**How Celebrity Attributes Damage Customer-Brand Relationship in Live Streaming Commerce: A Dark Side**

Zhucheng Shao[a], Jessica Sze Yin Ho[b]
Garry Wei-Han Tan[c,d,e], Keng-Boon Ooi[f,g,h,i], Prianka Sarker[j], Yogesh K. Dwivedi[k,l,]

**Zhucheng Shao**
[a]School of Social Sciences, Edinburgh Business School,
Heriot-Watt University Malaysia, Malaysia
Email: zs2037@hw.ac.uk

**Jessica Sze Yin Ho**
[b]School of Social Sciences, Edinburgh Business School,
Heriot-Watt University Malaysia, Malaysia
Email: j.ho@hw.ac.uk

**Garry Wei-Han Tan**
[c]UCSI Graduate Business School,
UCSI University, Kuala Lumpur, Malaysia

[d]School of Economics and Management,
Yunnan Normal University, Kunming, China

[e]School of Business, Faculty of Business, Design, and Arts
Swinburne University of Technology Sarawak Campus, Malaysia.
Email: garrytanweihan@gmail.com

**Keng-Boon Ooi**
[f]UCSI Graduate Business School,
UCSI University, Kuala Lumpur, Malaysia
Email: ooikengboon@gmail.com

[g]FORE School of Management, New Delhi, India

[h]School of Business, Faculty of Business, Design, and Arts
Swinburne University of Technology Sarawak Campus, Malaysia.

[i]School of Finance and Economics,
Nanchang Institute of Technology, Nan Chang City, China

**Prianka Sarker**
[j]Department of Marketing Retail and Tourism
Manchester Metropolitan University, UK
Email: P.sarker@mmu.ac.uk

**Yogesh K. Dwivedi**
**(Corresponding author)**
[k]Digital Futures for Sustainable Business & Society Research Group,
School of Management, Swansea University – Bay Campus, Swansea, UK

[l]Symbiosis International (Deemed University), Pune, Maharashtra, India
Email: Y.K.Dwivedi@swansea.ac.uk

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## Abstract

This study examines the effect of celebrity attributes on customer-brand relationships from a dark side in live streaming commerce by extending a Stimulus-Organism-Response theory. An online self-administered questionnaire was conducted to collect the data with 317 valid replies and analyse it using a multi-analytical hybrid structural equation modelling-artificial neural network (SEM-ANN) approach. The results reveal that, in addition to a positive correlation from brand betrayal to brand hate, a negative reputation can drive both brand betrayal and brand hate, while advertisement inauthenticity and expertise scarcity induce brand betrayal only. In turn, brand hate can generate all the negative outcomes, while brand betrayal cannot lead to brand revenge and retaliation. The study implications enrich the extant literature on customer-brand relationships and live streaming commerce, reveal the stimuli in celebrity attributes and responses in brand outcomes, and highlight the effect of brand betrayal and brand hate that bridge stimuli and responses. The practical implications suggest practitioners focus on a high congruence between celebrities and brands when adopting endorsements, building a continual consumer-brand relationship and proper remedy. The originality of this research is the higher-order construct of brand hate and integrated brand outcomes.

**Keywords: Celebrity endorsement, brand hate, brand betrayal, Customer-brand relationships, S-O-R theory, customer-brand relationships.**

1. Introduction

As live streaming commerce has grown in popularity in recent years, more electronic sellers (e-sellers) realise that celebrities' massive followers and attention will generate huge profits and customer-brand relationships in the live streaming industry (Clement Addo et al., 2021). This leads celebrities to be invited to endorse brands and participate in live streaming to provide product recommendations and information sharing to audiences (Sun et al., 2019). E-sellers view celebrities as their dominant marketing strategy to raise their brand awareness reliably, as celebrities may develop even closer relationships with their audience through live streaming commerce, where they can frequently para-social interact, connect, and update their followers with greater ease (Park and Lin, 2020).

However, although e-sellers increasingly adopt celebrities to endorse brands in live streaming, it is not always true that the more famous the celebrities are, the better. Emerging problems in the live streaming commerce industry are that e-sellers pay more attention to the fame of celebrities but ignore the personal attributes that match up with brands (Park and Lin, 2020). In the match-up hypothesis, celebrities and their endorsements will be more compelling if they perceive a superior fit between personal attributes and the brands they endorse (Till and Busler, 2000). In live streaming commerce, audiences will evaluate the celebrity attributes and the endorsement content to determine if they are appropriate to the brand image (Park and Lin, 2020). When audiences realise a discrepancy between celebrities and brands, they are more inclined to view celebrities as profit-seekers with commercial aims, thus producing negative attitudes toward the brands (Till and Busler, 2000). Hence, despite e-sellers being well-intentioned in inviting celebrity endorsements, whether they eventually transfer into positive brand awareness varies significantly and usually might have the opposite effects, i.e., brand betrayal, brand hate, and subsequent brand repercussions (Fetscherin, 2019; Jabeen et al., 2022). As increasing numbers of e-sellers realise this problem in live streaming commerce, this study is necessary to examine the impact of celebrity attributes on customer-brand relationships from dark perspectives disclosed in academics.

The current studies explain various effects by focusing on the negative aspects of customer-brand relationship, such as brand avoidance (Bayarassou et al., 2020; Costa and Azevedo, 2022), brand revenge (Fetscherin, 2019; Grégoire et al., 2009), brand retaliation (Fetscherin, 2019; Grégoire and Fisher, 2008; Hegner et al., 2017; Jabeen et al., 2022; Zarantonello et al., 2016), brand switching (Fetscherin, 2019), brand complaint (Fetscherin, 2019), word of mouth (Dwivedi et al., 2021; 2023; Rodrigues et al., 2021; Zarantonello et al., 2016), whereas the majority of scholars overlap clarification of brand repercussions with senses of disappointment. Apart from Jabeen et al. (2022), most brand dark sides research emphasised if brand relationships facilitate consumer response, rather than elucidating how external stimuli as an intervened measurement lead to negative brand attitudes, thus shaping adverse brand outcomes. Besides, the existing studies prefer to investigate a single brand attitude from brand hate or betrayal instead of combining both. Although Jabeen et al. (2022) considered both hate and betrayal attributes in their research, the possible causal relationship between hate and betrayal did not reflect accordingly.

The novelty of this study will first innovate the theoretical framework by adopting a Stimulus-Organism-Response theory to link the antecedents (i.e., celebrity endorsement attributes) and repercussions (i.e., brand outcomes) in brand dark attitude literature, as few scholars have adopted the S-O-R theory in brand research except Jabeen et al. (2022). Second, this study fills in the insufficiency of the brand's dark sides, including brand hate and brand betrayal in the live streaming industry. Differing from previous studies that adopted an independent brand's dark perspective, either brand betrayal (Grégoire et al., 2009; Grégoire and Fisher, 2008) or brand hate (Fetscherin, 2019; Hegner et al., 2017; Rodrigues et al., 2021; Zarantonello et al., 2016), this study combines them. Noteworthy, brand hate is not a general hate dimension but a formative second-order construct consisting of disgust, contempt, and anger. The originality of the second-order construct comes from Fetscherin (2019) and is refined further from his research to conclude elements that compose brand hatred. Third, this study contributes to a more comprehensive entirety of customers' responses when experiencing bad customer-brand relationships. By integrating previous research (Fetscherin, 2019; Hegner et al., 2017), this study adopts brand outcomes, including revenge, avoidance, retaliation, switching, and complaint. Conspicuously, previous studies involved in brand punishment outcomes typically chose to examine either brand revenge or brand retaliation. In contrast, this study elaborates both in detail through the meaning proposed by Zourrig et al (2009). They thought revenge was distinct from retaliation in terms of reason, effect, and action. Revenge is a long-term state of mind that will harm the brand, whereas retaliation is more of a short-term action (Zourrig et al., 2009). In practice, the contribution of this study will guide e-sellers to formulate more targeted strategies to improve the congruence between celebrities and brands when screening celebrity endorsements, to avoid mindlessly pursuing big-name celebrities but having opposite performances and repercussions.

## 2. Literature review

### 2.1 Live streaming commerce

Live streaming commerce is a subset of combining social commerce and e-commerce that incorporates real-time video and text chat channels for real-time social engagement (Kang et al., 2021). It offers a platform where celebrities (as streamers) and audiences can jointly generate value (Lo, 2022). Celebrities` interactions and endorsements can be reflected on screen and conveyed to audiences in real-time, even if they are physically apart (Wongkitrungrueng et al., 2020). Audiences react in writing and are able to perceive synchronous communication while interacting with celebrities (Sun et al., 2019).

Previous studies on live streaming commerce primarily followed two research orientations, as the summary shown in Appendix 1. Firstly, studies focus on consumers' motivation to watch or participate in live streaming. Theoretical lenses involving Uses and Gratification theory (Cai and Wohn, 2019), Technology Acceptance Model (Cai et al., 2018), Flow theory (Chen and Lin, 2018; Li et al., 2018), Stimuli-Organism-Response theory (Hu and Chaudhry, 2020; Kang et al., 2021) and affordance lens (Sun et al., 2019) are widely adopted by researchers. This research orientation found that factors will initially attract consumer motivation to watch, thus enhancing their subsequent intention, such as continuous interaction, trust, and engagement in live streaming commerce. The second orientation is concerned with actual consumer purchase behaviour in live streaming commerce, including purchase intention (Lu and Chen, 2021; Meng et al., 2021), impulsive consumption (Lo, 2022), and hedonic consumption (Xu et al., 2020). Researchers' study of this research orientation is typically attached to one or various live streaming platforms and suggests external factors influencing consumer purchase behaviour.

Based on the two research orientations above, scholars explored various external factors as antecedents, such as social presence (Ang et al., 2018; Leeraphong and Sukrat, 2018; Ming et al., 2021; Sun et al., 2019), engagement (Cao et al., 2022), watching motivation (Cai and Wohn, 2019; Todd and Melancon, 2017), trust (Guo et al., 2021) and attitude (Chen and Lin, 2018), while few scholars focused on celebrity attributes except Park and Lin (2020). Nevertheless, Park and Lin (2020) merely explored the fitting of celebrity and living content, rather than focusing on the customer-brand relationships in live streaming commerce. It is perceptibly insufficient to disclose the dark side of celebrity attributes in existing studies. Therefore, this study explains how celebrity attributes in live streaming commerce damage customer-brand relationships.

## 2.2 S-O-R theory

Based on environmental psychology, the S-O-R theory offers a progressive process that takes into account the nuances of human conduct (Mehrabian and Russell, 1974). Floh and Madlberger (2013) proposed that the stimuli (S) influence people's internal affective states (O), which in turn prompts approach- or avoidance-like behaviours (R). This theory has been widely used in social commerce (s-commerce) and electronic commerce (e-commerce) research to examine consumer behaviours, including website sickness (Friedrich et al., 2019), consumer loyalty (Wu and Li, 2018; Yuan et al., 2020), eWOM (Cambra-Fierro et al., 2017), online brand communities (Ul Islam and Rahman, 2017).

Reviewing the existing literature on customer-brand relationships, the negative celebrity attributes in endorsements are seen as antecedents of brand sensations or emotions that customers experience over time due to a collection of negative experiences (Curina et al., 2021). This study thus proposed negative reputation (NG), unenthusiastic interactivity (UI), advertisement inauthenticity (AI) and expertise scarcity (ES) that were extracted from crucial segments surrounding fame, interaction, endorsement, and knowledge among celebrities (Hegner et al., 2017; Jabeen et al., 2022; Rodrigues et al., 2021). These antecedents comprise stimuli in the S-O-R theory. Following that, the negative celebrity attributes that audiences experience when watching live broadcasting can manifest in a variety of ways (Fetscherin, 2019; Grégoire et al., 2009); especially for current audiences, they are likely to be more significant because they represent a relationship history (Jabeen et al., 2022).Based on it, this study accordingly proposed brand hate and betrayal as negative attitudes (Rodrigues et al., 2021), representing organisms in the S-O-R theory. Customers may penalise brands in some ways as a result of having lousy brand encounters, according to Funches et al. (2009), proving that brand retaliation and vengeance are potential outcomes of customers' negative emotions (Fetscherin, 2019; Jabeen et al., 2022). In addition to retaliation and revenge, scholars discovered reacted outcomes such as brand avoidance (Rodrigues et al., 2021), complaint and switching (Zarantonello et al., 2016), and so on in previous studies. Therefore, this study, through summarising the existing literature, proposes brand revenge, brand avoidance, brand retaliation, brand switching, and brand complaint as the adverse outcomes after encountering dark customer-brand relationships, which represent responses to the S-O-R theory.

The rationale of the S-O-R theory involves the following: first, it has previously been adopted to examine complicated consumer behaviours, especially in the digital commerce milieu (Jabeen et al., 2022; Liu et al., 2021; Xu and Wang, 2018). As such, given the similarity between the live industry and digital commerce that collectively emphasises parasocial interaction and real-time shopping experience, the theory is suitable for revealing customer-brand dynamics and the resulting brand consequences in live streaming commerce. Second, compared with the advancement of immersed flow experience by interactions between celebrities and audiences, which is far beyond traditional commerce, the unique characteristics of live streaming commerce centred around these instantaneous social dynamics can be effectively encapsulated through the S-O-R theory. Hence, drawing on the theory, a dynamic model can be developed to illustrate how the attributes of celebrities can negatively impact customer-brand relationships. Third, in terms of adverse brand consequences, the S-O-R theory provides a theoretical basis for contemplating potential overt and covertly punished outcomes, especially involving a shift in consumer allegiance prompted by feelings of animosity or betrayal. Accordingly, considering that the theoretical foundation is rooted in understanding internal organisms' emotional makeup, it is thus well-aligned for capturing and elucidating negative emotions, such as brand hate and betrayal (Jabeen et al., 2022). As a result, the study offers a solid theoretical foundation for comprehending many facets of consumer psychology and behaviour.

## 2.3 Rationale of adopted constructs and variables

Drawing upon the S-O-R theory, this study develops four constructs (i.e., negative reputation, unenthusiastic interactivity, advertisement inauthenticity and expertise scarcity) in the stimulus as antecedents, and five negative outcomes (i.e., brand revenge, avoidance, retaliation, switching and complaint) in the response as consequences. In terms of antecedents, the respective rationale encompasses the negative reputation, possibly disseminated through celebrities' improper behaviour or negative news, which can directly impact consumers' perceptions of a brand. Such adverse stimuli may lead consumers to develop negative sentiments, influencing their reactions and brand engagement (Costa and Azevedo, 2022). Besides, if a celebrity appears indifferent or disinterested during a live broadcast, audiences may feel neglected, affecting their interactive experience with the brand and consequently forming a negative impression (Liu et al., 2020). Similarly, audiences may feel misled if a celebrity's promotional activities lack authenticity during a livestream. It can potentially harm the brand's reputation and diminish customer trust (Loebnitz and Grunert, 2022). Furthermore, in cases where a celebrity does not possess substantial knowledge of the endorsed brands, it may lead to scepticism among audiences regarding the genuineness and reliability of their endorsement. This scepticism, in turn, can impact consumer choices and sway purchasing decisions (Wang and Scheinbaum, 2018). Therefore, these stimulating factors encompass the negative sentiments that celebrities may evoke during live broadcasts, aiding in identifying key roles contributing to the adverse impact of celebrities on customer-brand relationships.

In terms of consequences, brand retaliation, revenge, and complaints are considered active brand punishment. Although retaliation and revenge are similar in conceptualisation, the former involves consumers openly expressing their discontent with the brands through platforms, such as social media, aiming to attract the brands' attention, while the latter refers to a more severe measure that consumers take retaliatory measures, attempting to express their dissatisfaction with the brand through various means (Jabeen et al., 2022; Wei et al., 2023). Besides, brand complaints denote consumers conveying their dissatisfaction and grievances to the brand through avenues (Zhang and Wang, 2023). In contrast, brand avoidance and switching are regarded as passive punishments. Avoidance is considered as consumers potentially opting to steer clear of products or services associated with the brand to prevent further negative experiences (Khan and Lee, 2014). Switching implies that consumers may choose to shift to other competing brands to circumvent the negative impact associated with celebrities (Wu et al., 2018).

In terms of the interconnections among five responses, brand might be associated with retaliation and complaint, since all of them express consumers' dissatisfaction with specific brands. Contrastingly, brand avoidance is interconnected with switching, as both involve avoiding being associated with brands and potentially leading consumers to seek alternatives (Jabeen et al., 2022). Hence, the five types of responses contribute to understanding the various actions consumers may take when faced with the negative impact of celebrity behaviours, thereby comprehensively revealing how celebrity actions influence brand relationships.

## 3. Hypothesis

### 3.1 Negative reputation

Reputation refers to the current evaluation of an entity's desirability made by outsiders (Standifird, 2001). In the live streaming industry, celebrities, as entities acknowledge and accept assessments made by audiences and customers. Till and Shimp (1998) discovered the effects of negative reputations on celebrity endorsers; a lower evaluation of the celebrity might result in a more inadequate assessment of the brand (Zhou and Whitla, 2013), thus damaging customers' perceived attitudes to brands that they endorse. Specifically, negative reputations can undermine consumers' trust and expectations in brands, which is bound to make consumers feel deceived by the brand, thus triggering a sense of betrayal. Simultaneously, consumers may develop a dislike for the brand due to its negative reputation, giving rise to brand hate. Hence, this study hypothesises:

H1. Negative reputation positively correlates to (a) brand betrayal and (b) brand hate.

### 3.2 Unenthusiastic interactivity

Interaction refers to online contact and communication between celebrities and audiences (Chen and Lin, 2018), while unenthusiastic interactivity indicates that celebrities have poor performance for audiences in terms of verbal or nonverbal actions, collaborative activities, and timing of personal expression (Adipradana et al., 2023; Li et al., 2021; Sim et al., 2023). According to Thomson (2006), positive interaction between celebrities and consumers may foster boosted brand loyalty and predict desirable brand outcomes. On the dark side, a shortage of interaction may lead to adverse attitude towards brand. In live streaming commerce, such indifferent interactions are bound to make audiences feel neglected and unimportant, thus disrupting their relationship and causing a sense of betrayal by the brands. Also, indifferent interactions can evoke a sense of disgust among audiences, giving rise to brand hate. Hence, this study hypothesises:

H2. Unenthusiastic interactivity positively correlates to (a) brand betrayal and (b) brand hate.

### 3.3 Advertisement inauthenticity

Advertisement inauthenticity is regarded as a quality produced rationally guiding an individual's subjective impression rather than a trait intrinsic to the objective reality of advertisements (Napoli et al., 2016). Audiences watching live broadcasting may perceive the advertisement as not genuine according to both their objective facts and subjective sentiments (Napoli et al., 2016; Rodrigues et al., 2021), as the advertisement's promise is not met in a specific, ongoing, and consistent way (Hede and Thyne, 2010), thus leading to the emergence of negative brand attitudes (Mohd Johan et al., 2022; Napoli et al., 2016). In live streaming commerce, untruthful advertising can make consumers feel that the brands lack integrity in promoting their products, thereby triggering a sense of betrayal towards them. Equally, consumers may develop brand hate due to their lack of trust in the brands throughout the process. Hence, this study hypothesises:

H3. Advertisement inauthenticity positively correlates to (a) brand betrayal and (b) brand hate.

### 3.4 Expertise scarcity

Expertise is the level at which one is deemed capable of making accurate claims on pertinent abilities (Friedman et al., 1976), while expertise scarcity in live streaming commerce indicates that celebrities have a limited breadth of experience, qualification, and professionalism related to endorsed brands (Rungruangjit, 2022). Teo and Liu (2007) pointed out that celebrity endorsements with high competence may affect consumer attitudes toward brands; contrarily, a lack of expertise may render celebrities less credible in the promotion of products or services, thereby eliciting a sense of betrayal from consumers towards the brands. Also, consumers may develop brand hate due to their dissatisfaction with the celebrities. Hence, this study hypothesises:

H4. Expertise scarcity positively correlates to (a) brand betrayal and (b) brand hate.

### 3.5 Betrayal betrayal

Brand betrayal is a condition that arises when a brand, with which a customer has previously established a connection, violates a moral duty perceived as essential to the relationship (Reimann et al., 2018). Elliott and Yannopoulou (2007) have highlighted that the feeling of betrayal is intricately linked to emotions like disappointment, anger, and frustration, all of which play pivotal roles in influencing brand hate. Besides, as Aumer-Ryan and Hatfield (2007) mentioned, brand hate can be triggered by a perception of betrayal stemming from brand transgressions. In turn, negative customer-brand attitudes are prone to escalation in the presence of a perceived betrayal by the brand, especially brand hate. Hence, this study hypothesises:

H5. Brand betrayal positively correlates to brand hate.

When consumers experience brand betrayal, there is a heightened likelihood that they will take proactive measures to articulate their negative sentiments. Accordingly, the betrayal experience may incite consumers' emotional reactions, prompting them to undertake specific actions in response to their adverse encounters with the brands (Bayarassou et al., 2020). Precisely, positive actions may materialise as consumers become more inclined to enact deliberate revenge measures to underscore their expression of dissatisfaction with the brands (Hutzinger and Weitzl, 2023). Hence, this study hypothesises:

H6a. Brand betrayal positively correlates to brand revenge.

When customers perceive disloyalty from brands, they tend to proactively take measures to abstain from using those particular brands. Hence, instances of brand betrayal may instigate a compelling inclination to steer clear of specific brands to sidestep unfavourable encounters. As Bayarassou et al. (2020), Costa and Azevedo (2022) argued, when consumers perceive brand betrayal through negative experiences or inconsistent brand messaging, such betrayal can erode trust and loyalty, ultimately leading to brand avoidance. Hence, this study hypothesises:

H6b. Brand betrayal positively correlates to brand avoidance.

The experience of brand betrayal has the potential to elicit anger and dissatisfaction among consumers, prompting them to undertake direct retaliatory measures as a response to their negative sentiments (Hutzinger and Weitzl, 2023). In contrast to revenge, which implies that consumers take enduring actions against specific brands, retaliation is characterised by immediate and short-term punitive actions (Fetscherin, 2019). Therefore, these retaliatory measures may manifest since consumers openly express dissatisfaction, offer criticism, or employ other targeted responses to counteract the brand perceived as betraying them as a means to defend their rights and appeals. Hence, this study hypothesises:

H6c. Brand betrayal positively correlates to brand retaliation.

The feeling of betrayal may stimulate a strong inclination for alternatives in the minds of consumers, compelling them to actively explore and select other brands as substitutes to replace the disloyal experiences linked with the betrayed one (Wu et al., 2018). As such, in instances where consumers sense brand betrayal, they are more likely to respond proactively by actively switching to alternative brands (Fetscherin, 2019). Hence, this study hypothesises:

H6d. Brand betrayal positively correlates to brand switching.

The experience of brand betrayal may evoke dissatisfaction and disappointment among consumers, leading them to express their discontent by lodging complaints against the perceived disloyalty (Tronvoll, 2012). To be concrete, these actions may materialise as consumers articulate their concerns in written or verbal ways, with the expectation that the brand will take corrective measures to enhance and mend the relationship (Zhang and Wang, 2023). Consequently, in instances where consumers perceive brand betrayal, they are likely to proactively respond by filing complaints. Hence, this study hypothesises:

H6e. Brand betrayal positively correlates to brand complaint.

### 3.6 Brand hate

Brand hate is a term for the unfavourable impact, emotions, and sentiments customers create for a brand that makes them feel angry, irritated, disgusted, enraged, and agitated (Jabeen et al., 2022). It might evoke intense anger and hostility in consumers, compelling them to take purposeful retaliatory actions in the long term to counteract the negative sentiments stemming from the brand (Bayarassou et al., 2020; Hutzinger and Weitzl, 2023). Hence, this study hypothesises:

H7a. Brand hate positively correlates to brand revenge.

The sentiment of brand hate can evoke intense negative emotions directed at the brand, causing consumers to consciously avoid any affiliation with the brand, encompassing the avoidance of purchasing and consuming its products or services (Costa and Azevedo, 2022). Therefore, when consumers harbour feelings of brand hate, they are inclined to proactively take measures to abstain from using the brand (Bayarassou et al., 2020). Hence, this study hypothesises:

H7b. Brand hate positively correlates to brand avoidance.

Similar to brand revenge, when consumers harbour feelings of brand hate, they are highly likely to take proactive actions to retaliate against the brand (Costa and Azevedo, 2022). Although brand revenge may lead to a public relations nightmare and potential long-term damage, brand retaliation aims for a more calculated and controlled resolution in the short term. As a result, the hate might stimulate consumers' hostility and a desire for confrontation, which makes them more inclined to adopt direct and immediate retaliatory actions to counteract the negative sentiments (Fetscherin, 2019; Hegner et al., 2017). Hence, this study hypothesises:

H7c. Brand hate positively correlates to brand retaliation.

The feelings of hate likely provoke strong aversion towards the brand, causing consumers to be more inclined to actively search for and choose alternative brands to replace the negative experiences associated with the hated brand (Fetscherin, 2019). In this regard, when consumers harbour feelings of brand hate, they are inclined to take proactive actions by switching to other brands (Wu et al., 2018). Hence, this study hypothesises:

H7d. Brand hate positively correlates to brand switching.

Brand hate might incite dissatisfaction and anger among consumers, prompting them to express their strong aversion towards the brand by filing complaints (Tronvoll, 2012). Based on it, in instances where feelings of brand hate are generated, consumers are more likely to take proactive actions by filing complaints (Hutzinger and Weitzl, 2023). Hence, this study hypothesises:

H7e. Brand hate positively correlates to brand complaint.

3.7 Conceptual model

The conceptual model is indicated in Fig. 1.

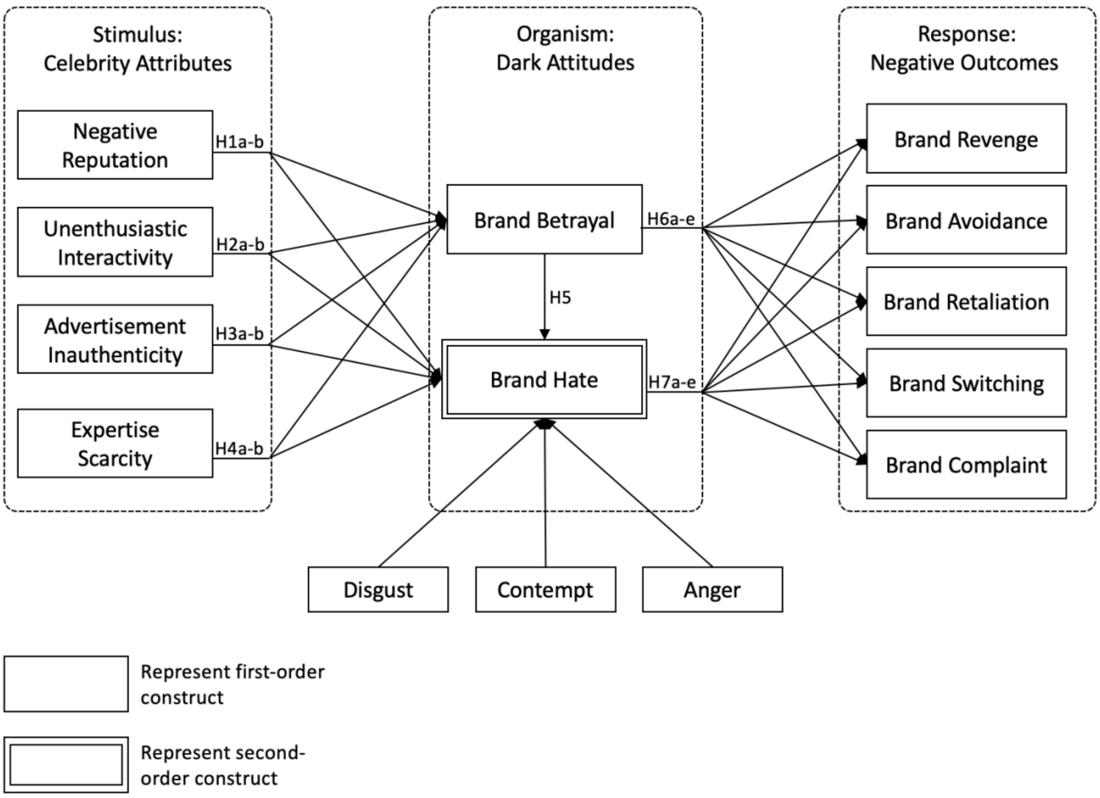


Fig. 1 Conceptual Model

## 4. Method

### 4.1 Data collection

Although the live streaming industry is not currently flourishing in Malaysia, higher social commerce penetration rates and internet coverage ensure that the live streaming industry will remain a niche in Malaysia, as more than 80% and 70% of internet users are active in social media and e-commerce, respectively, which will primarily form the potential audiences that watch and engage in live streaming commerce (Boxme, 2021). Therefore, we targeted the Malaysian market and chose Malaysian users to study. A well-designed and executed self-administered questionnaire survey was conducted through Google Forms. Respondents were identified using a convenience sampling method, reaching out to individuals with prior engagement in live streaming commerce through social media platforms, such as Facebook groups, Instagram, and Twitter tags with the keywords “live streaming commerce”. These social media platforms were selected due to their categorisation of specific interest groups and product/service categories. Before proceeding with the questionnaire, participants were required to answer a screening question to confirm their experiences in the live industry. This screening process helped tailor the survey to the specific requirements of individuals with live-streaming experience, while those who did not complete the screening question or lacked live-streamed experiences were excluded from the study. A total of 345 responses were received, and 317 were viewed as valid for analysis. The sample's demographics were compared to the internet population of Malaysia to verify representativeness. Most responders are in their 20s, followed by those in their 30s who are middle-aged. More than 70% of Malaysian Internet users have monthly incomes of less than RM3000, according to the sample's income, which is consistent with the Internet User Survey Report 2020 (MCMC, 2020). Consequently, this research has no problems with sample representativeness since the sample's demographics and income level are comparable to the study (MCMC, 2020).

### 4.2 Profile of respondents

Table 1 demonstrates 317 valid replies, with 54.3% male (n=172) and 45.7% (n=145). Most participants are between 21 and 25, occupying 42.9% (n=136), and 53% hold a bachelor`s degree (n=168). Monthly income ranged from less than RM2,500 (n=92, 29%) and RM2,500 – RM3,169 (n=44, 13.9%), taking into the largest and second-largest percentages, respectively. As for the live streaming commerce experience, most participants have engaged in it in the past half year (n=131, 41.3%). Facebook Live (n=269, 84.9%), Instagram Live (n=175, 55.2%), Lazada Live (n=141, 44.5%), and Shopee Live (n=97, 30.6%) are the top 4 popular live streaming platforms that Malaysian participants chose to watch. In the past six months of purchase frequency, 41.3% (n=131) of participants have made 1-3 purchases and 32.8% (n=104) have made 4-6 purchases in live streaming commerce.

Table 1 Respondent profile

| Constructs | Items | Number | Percentage (%) |
|---|---|---|---|
| Gender | Male | 172 | 54.3 |
| | Female | 145 | 45.7 |
| Age | 20 or below | 9 | 2.8 |
| | 21-25 | 136 | 42.9 |
| | 26-30 | 83 | 26.2 |
| | 31-35 | 7 | 2.2 |
| | 36-40 | 23 | 7.3 |
| | 41-45 | 29 | 9.1 |
| | 46-50 | 9 | 2.8 |
| | 51 or above | 21 | 6.6 |
| Education level | High school or below | 21 | 6.6 |
| | Diploma | 74 | 23.3 |
| | Bachelor | 168 | 53.0 |
| | Master | 33 | 10.4 |
| | Ph.D | 21 | 6.6 |
| Monthly income | Less than RM2500 | 92 | 29.0 |
| | RM2500-RM3169 | 44 | 13.9 |
| | RM3170-RM3969 | 7 | 2.2 |
| | RM3971-RM4849 | 20 | 6.3 |
| | RM4850-RM5879 | 25 | 7.9 |
| | RM5880-RM7099 | 37 | 11.7 |
| | RM7110-RM8699 | 29 | 9.1 |
| | RM8700-RM10959 | 18 | 5.7 |
| | RM10960-RM15039 | 25 | 7.9 |
| | More than RM15039 | 20 | 6.3 |
| Live streaming commerce purchase experience | Less than 6 months | 131 | 41.3 |
| | 6 months - 1 year | 43 | 13.6 |
| | 1 - 1.5 years | 35 | 11.0 |
| | 1.5 -2 years | 55 | 17.4 |
| | More than 2 years | 53 | 16.7 |
| Live streaming platform types* | Instagram live | 175 | 55.2 |
| | Facebook live | 269 | 84.9 |
| | Pinterest live | 24 | 7.6 |
| | Twitter | 8 | 2.5 |
| | Tik Tok | 51 | 16.1 |
| | Shopee live | 97 | 30.6 |

| | | | |
|---|---|---|---|
| | Lazada live | 141 | 44.5 |
| Live streaming commerce purchase frequency | 1 - 3 times | 131 | 41.3 |
| | 4 - 6 times | 104 | 32.8 |
| | 7 - 9 times | 32 | 10.1 |
| | More than 9 times | 50 | 15.8 |

*Note: a. * Respondents are allowed to choose from more than one item.*

4.3 Research instrument

The survey comprises two distinct sections. To be specific, demographic information is included in section A, while section B assesses respondents' perceptions of the construct. All measurements were adapted from prior research (see Table 2). Aligning with similar processes in past literature like Tan et al. (2014) and Wu et al. (2023), before beginning the questionnaire, participants are briefed on the definition relevant to live streaming commerce in the questionnaire, whereby the term is defined as a form of e-commerce that combines real-time video broadcasting with online shopping capabilities. Sellers are able to showcase products, answer inquiries, and promote items through live-streamed platforms, while audiences can interact and make purchases online during the broadcast. Based on the definition, a brief scenario and example are also provided to enlighten their understanding of the research context that encompasses fashion influencers might host a live stream showcasing clothing items and allow audiences to purchase them while watching, or chefs could live stream cooking a recipe and offer kitchen products for sale during the broadcast. Subsequently, participants are asked to imagine a brand that a celebrity is promoting in the context of live streaming commerce, referred to as brand 'X'. Before conducting the main data collection in the primary study, involving the collection of actual data, 65 respondents with over three years of experience in buying through live-streaming commerce were asked to participate in a pilot test. Based on their comments, a few measurement items were altered or eliminated as necessary, as shown in Table 2.

4.4 Statistical analysis

The study used SmartPLS (version 3.3.3) and Partial Least Squares Structural Equation Modeling (PLS-SEM) in the first step of the evaluation of the proposed conceptual model. For complex model prediction and theory construction, the PLS-SEM is initially more successful than covariance-based Structural Equation Modelling (CB-SEM). Second, PLS-SEM only marginally constrains the sample size and non-normal distributions (Leong et al., 2018). Given that Mardia's multivariate skewness (= 17.12) and kurtosis (= 184.09) both had p-values less than 0.001, the analysis proved that the data is not multivariate normal (Zhang et al., 2021). As a result, it was determined that PLS-SEM would be more appropriate for this research than CB-SEM. Besides, this study adopted an Artificial Neural Network (ANN) to estimate the complicated linear and non-linear interactions in the second stage, as the PLS-SEM can only detect linear correlations, but ANN can evaluate the importance of predictors (Al-Sharafi et al., 2022). The sample size calculated by G*power demonstrated sufficient statistical power, using an effect size of 0.15, an alpha value of 0.05, and a power level of 0.95.

### 4.5 Common method variance

Since both endogenous and exogenous components were gathered using a single instrument, common method variance (CMV) may arise (Binwani and Ho, 2019). Procedurally, the questionnaire used simple language and short questions and gave explanations for unfamiliar terminology to decrease ambiguity and remedy potential procedural issues (Podsakoff et al., 2003). Statistically, we followed Harman`s single factor method test and found that the extraction sums of squared loading are 30.366%, far less than the benchmark (50.00%) (Podsakoff et al., 2003). Consequently, this study will not exist on the CMV issues.

### 4.6 Assessing the outer measurement model

The outer measurement model assessed the constructs' reliability and validity. Table 3 illustrated that Cronbach`s Alpha for all lower order constructs ranged between 0.717 and 0.934, showing an excellent internal consistency as the value is above the benchmark value of 0.7 (Chin et al., 2003). the composite reliability (CR) measured all were between 0.824 and 0.954, which were far greater than the benchmark of 0.7, thus demonstrating good reliability (Chin et al., 2003). In addition, the average variance extracted (AVE) from every construct is greater than 0.5, indicating that the convergent validity of our measurement is adequate (Chin et al., 2003). Apart from UI1 and ES3, factor loadings were all higher than 0.7 with satisfactory results. According to Fong and Law (2013), UI1 and ES3 could remain as the AVE was over 0.5, and their factor loadings were between 0.4 and 0.7.

The Heterotrait-Monotrait (HTMT) ratio in Table 4 was used to evaluate the discriminant validity, demonstrating that the HTMT values ranged from 0.165 to 0.892. Hence, our model has good discriminant validity as all the values are below 0.9 (Henseler et al., 2015; Voorhees et al., 2016).

Table 2 Measurement and source

| **Construct** | **Initial item** | **Revised item** | **Source** |
|---|---|---|---|
| Negative reputation (NR) | NR1: Celebrities who fall into negative reputations are not trustworthy. | Same as the initial item | (Liu et al., 2020; Wang et al., 2017) |
| | NR2: Celebrities who fall into negative reputations are not respectable. | | |
| | NR3: My attitudes toward brands are related to celebrities` reputations. | | |
| | NR4: I will not choose brands that are endorsed by celebrities with negative reputations. | | |
| Unenthusiastic interactivity | UI1: I hardly exchange and share my opinions with celebrities. | UI1: In live broadcastings with celebrities as streamers, I hardly exchange and share my opinions with celebrities. | (Hou et al., 2019) |
| | UI2: Celebrities provide hard opportunities to respond and ask audiences questions. | UI2: In live broadcastings with celebrities as streamers, celebrities hardly provide opportunities to respond and ask questions to audiences. | |

| | | | |
|---|---|---|---|
| | UI3: Celebrities ignore two-way communication and interaction with audiences. | UI3: In live broadcastings with celebrities as streamers, celebrities ignore two-way communication and interaction with audiences. | |
| | UI4: Celebrities are not doing well in listening to audiences` opinions and feedback. | UI4: In live broadcastings with celebrities as streamers, celebrities are not doing well in listening to audiences` opinions and feedback. | |
| Advertisement inauthenticity (AI) | AI1: I think celebrities, by false advertising, are less respectable and desirable. | Same as the initial item | (Wang et al., 2017) |
| | AI2: Celebrity through inauthentic advertising to endorse will push me to reduce goodwill and impression toward brands. | | |
| | AI3: The advertisements that celebrities endorsed were not always reliable. | | |
| | AI4: The advertisements that celebrities endorsed were not always an authentic source of information. | | |
| Expertise scarcity | ES1: I think brands with celebrity endorsers who are experts are more reputable. | Same as the initial item | (Zhou and Whitla, 2013) |

| | | | |
|---|---|---|---|
| | ES2: I am willing to trust brands that are endorsed by celebrities with full expertise compared with lacking expertise. | | |
| | ES3: I will pay less attention to brands that endorse using celebrities with expertise scarcity. | | |
| | ES4: I think brands with celebrity endorsers who are experts are more trustworthy. | | |
| Brand betrayal (BB) | BB1: I think some brands have betrayed me. | BB1: I think the brand 'X' has betrayed me. | (Grégoire et al., 2010; Jabeen et al., 2022; Reimann et al., 2018) |
| | BB2: Some brands violated the promise that I made to myself. | BB2: The brand 'X' violated the promise that I made to myself. | |
| | BB3: Some brands let me down when I need help. | BB3: The brand 'X' lets me down when I need help. | |
| | BB4: I felt cheated by some brands. | BB4: I felt cheated by the brand 'X'. | |
| Contempt (c) | C1: I want to stop supporting some brands. | C1: I want to stop supporting the brand 'X'. | (Kucuk, 2019) |

| | | | |
|---|---|---|---|
| | C2: I want to disassociate myself from some brands. | C2: I want to disassociate myself from the brand 'X'. | |
| | C3: There is no way some brands can express me. | C3: There is no way the brand 'X' can express me. | |
| Disgust (D) | D1: I abhor what some brands stand for. | D1: I abhor what the brand 'X' stands for. | (Kucuk, 2019) |
| | D2: I find some brands repulsive. | D2: I find the brand 'X' repulsive. | |
| | D3: I detest some brands to the hilt. | D3: I detest the brand 'X' to the hilt. | |
| Anger (A) | A1: I am furious with some brands. | A1: I am furious with the brand 'X'. | (Kucuk, 2019) |
| | A2: Some brands have upset me so much. | A2: The brand 'X' has upset me so much. | |
| | A3: I am enraged with some brands. | A3: I am enraged with the brand 'X'. | |
| Brand revenge (REV) | REV1: When I hate one brand or this brand betrays me, I want to take measures to cause trouble for the brand in the long term. | Same as the initial item | (Grégoire et al., 2010) |
| | REV2: When I hate one brand or this brand betrays me, I want to penalize the brand in some ways in the long term. | | |
| | REV3: When I hate one brand or this brand betrays me, I want to cause inconvenience to the brand in the long term. | | |

| | | | |
|---|---|---|---|
| | REV4: When I hate one brand or this brand betrays me, I want to boycott the brand in the long term.<br>REV5: When I hate one brand or this brand betrays me, I want to make the brand receive what is a due penalty. | | |
| Brand avoidance (AVO) | AVO1: When I hate one brand or this brand betrays me, I want to keep it as far away from me as the brand.<br>AVO2: When I hate one brand or this brand betrays me, I want to avoid browsing or purchasing the brand.<br>AVO3: When I hate one brand or this brand betrays me, I want to stop the relationship with the brand.<br>AVO4: When I hate one brand or this brand betrays me, I want to withdraw my future business from the brand. For example, if I have been a premium member of this brand, I will voluntarily withdraw my membership from it. | Same as the initial item | (Grégoire et al., 2010) |
| Brand retaliation (RET) | RET1: When I hate one brand or this brand betrays me, I want to harm the brand in some way in the short term. | Same as the initial item | (Jabeen et al., 2022) |

| | | | |
|---|---|---|---|
| | RET2: When I hate one brand or this brand betrays me, I want to take actions that put the brand in trouble in the short term.<br>RET3: When I hate one brand or this brand betrays me, I want to vent my resentment toward the brand.<br>RET4: When I hate one brand or this brand betrays me, I want to get even with the brand. | | |
| Brand switching (SWI) | SWI1: When I hate one brand or this brand betrays me, I will not continue to buy products from this brand.<br>SWI2: When I hate one brand or this brand betrays me, I need to buy other brands as a replacement next time.<br>SWI3: When I hate one brand or this brand betrays me, I have an intention to switch from this brand and use other brands instead.<br>SWI4: When I hate one brand or this brand betrays me, the possibility of switching from this brand to another is high. | Same as the initial item | (Wu and Li, 2018) |

| | | | |
|---|---|---|---|
| Brand complaint (COM) | COM1: When I hate one brand or this brand betrays me, I will take legal action against the brand.<br>COM2: When I hate one brand or this brand betrays me, I will report the brand to the Consumer Protection Association or Governmental Agency.<br>COM3: When I hate one brand or this brand betrays me, I will reach out to the media to protest their actions.<br>COM4: When I hate one brand or this brand betrays me, I will complain to the brand for their customer service or representative. | Same as the initial instrument | (Grégoire et al., 2010) |

Note: The revised item means that the amendments after the pilot test and face validity test.

Table 3 Loading, Cronbach`s Alpha, CR and AVE

| Constructs | Items | Loadings | Cronbach's Alpha | CR | AVE |
|---|---|---|---|---|---|
| NR | NR1 | 0.772 | 0.798 | 0.869 | 0.624 |
| | NR2 | 0.803 | | | |
| | NR3 | 0.719 | | | |
| | NR4 | 0.861 | | | |
| UI | UI1 | 0.649 | 0.853 | 0.895 | 0.684 |
| | UI2 | 0.832 | | | |
| | UI3 | 0.886 | | | |
| | UI4 | 0.914 | | | |
| AI | AI1 | 0.763 | 0.717 | 0.824 | 0.539 |
| | AI2 | 0.719 | | | |
| | AI3 | 0.741 | | | |
| | AI4 | 0.711 | | | |
| ES | ES1 | 0.836 | 0.801 | 0.872 | 0.631 |
| | ES2 | 0.819 | | | |
| | ES3 | 0.662 | | | |
| | ES4 | 0.848 | | | |
| BB | BB1 | 0.725 | 0.814 | 0.878 | 0.644 |
| | BB2 | 0.842 | | | |
| | BB3 | 0.785 | | | |
| | BB4 | 0.851 | | | |
| DI | DI1 | 0.867 | 0.858 | 0.914 | 0.779 |
| | DI2 | 0.897 | | | |
| | DI3 | 0.885 | | | |
| CO | CO1 | 0.902 | 0.805 | 0.886 | 0.723 |
| | CO2 | 0.882 | | | |
| | CO3 | 0.760 | | | |
| AN | AN1 | 0.898 | 0.878 | 0.925 | 0.804 |
| | AN2 | 0.884 | | | |
| | AN3 | 0.908 | | | |
| RVE | REV1 | 0.879 | 0.877 | 0.912 | 0.676 |
| | REV2 | 0.838 | | | |
| | REV3 | 0.878 | | | |
| | REV4 | 0.664 | | | |
| | REV5 | 0.830 | | | |
| AVO | AVO1 | 0.874 | 0.906 | 0.934 | 0.780 |
| | ACO2 | 0.897 | | | |
| | ACO3 | 0.907 | | | |
| | ACO4 | 0.856 | | | |
| RET | RET1 | 0.929 | 0.936 | 0.954 | 0.839 |

| | | | | | |
|---|---|---|---|---|---|
| | RET2 | 0.930 | | | |
| | RET3 | 0.899 | | | |
| | RET4 | 0.906 | | | |
| SWI | SWI1 | 0.875 | 0.894 | 0.926 | 0.758 |
| | SWI2 | 0.878 | | | |
| | SWI3 | 0.883 | | | |
| | SWI4 | 0.847 | | | |
| COM | COM1 | 0.873 | 0.882 | 0.918 | 0.738 |
| | COM2 | 0.885 | | | |
| | COM3 | 0.875 | | | |
| | COM4 | 0.801 | | | |

*Notes: NR = Negative reputation; UI = Unenthusiastic interactivity; AI = Advertisement inauthenticity; ES = Expertise scarcity; BB = Brand betrayal; DI = Disgust; CO = Contempt; AN = Anger; REV = Brand revenge; AVO = Brand avoidance; RET= Brand retaliation; SWI = Brand switching; COM = Brand complaint.*

Table 4 Heterotrait-Monotrait (HTMT) ratio

| | AI | AN | AVO | BB | CO | COM | DI | ES | NR | RET | REV | SWI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AI | | | | | | | | | | | | |
| AN | 0.380 | | | | | | | | | | | |
| AVO | 0.582 | 0.541 | | | | | | | | | | |
| BB | 0.453 | 0.648 | 0.571 | | | | | | | | | |
| CO | 0.471 | 0.686 | 0.538 | 0.811 | | | | | | | | |
| COM | 0.264 | 0.483 | 0.432 | 0.577 | 0.345 | | | | | | | |
| DI | 0.463 | 0.822 | 0.534 | 0.623 | 0.830 | 0.367 | | | | | | |
| ES | 0.460 | 0.227 | 0.410 | 0.377 | 0.399 | 0.137 | 0.451 | | | | | |
| NR | 0.523 | 0.355 | 0.460 | 0.452 | 0.597 | 0.243 | 0.504 | 0.540 | | | | |
| RET | 0.165 | 0.575 | 0.233 | 0.398 | 0.309 | 0.600 | 0.495 | 0.144 | 0.265 | | | |
| REV | 0.242 | 0.698 | 0.446 | 0.533 | 0.45 | 0.723 | 0.536 | 0.228 | 0.326 | 0.892 | | |
| SWI | 0.598 | 0.395 | 0.877 | 0.525 | 0.515 | 0.325 | 0.427 | 0.414 | 0.533 | 0.101 | 0.246 | |
| UI | 0.471 | 0.155 | 0.227 | 0.286 | 0.263 | 0.199 | 0.151 | 0.281 | 0.365 | 0.204 | 0.212 | 0.221 |

*Notes:*
*a. NR = Negative reputation; UI = Unenthusiastic interactivity; AI = Advertisement inauthenticity; ES = Expertise scarcity; BB = Brand betrayal; DI = Disgust; CO = Contempt; AN = Anger; REV = Brand revenge; AVO = Brand avoidance; RET = Brand retaliation; SWI = Brand switching; COM = Brand complaint.*
*b. The square root of the average variation taken is represented by the diagonal components (in italics).*

4.7 Inspecting the inner structural model

Given that the existence of higher order constructs increases the likelihood of multicollinearity among lower order constructs, we conducted a correlation analysis between indicators using variance inflation factors (VIF) through two stages assessment, as suggested by previous studies (Shao & Pan, 2019). Table 5 presented all the VIF values in stage one, except formative variables (anger, contempt and disgust), which ranged from 1.193 to 2.006, which were far lower than the threshold of 3 (Leong et al., 2011; Wong et al., 2015). In the second stage, we assessed the outer measurement model for the reflective-formative construct, consisting of disgust, contempt and anger (Sarstedt et al., 2019). Table 6 showed that VIF results in stage two were between 1.964 and 2.688, which is also significantly less than the threshold (Fong and Law, 2013). Therefore, there were no multicollinearity problems for higher or lower order constructs in this study.

Table 5 VIF (Stage one)

| | AI | AVO | BB | BH | COM | ES | NR | RET | REV | SWI | UI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AI | | | 1.337 | 1.413 | | | | | | | |
| AVO | | | | | | | | | | | |
| BB | | 1.732 | | 2.006 | 1.732 | | | 1.732 | 1.732 | 1.732 | |
| BH | | 1.732 | | | 1.732 | | | 1.732 | 1.732 | 1.732 | |
| COM | | | | | | | | | | | |
| ES | | | 1.286 | 1.381 | | | | | | | |
| NR | | | 1.389 | 1.564 | | | | | | | |
| RET | | | | | | | | | | | |
| REV | | | | | | | | | | | |
| SWI | | | | | | | | | | | |
| UI | | | 1.193 | 1.222 | | | | | | | |

*Notes:*

*a. NR = Negative reputation; UI = Unenthusiastic interactivity; AI = Advertisement inauthenticity; ES = Expertise scarcity; BB = Brand betrayal; BH = Brand hate; REV = Brand revenge; AVO = Brand avoidance; RET = Brand retaliation; SWI = Brand switching; COM = Brand complaint.*

Table 6 VIF (Stage two)

| | BH | AN | CO | DI |
|---|---|---|---|---|
| BH | | | | |
| AN | 2.099 | | | |
| CO | 1.964 | | | |
| DI | 2.688 | | | |

*Notes:*

*a. BH = Brand hate; AN = Anger; CO = Contempt; DI = Disgust.*

In addition, we used a bootstrapping approach to evaluate the structural model to explain the path relationship and explanatory power (Ho et al., 2017). As shown in Table 7, the results implied that all the hypotheses apart from H2a, H2b, H3b, H4b, H6a and H6c were supported. H2a, H2b, H3b, H4b, H6a and H6c were insignificant as the P values were far more than 0.01.

Table 7 Structural model assessment`s outcome

| PLS Path | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values | Bias Corrected Confidence Interval | | Remarks |
|---|---|---|---|---|---|---|---|---|
| AI -> BB$^{**}$ | 0.193 | 0.197 | 0.059 | 3.250 | 0.001 | 0.085 | 0.305 | Significant |
| AI -> BH $^{ns}$ | 0.108 | 0.112 | 0.057 | 1.875 | 0.061 | 0.014 | 0.225 | Not Significant |
| BB -> AVO$^{***}$ | 0.249 | 0.244 | 0.064 | 3.892 | 0.000 | 0.131 | 0.368 | Significant |
| BB -> BH$^{***}$ | 0.556 | 0.554 | 0.056 | 9.944 | 0.000 | 0.454 | 0.649 | Significant |
| BB -> COM$^{***}$ | 0.365 | 0.369 | 0.073 | 5.029 | 0.000 | 0.226 | 0.521 | Significant |
| BB -> RET $^{ns}$ | 0.040 | 0.047 | 0.072 | 0.548 | 0.584 | -0.098 | 0.198 | Not Significant |
| BB -> REV $^{ns}$ | 0.120 | 0.127 | 0.069 | 1.724 | 0.085 | -0.014 | 0.262 | Not Significant |
| BB -> SWI$^{***}$ | 0.311 | 0.310 | 0.078 | 3.990 | 0.000 | 0.170 | 0.453 | Significant |
| BH -> AVO$^{***}$ | 0.373 | 0.381 | 0.074 | 5.061 | 0.000 | 0.221 | 0.499 | Significant |
| BH -> COM$^{*}$ | 0.183 | 0.185 | 0.088 | 2.078 | 0.038 | -0.018 | 0.338 | Significant |
| BH -> RET$^{***}$ | 0.461 | 0.458 | 0.082 | 5.606 | 0.000 | 0.297 | 0.616 | Significant |
| BH -> REV$^{***}$ | 0.516 | 0.512 | 0.069 | 7.443 | 0.000 | 0.369 | 0.655 | Significant |
| BH -> SWI$^{**}$ | 0.230 | 0.234 | 0.083 | 2.779 | 0.006 | 0.069 | 0.377 | Significant |
| ES -> BB$^{*}$ | 0.137 | 0.138 | 0.065 | 2.106 | 0.036 | 0.016 | 0.255 | Significant |
| ES -> BH $^{ns}$ | 0.011 | 0.009 | 0.059 | 0.193 | 0.847 | -0.101 | 0.124 | Not Significant |
| NR -> BB$^{**}$ | 0.202 | 0.202 | 0.074 | 2.721 | 0.007 | 0.045 | 0.339 | Significant |
| NR -> BH$^{**}$ | 0.173 | 0.175 | 0.054 | 3.172 | 0.002 | 0.050 | 0.268 | Significant |
| UI -> BB $^{ns}$ | 0.106 | 0.109 | 0.058 | 1.831 | 0.068 | -0.005 | 0.237 | Not Significant |
| UI -> BH $^{ns}$ | -0.026 | -0.030 | 0.057 | 0.451 | 0.652 | -0.143 | 0.077 | Not Significant |

*Notes:*

*a. NR = Negative reputation; UI = Unenthusiastic interactivity; AI = Advertisement inauthenticity; ES = Expertise scarcity; BB = Brand betrayal; BH = Brand hate; REV*

*= Brand revenge; AVO = Brand avoidance; RET = Brand retaliation; SWI = Brand switching; COM = Brand complaint.*
*b. * Significant at P < 0.05 level; ** Significant at P < 0.01 level; *** Significant at P < 0.001 level.*
*c. $^{ns}$ = Not supported.*

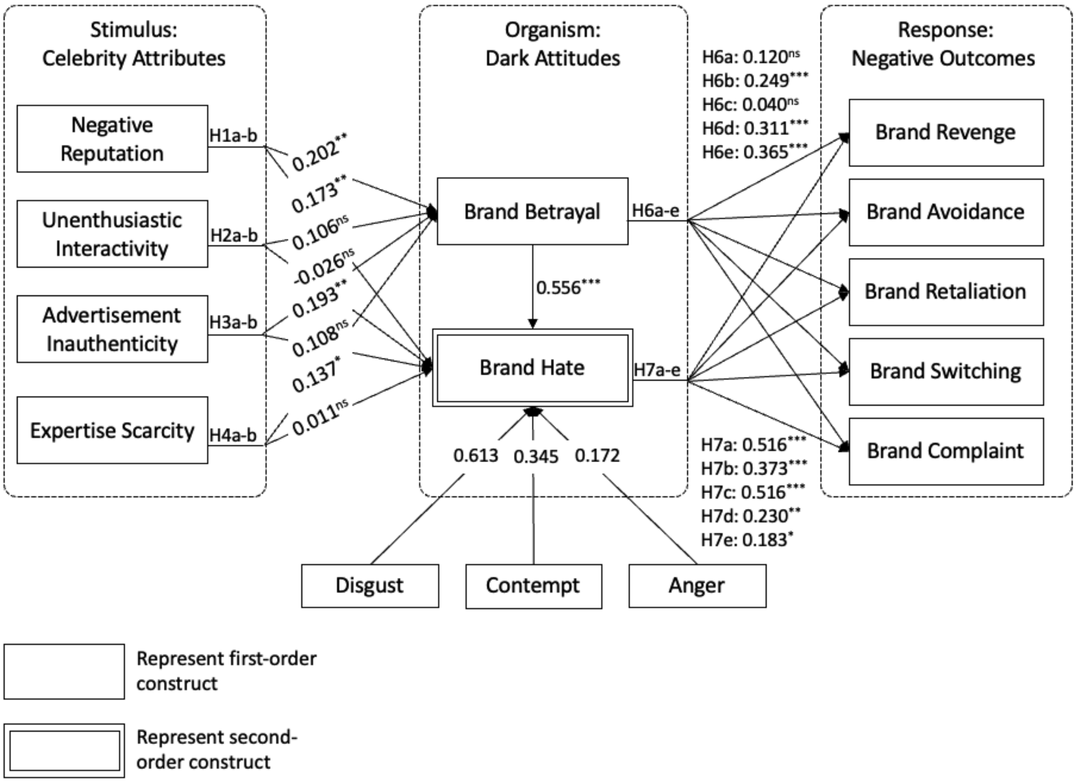


Fig. 2. Results of the hypothesis test.

4.8 The predictive relevance and effect size

The effect sizes of the outcome variables were examined using the $f^2$ values. The criteria for high, medium, and small effects were correspondingly 0.35, 0.15, and 0.02 (Moedeen et al., 2023; Shao, 2024). Table 8 showed all the $f^2$ values ranged from 0.001 to 0.461, implying the effect size from no effect to high effect, separately. In addition, Table 9 presented all the $Q^2$ ranging from 0.133 to 0.364 that were greater than zero, demonstrating that the conceptual model's endogenous components had predictive importance. To address the predictive model assessment in PLS-SEM, this study also used a PLS Predict developed by Shmueli et al. (2019). It was stated that the linear regression model (LM) has a good predictive performance since none of the PLS indicators had a lower root mean squared error (RMSE) value than the LM (Shmueli et al., 2019). Therefore, predictive performance in this model is explained sort in ascending order: BB (20.6%), RET (23.3%), SWI (23.9%), COM (24.9%), AVO (31.9%), REV (35.7%) and BH (46.6%).

Table 8 Effect size

| | AVO | BB | BH | COM | RET | REV | SWI |
|---|---|---|---|---|---|---|---|
| AI | | 0.036 | 0.016 | | | | |
| AVO | | | | | | | |
| BB | 0.052 | | 0.461 | 0.102 | 0.001 | 0.013 | 0.073 |
| BH | 0.117 | | | 0.026 | 0.159 | 0.237 | 0.04 |
| COM | | | | | | | |
| ES | | 0.018 | 0 | | | | |
| NR | | 0.037 | 0.039 | | | | |
| RET | | | | | | | |
| REV | | | | | | | |
| SWI | | | | | | | |
| UI | | 0.012 | 0.001 | | | | |

*Notes:*

*NR = Negative reputation; UI = Unenthusiastic interactivity; AI = Advertisement inauthenticity; ES = Expertise scarcity; BB = Brand betrayal; BH = Brand hate; REV = Brand revenge; AVO = Brand avoidance; RET = Brand retaliation; SWI = Brand switching; COM = Brand complaint.*

Table 9 Predictive relevance

| | SSO | SSE | $Q^2$ (=1-SSE/SSO) | $R^2$ |
|---|---|---|---|---|
| AVO | 1268 | 954.692 | 0.247 | 0.319 |
| BB | 1268 | 1098.922 | 0.133 | 0.206 |
| BH | 951 | 604.471 | 0.364 | 0.466 |
| COM | 1268 | 1036.154 | 0.183 | 0.249 |
| RET | 1268 | 1019.335 | 0.196 | 0.233 |
| REV | 1585 | 1222.146 | 0.229 | 0.357 |
| SWI | 1268 | 1041.353 | 0.179 | 0.239 |

*Note:*

*NR = Negative reputation; UI = Unenthusiastic interactivity; AI = Advertisement inauthenticity; ES = Expertise scarcity; BB = Brand betrayal; BH = Brand hate; REV = Brand revenge; AVO = Brand avoidance; RET = Brand retaliation; SWI = Brand switching; COM = Brand complaint.*

4.9 Artificial neural network analysis

Artificial neural network (ANN) is a complex system composed of simple processing units with capabilities to retain learned knowledge and make it usable, which has been shown to outperform traditional regression methods as a type of machine learning (Shao, 2023; Wu et al., 2023). Seven Models (A-G) are constructed that represent BB, BH, REV, AVO, RET, SWI, and COM, respectively. As demonstrated in Table 10, the mean values of RMSE on Models ranged from 0.887 to 1.145, concluding that the predictive accuracies are between moderate and less-predictive levels. Furthermore, this study adopts the sensitivity analysis to determine the relative importance of exogenous variables concerning the endogenous variables through the normalization process to rank the exogenous constructs (Iva Adeline et al., 2023), as demonstrated in Table 11. Concretely, the result showed that NR (100% normalized relative importance) is the most significant predictor in BB, followed by AA (91.069%) and ES (49.866%) in Model A. In Model B, BB (100%) is the most critical predictor in BH, followed by NR (38.480%). Besides, as Model C and E are only one neuron component (BH), the sensitivity analysis illustrated 100% normalized significance. In model D, BH (100%) is the most predictor of AVO, and the second is BB (96.25%). Moreover, BB (100%) is the most significant predictor of SWI, followed by BH (42.86%) in Model F. Eventually, as Model G showed, BB (100%) also is the most critical predictor of COM, followed by BH (46.95%).

Table 10: RMSE values

| Neural Network | Model A | | Model B | | Model C | | Model D | | Model E | | Model F | | Model G | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Input: NR, AI, ES | | Input: NR, BB | | Input: BH | | Input: BB, BH | | Input: BH | | Input: BB, BH | | Input: BB, BH | |
| | Output: BB | | Output: BH | | Output: REV | | Output: AVO | | Output: RET | | Output: SWI | | Output: COM | |
| | Training RMSE | Testing RMSE | Training RMSE | Testing RMSE | Training RMSE | Testing RMSE | Training RMSE | Testing RMSE | Training RMSE | Testing RMSE | Training RMSE | Testing RMSE | Training RMSE | Testing RMSE |
| ANN1 | 1.136 | 1.144 | 0.903 | 0.936 | 1.027 | 1.067 | 1.033 | 0.946 | 1.109 | 1.151 | 1.056 | 1.069 | 1.119 | 1.016 |
| ANN2 | 1.115 | 1.099 | 0.889 | 0.919 | 1.041 | 1.097 | 1.086 | 0.926 | 1.109 | 1.131 | 1.076 | 1.041 | 1.063 | 1.082 |
| ANN3 | 1.111 | 0.907 | 0.944 | 0.887 | 1.088 | 1.142 | 1.020 | 0.916 | 1.103 | 1.062 | 1.111 | 1.212 | 1.069 | 1.046 |
| ANN4 | 1.158 | 1.281 | 0.884 | 0.880 | 1.061 | 1.126 | 1.000 | 1.000 | 1.098 | 1.218 | 1.099 | 0.934 | 1.037 | 1.056 |
| ANN5 | 1.142 | 1.135 | 0.967 | 0.884 | 1.069 | 1.014 | 1.007 | 0.945 | 1.131 | 0.989 | 1.089 | 1.028 | 1.019 | 1.034 |
| ANN6 | 1.168 | 1.300 | 0.935 | 0.803 | 1.114 | 0.938 | 1.018 | 1.071 | 1.137 | 1.264 | 1.082 | 1.100 | 1.077 | 1.068 |
| ANN7 | 1.083 | 1.108 | 0.912 | 0.841 | 1.084 | 1.046 | 1.090 | 1.066 | 1.113 | 1.223 | 1.128 | 1.187 | 1.004 | 1.074 |
| ANN8 | 1.165 | 1.102 | 0.895 | 0.990 | 1.105 | 1.015 | 1.004 | 1.050 | 1.070 | 1.168 | 1.049 | 1.033 | 1.090 | 0.923 |
| ANN9 | 1.184 | 1.155 | 0.929 | 0.825 | 1.061 | 0.951 | 0.998 | 1.117 | 1.132 | 1.127 | 1.092 | 1.116 | 1.023 | 1.026 |
| ANN10 | 1.161 | 0.955 | 0.911 | 0.905 | 1.007 | 1.189 | 1.034 | 0.933 | 1.120 | 1.119 | 1.042 | 1.079 | 1.061 | 1.179 |
| Mean | 1.142 | 1.119 | 0.917 | 0.887 | 1.066 | 1.059 | 1.029 | 0.997 | 1.112 | 1.145 | 1.082 | 1.080 | 1.056 | 1.050 |
| SD | 0.031 | 0.122 | 0.026 | 0.055 | 0.034 | 0.082 | 0.033 | 0.073 | 0.020 | 0.081 | 0.027 | 0.081 | 0.035 | 0.064 |

Table 11: ANN results and comparison to PLS-SEM

| PLS Paths | Original sample (O)/path coefficient | ANN results: normalised relative importance (%) | Ranking (PLS-SEM) [Based on path coefficientl | Ranking (ANN) [Based on normalised relative importance] | Remark |
|---|---|---|---|---|---|
| Model A (Output: BB) | | | | | |
| NR->BB | 0.202 | 100.000% | 1 | 1 | Match |
| AI->BB | 0.193 | 91.069% | 2 | 2 | Match |
| ES->BB | 0.137 | 49.866% | 3 | 3 | Match |
| Model B (Output: BH) | | | | | |
| NR->BH | 0.173 | 38.480% | 2 | 2 | Match |
| BB->BH | 0.556 | 100.000% | 1 | 1 | Match |
| Model C (Output: REV) | | | | | |
| BH->REV | 0.461 | 100.000% | 1 | 1 | Match |
| Model D (Output: AVO) | | | | | |
| BB->AVO | 0.249 | 96.250% | 2 | 2 | Match |
| BH->AVO | 0.373 | 100.000% | 1 | 1 | Match |
| Model E (Output: RET) | | | | | |
| BH->RET | 0.516 | 100.000% | 1 | 1 | Match |
| Model F (Output: SWI) | | | | | |
| BH->SWI | 0.23 | 42.860% | 2 | 2 | Match |
| BB->SWI | 0.311 | 100.000% | 1 | 1 | Match |
| Model G (Output: COM) | | | | | |
| BH->COM | 0.183 | 46.950% | 2 | 2 | Match |
| BB->COM | 0.365 | 100.000% | 1 | 1 | Match |

## 5. Discussion

Regarding stimulus-organism, the supported hypotheses H1a and H1b state that celebrities endorsed with poor reputations will lead to consumers` negative opinions, thus ultimately causing brand hate and betrayal in live streaming commerce. Besides, if celebrities hardly manage their reputations in public, brands that they endorse are also barely trusted by the consumers, as consumers impossibly trust how celebrities who cannot even maintain personal word of mouth can empower positive brand images and seek the privilege of consumers. Similarly, suppose brands choose celebrities who have a negative reputation to endorse, even if they are big names. In that case, consumers will still feel cheated, thus resulting in an aversion to brands (Park & Chang, 2022). Second, the unsupported hypotheses H2a and H2b imply that the degree of interactivity will not be a dominant element that impacts brand attitudes. Although enthusiastic interaction admittedly promotes brand love and loyalty in previous studies (Liu et al., 2020; Wang et al., 2017; Yi et al., 2023), unenthusiastic interaction has little influence on brand hate and betrayal in the dark side. As a result, consumers may focus more on the products themselves while watching live streaming commerce. The interaction with celebrities is only concerned with whether they have elaborated on the features and details of endorsed products. If they have shown the effects well enough, even if their interaction is unenthusiastic, the negative attitude of consumers toward the brand is unimpaired. Third, the supported hypotheses H3a and H4a confirm that untrustworthy advertising and lacking expertise certainly influence brand betrayal, whereas their impact on brand hate is little, as illustrated by unsupported H3b and H4b. When consumers discover that a celebrity-endorsed brand is using false advertising or is being unprofessional in disseminating product features during live broadcasting, they may believe that the celebrity's relationships involve moral violations, and they may withdraw their current business from this brand. In contrast, this degree of breach will not result in hating the brand. The results might be because there is still a margin between betrayal and hate; hate cannot be merely led by advertising and expertise attributes. Regarding organism, the supported hypothesis H5 confirms brand betrayal positively impacts brand hate in live streaming commerce, which is aligned with previous findings (Bayarassou et al., 2020). The result states that when the sense of betrayal accumulates to a certain level, it can fuel brand hatred.

Regarding organism-response, the supported hypotheses H6b, H6d and H6e confirmed that brand betrayal positively influences brand avoidance, switching, and complaint, separately. Previous studies also state the same results (Bayarassou et al., 2020; Hegner et al., 2017), while the unsupported hypotheses H6a and H6c reveal that brand betrayal has no effect on brand revenge and retaliation, which is inconsistent with previous studies from different research backgrounds (Jabeen et al., 2022; Reimann et al., 2018). The results could be explained by the fact that the degree of punishment for vengeance and retaliation is higher than for other brand outcomes (i.e., avoidance, switching, and complaint). Mere betrayal will not raise consumers` negative attitudes toward brands to such an extent. When consumers feel betrayed in live streaming commerce, they will complain about the brand, avoid their subsequent business with the brand, and switch to a succedaneum rather than punish the brand through active actions, such as revenge and avoidance.

In addition, the supported hypotheses H7a-e show brand hate`s admitted impact on revenge, avoidance, retaliation, switching, and complaint, respectively. Similarly, the positive relationship between brand hate and subsequent punishment suggests that the consumers reject or refrain from further use of this brand on the one hand and actively retaliate against it to seek vengeance and carry out some harmful actions on the other hand. In this regard, if consumers despise the brand, they will engage in a series of punishments, both passive (i.e., avoidance, switching, complaint) and active (i.e., retaliation, revenge). Differing from betrayal, hate is more anger, contempt, and disgust with attitudes toward brands, thus resulting in more entire and severe vengeance than betrayal.

## 6. Implications

### 6.1 Theoretical implications

The theoretical implications include the following aspects. First, this study advances the conceptualisation of brand betrayal and hate by examining both antecedent and consequence dimensions in the same conceptual contexts, which enriches the literature contents. Apart from Zarantonello et al. (2016) and Hegner et al. (2017), few scholars have focused on entire dimensions like this study, as they merely explore the antecedent or consequence of brand hate or betrayal, ignoring combining both perspectives on the same conceptual model. In antecedents, this study proposes four components under celebrity attributes, which differ from a general dimension in customer-brand relationships in previous studies but focus on the specific perspective. In outcomes, we propose a series of repercussions on consumer punishment after experiencing brand hate or betrayal, including active penalties (i.e., revenge and retaliation) and passive punishments (i.e., avoidance, switching, and complaint); such conceptualisation helps to crystallise the various consumer coping behaviours.

Second, the conceptual model considers brand hate and betrayal, as well as their causal relationship, which are critical components of the customer-brand relationship. However, they have been widely isolated in previous studies except by Bayarassou et al. (2020), despite recognising that the transition from betrayal to hate is obvious. By examining hate and betrayal in the same model, this study diverts future scholars' attention to an understudied yet crucial dimension to comprehend. Especially by highlighting the positive effect of brand betrayal on the strength of association between celebrity attributes as antecedents of brand hate, this study demonstrates how the existing betrayal can aggravate hate states even further since consumers also do not like to be more disappointed in a negative brand relationship.

Given that the motivations to explore both stem from the insufficiencies in past literature, by examining brand hate and betrayal simultaneously, researchers gain a more comprehensive understanding of the dynamics at play when consumers experience negative emotions towards specific brands. Both are interrelated concepts that influence each other and revealing them together provides insights into how these emotions evolve and manifest in consumer responses. Drawing upon it, this study integrated lens enhances the theoretical framework and contributes to a more holistic comprehension of the multifaceted nature of complicated behaviours in response to negative brand experiences.

### 6.2 Practical implications

The practical implications include the following aspects. First, since negative reputation, advertisement inauthenticity, and expertise scarcity positively influence brand betrayal, e-sellers should meticulously consider a high match-up of celebrity characteristics, endorsement characteristics and brand image before they employ celebrities as endorsers and develop endorsement strategies. Concretely, regarding negative reputation, considering that audiences are frequently engaged in real-time interactions during live-streamed activities, any negative associations with endorsers have an immediate and significant impact. The nature of real-time interactions in live streaming commerce amplifies the consequences of negative fame, making it imperative for e-sellers to steer clear of celebrities with existing negative reputations.

Regarding advertisement inauthenticity, endorsers are required to align their messaging with the brand values and deliver authentic content to the audiences during the live-streamed activities. To be specific, practitioners should exercise caution with excessively scripted endorsements or content that seems forced, since it may swiftly engender perceptions of inauthenticity among audiences. As such, practitioners should underscore the significance of authentic communication and genuine product integration in their collaborations with celebrities as endorsers, to alleviate the potential impact of advertising inauthenticity on dark customer-brand attitudes (i.e., brand hate and betrayal).

Concerning the scarcity of expertise, practitioners should guarantee that celebrities undergo thorough product training to furnish them with the requisite product knowledge and brand insights, before devoting them to authentic live-streamed sessions. Therefore, regular updates are imperative to keep celebrities abreast of any brand's offerings or messaging alterations. Furthermore, when engaging celebrities as endorsers, their ability to project professionalism and respond confidently to audience queries during live-streamed sessions substantially shapes the perception of expertise.

Moreover, given the direct impact of brand betrayal on brand hate, it is imperative for practitioners to promptly implement measures to rectify consumers' negative perceptions toward endorsed brands, especially when individuals harbour feelings of animosity resulting from brand betrayal but have not yet advanced to a state of brand hatred. One suggested strategy could entail addressing each online review gathered on live streaming commerce platforms and clarifying the resolution process for the identified issues. While this strategy may require dedicated resources and entail associated costs, given the cascading impacts of a tarnished reputation, deceptive advertising, and a perceived lack of expertise contributing to negative perceptions, the investment of both expense and effort could prove prudent.

Additionally, as practitioners, it is crucial to recognize that each repercussion is instigated by a distinct form of hatred or betrayal, necessitating tailored management of underlying emotions. When consumers have advanced to the stages of brand betrayal or hatred, they are bound to employ both active and passive measures to penalise the brand. These punishments can not only result in financial setbacks stemming from reducing or ceasing their usage, but also retaliate, causing harm to the brand's image and equity. Hence, practitioners are advised to immediately and meticulously handle the most loyal customers with the greatest care, as the most devoted customers may transform into the most ardent detractors if they perceive deception from the business. Subsequently, practitioners' attention can then be directed toward resolving other cases.

## 6.3 Limitations and future research

Although this study provides valuable contributions to theoretical and practical degrees separately, it also has certain research-designed, methodological, and theoretical limits that can be further addressed and solved in future research. In terms of research design, this study primarily focuses on Malaysian consumers as the target sample to investigate. Given the difference in socioeconomic and cultural variations, the results from one nation might limit their suitability in other countries. Future studies are suggested to launch the investigation in various countries, especially in Western countries, to examine if similar results are presented in countries with different backgrounds, consumption discrepancies, and cultural contexts. In terms of methodology, given that cross-sectional survey-based research might restrict the long-term predictability of negative brand outcomes. Thus, to verify the results and findings, future studies are suggested to extend the data collection time with longitudinal study, and propose more valuable insights into how brand hate and betrayal grow over time as consumers perceive and evaluate celebrities with time. In terms of theory, this study adopts the S-O-R theory by incorporating four stimuli as antecedents, two internal states, and five responses as consequences. The conceptualization is theoretically sound and consistent with other studies that have applied the S-O-R theory to brand contexts. To better explore consumer`s behaviour and impact upon experiencing stimulus and organism, future studies are suggested to use the Stimulus-Organism-Behaviour-Consequence (SOBC) approach to provide more value and in-depth contributions in this field, as it is superficially explored at the moment.

Additionally, future research, when collecting demographic information, is suggested to inquire about the occupations of the target sample and include an investigation into the types of brands that they are inclined to purchase when engaging with celebrity live-streaming. This action empowers brands to tailor their messaging and product offerings to align with the specific preferences associated with diverse occupations, thereby increasing resonance with the target demographic. Moreover, investigating the types of brands favoured by individuals from various occupations allows for refining celebrity endorsement strategies. Aligning celebrities with specific occupational groups' preferences enhances endorsements' authenticity and relevance, fostering stronger connections between celebrities, brands, and consumers in live streaming commerce.

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