable fashion brands influence consumers? (3) How do sustainable fashion brand clusters categorized by emotions influence public engagement? We analyze Twitter data between 2009 and 2023 using computational analyses to explore the reality of the effectiveness of sustainable fashion brands' communication on consumer engagement.

Literature Review. Emotions have already been recognized as an essential cause of human behavior (Schreiner et al., 2021). Emotions have been widely used as the content strategy in advertising as they develop viewers' positive responses (Tafesse & Wien, 2018). Among various behavioral responses, consumer engagement refers to consumers' cognitive, emotional, behavioral, and social reactions, which may emerge while interacting with related or focal consumers and brands (Hollebeek et al., 2014). This concept elaborates on dynamic consumer-brand and consumer-consumer relationships that may create values (Vargo & Lush, 2008). Considering that consumer-brand interactions in social media generate a wealth of textual data, which may contain undiscovered knowledge, we investigate one social media platform known to create and share a public opinion (e.g., Twitter). In particular, we are interested in opinion mining, so sentiment analysis is utilized to study opinions, feelings, and emotions expressed in social media messages, which may create responses from viewers (He et al., 2013).

Methods This study adopted a content analytic approach to explore the proposed research questions. Researchers collected all tweets (n = 147,857) created on Twitter, one of the most popular social media platforms, of 77 sustainable fashion brands listed in Remake.com, a non-profit global advocacy organization for sustainability. After excluding retweets and replies, researchers analyzed 55,605 tweets. The oldest tweet was created on February 7, 2009, and the newest one was on February 3, 2023.

Guided by the National Research Council (NRC) Word-Emotion Association Lexicon (Mohammad & Turney, 2013), researchers computationally counted emotions, including anger (M = .135, *SD* = .374), anticipation (*M* = .619, *SD* = .837), disgust (*M* = .080, *SD* = .242), sadness (*M* = .185, *SD* = .444), surprise (*M* = .238, *SD* = .500), trust (*M* = .607, *SD* = .831), fear (*M* = .143, *SD* = .399), and joy (*M* = .603, *SD* = .844), of words in each tweet using an R package, *syuzhet* (v1.0.4; Jockers, 2017). Note that a tweet may have more than one word for each emotion. This study used Twitter's manifest content to gauge the degree of public engagement (the information of likes and shares).

Results For RQ1, Poisson regressions revealed that the sum of emotions (*M* = 2.61, *SD* = 2.96) in each tweet is unrelated to likes and shares. It means just a higher number of emotional words in a social media message does not guarantee higher public engagement in the message.

For RQ2, additional Poisson regressions showed anticipation (β = .037), disgust (β = .633), trust (β = .088), and fear (β = .902) increased, and anger (β = -.060), sadness (β = -.970), surprise (β = -.035), and joy (β = -.489) decreased likes significantly ($ps < .001$) while anger (β = .032), disgust (β = .790), surprise (β = .286), trust (β = .023), and fear (β = .893) increased and anticipation (β = -.141), sadness (β = -1.46), and joy (β = -.563) decreased shares significantly ($ps < .001$).

For RQ3, researchers clustered the sustainable fashion brands based on the means of each emotion using k-means clustering, an unsupervised machine learning algorithm. Researchers assigned 3 to the k value according to the elbow plot. Researchers named the three clusters high emotional richness (*n* = 10), moderate emotional richness (*n* = 35), and low emotional richness (*n* = 32) guided by a radar chart. In the radar chart, the high emotional richness group area included the moderate emotional richness group area and the low emotional richness group area. ANOVAs with an independent variable having the three groups and a dependent variable (likes or shares) yielded the mean difference of likes among the three groups was significant, $F(2, 55{,}062) = 4.19$, $p < .05$, but the mean difference of likes among the same groups was not significant. A Tukey posthoc test specified that high emotional richness (*M* = 131, *SD* = 2,347) was significantly ($ps < .05$) higher than both moderate emotional richness (*M* = 45.7, *SD* = 2,688) and low emotional richness (*M* = 30.1, *SD* = 391) regarding the mean of likes. However, the mean of likes had no difference between the moderate and low groups.

Discussion, Implications, and Limitations

The results of the Twitter message published by 77 sustainable fashion brands show consumers tend to engage in more explicit emotional (e.g., using assertive and directive tone) messages than implicit sentiment messages (e.g., positive and encouraging), which is similar to findings by Ordenes et al. (2017) regarding consumer reviews. The cluster analysis results reveal that widely recognized sustainable brands (e.g., Stella McCartney, Patagonia) use highly emotional messages while self-claimed sustainable brands (e.g., Nike, Zara) share more practical and product-focused sustainable messages. Our findings provide insight to practitioners about the importance of using emotionally appealing messages to engage consumers for a sensitive topic like sustainability. A future study is encouraged to empirically examine the differential impacts of language types in social media messages on consumer engagement.

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