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A big data exploration of the informational and normative influences on the helpfulness of online restaurant reviews☆

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ABSTRACT

With the proliferation of user generated online reviews, uncovering helpful restaurant reviews is increasingly challenging for potential consumers. Heuristics (such as "Likes") not only facilitate this process but also enhance the social impact of a review on an Online Opinion Platform. Based on Dual Process Theory and Social Impact Theory, this study explores which contextual and descriptive attributes of restaurant reviews influence the reviewee to accept a review as helpful and thus, "Like" the review. Utilising both qualitative and quantitative methodologies, a big data sample of 58,468 restaurant reviews on Zomato were analysed. Results revealed the informational factor of positive recommendation framing and the normative factors of strong argument quality and moderate recommendation ratings, influence the generation of a reviewee "Like". This study highlights the important filtering function a heuristic can offer prospective customers which can also result in greater social impact for the Online Opinion Platform.

1. Introduction

With today's enhanced usage of online media and the proliferation of electronic word of mouth (eWOM), consumers are becoming increasingly reliant on user-generated reviews for evaluations of products and services when forming purchase decisions (Liu, Ozanne, & Mattila, 2018; Sparks & Browning, 2011). This behaviour is particularly prominent for customers of intangible and experience based services (i.e., restaurant dining), as user-generated content (UGC) has higher believability than information provided by brand owners (Eslami, Ghasemaghaei, & Hassanein, 2018; Li, Huang, Tan, & Wei, 2013). In fact, irrespective of whether a review is positive or negative, potential customers rely on feedback from other consumers to guide their future consumption behaviour (Cheng & Ho, 2015; Risselada, de Vries, & Verstappen, 2018).

Dedicated Online Opinion Platforms (OOPs), such as Zomato (zomato.com), provide consumers with unprecedented opportunities to communicate their opinions and experiences of hospitality service providers (Litvin, Goldsmith, & Pan, 2018). OOPs provide a community-based platform for not only engaged consumers to write restaurant reviews, but also for prospective customers (i.e., reviewees) to visit and read reviews which aid their decision making process (Li et al., 2013). Notably, as the number of reviews escalate, restaurant patrons are finding it more arduous and time consuming to read, digest, and select, credible information from the vast array of reviews (Eslami et al., 2018; Mudambi & Schuff, 2010). Such information overload can increase search and cognitive costs for the consumer (Li, Hou, Guan, Chong, & Pu, 2017). Subsequently, prospective customers look for heuristic information cues, such as "Likes", to help make this process easier and more efficient (Jia & Liu, 2018; Risselada et al., 2018).

By "liking" a post, the reader is demonstrating their appreciation for the content of the review or the "helpfulness" of the information presented. For subsequent readers, a "Like" acts as an indication of the usefulness of the review (Jia & Liu, 2018). According to Lo and Yao (2019) when sources of information are endorsed by their peers, they are automatically perceived to be more credible. Thus, irrespective of the review being positive or negative, the more "Likes" the review receives, the more credible and helpful the review is deemed (Lo & Yao, 2019; Risselada et al., 2018). Accordingly, it is critical to understand which aspects of the content within a review encourage reviewees to "Like" the review, and thus enhance its helpfulness.

Nowak, Szamrej, and Latané (1990) suggest people are prone to attitude change in response to persuasive arguments, or even the mere knowledge that others hold a certain opinion. This view is shared by

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Chang, Fang, and Huang (2015) who advocate reviewees are influenced by both the information provided (i.e., informational factors), and the reviewer's opinion expressed as cues, such as the rating given to the restaurant (i.e., normative factor). Subsequently, if the reviewee finds the review helpful, they will endorse the review by "liking" it (Chauhan & Pillai, 2013). Thus, reviewees incorporate "dual processing" by processing the informational and normative factors of the review to decide whether to take behavioural action (i.e., "Like" the review).

To act as a valuable source of information, OOPs strive to offer their visitors an online community that facilitates high customer engagement (through the posting of restaurant reviews) and social impact (an outcome of the perceived helpfulness of the reviews). In order to achieve these objectives, it is essential for proactive management to have an informed understanding of what role informational and normative factors have on influencing the helpfulness of a review. An understanding of the textual and content characteristics of online reviews, which subsequently influence review helpfulness through unprompted and spontaneous acceptance ("Likes"), is clearly limited (Liu et al., 2018). The current study attempts to fill this shortfall. By utilising content analysis of big data from over 58,000 online restaurant reviews, this paper explores the persuasive characteristics of consumer reviews.

Content analysis is employed as it provides a more comprehensive understanding into the association between consumer experiences, and their satisfaction with the product or service (Xiang, Schwartz, Gerdes, & Uysal, 2015). By utilising in-depth analysis of actual user-generated reviews, this research will provide new insights into the determinants of perceived helpfulness, which historically has been examined via hypothetical experiments or questionnaires (DeAndrea, Vendemia, & Vang, 2018). To further enhance the study's contribution, quantitative analysis is performed to gain additional insights to support the qualitative findings. Accordingly, this study addresses the following research question:

Which normative and informational characteristics of online restaurant reviews influence the perceived helpfulness of the review as indicated by "Likes"?

The current research makes several contributions. It is the first study to explore the influence of review characteristics of online consumer generated restaurant reviews on both, the review helpfulness and unhelpfulness, as indicated by "Likes" and "No Likes". By doing so, the study focuses on the actual content of legitimate restaurant reviews to enrich our understanding of the persuasive factors associated with the acceptance and helpfulness of user-generated online reviews. In contrast, it also explores the content of reviews deemed unhelpful by reviewees, to provide a greater understanding about unhelpful reviews. The study integrates both qualitative and quantitative methods to provide a triangulated understanding of the focal subject.

2. Literature review

2.1. Online reviews

The motivation to write an online review is often to influence consumer behaviour in accordance with the author's own preferences and experiences, as demonstrated by the star rating provided in the review (Huang, Chen, Yen, & Tran, 2015). However, Jiménez Fernando and Mendoza (2013) suggest the rating given to a product or service in a review is only persuasive when it is consistent with the content of the review and the consumer also scrutinizes the written content in the review. Furthermore, the perceived helpfulness of the review is based on both the information provided and the source of the review. For example, if the reviewer belongs to a genuine OOP, such as Zomato, the review is more prone to influence consumer behaviour as it is deemed a reliable platform for restaurant reviews (Jiménez Fernando & Mendoza, 2013).

For prospective customers, the impact of a review posted on an OOP is heightened by evidence of other consumers having previously read the review and signifying their perceived helpfulness of the message with a "Like". This is consistent with Risselada et al. (2018, p. 621) who suggest "consumers are influenced by others' opinions in evaluating reviews". Much like helpfulness votes given to reviews by reviewees (Risselada et al., 2018), "Likes" represent a social signal or a heuristic that encourages other consumers to accept the information provided in the review as reliable (Lo & Yao, 2019). In these instances, "Likes" amplify the social impact of the review (Jia & Liu, 2018). As an illustration, according to eMarketer (2018) visible "Likes" have resulted in almost 13% of additional sales, a finding that highlights the impact of consumer advocacy.

On the Zomato platform (Zomato.com), customers who have recently visited a restaurant can share their experience with others by providing a review and including an overall star rating ranging from 1 to 5 (low to high satisfaction). A prospective consumer (the reviewee) will then visit the OOP, read the review, and process both the normative (e.g., star rating) and informational facets (e.g., recommendation framing, argument quality) of the review (Eslami et al., 2018; Filieri, 2015; Ghasemaghaei, Eslami, Deal, & Hassanein, 2018). This dual processing of the message influences the readers perceived helpfulness of the review and their subsequent behaviour, which can range from liking the review (clicking "Like"), through to the ultimate decision to visit the restaurant. Therefore, the salient characteristics of online reviews that impact on a consumer's perception of helpfulness are pivotal in shaping consumer behaviour (Ghosh, 2018).

2.2. Review helpfulness

Review helpfulness refers to the perceived value of the review to potential consumers when making a purchase decision (Hong, Xu, Wang, & Fan, 2017; Ren & Hong, 2019). Consequently, helpful online reviews are instrumental in expediting the pre-purchase information search and subsequent selection process (Ghosh, 2018; Pentina, Bailey, & Zhang, 2018). Furthermore, perceived helpfulness is a critical attribute of online restaurant reviews as it emphasises consumers' feelings and experiences, significantly influencing booking intention (Lee, Jeong, & Lee, 2017). Although extant research indicates there is extensive analysis around the factors that increase review helpfulness, there are, however, inconsistencies in the literature (Fresneda & Gefen, 2019; Hong et al., 2017).

Table 1 presents a summary of past research investigating review helpfulness, highlighting the persuasive factors, measures and operationalization of helpfulness. Previous research reveals review helpfulness can be influenced by the star rating given to the product or service (e.g., Baek, Ahn, & Choi, 2012; Mudambi & Schuff, 2010), review valence (e.g., Agnihotri & Bhattacharya, 2016; Fresneda & Gefen, 2019), argument quality (e.g., Fresneda & Gefen, 2019; Ghose & Ipeirotis, 2011), reviewer expertise (e.g., Cheng & Ho, 2015; Zhou & Guo, 2017), reviewer disclosure (e.g., Forman, Ghose, & Wiesenfeld, 2008), review length (e.g., Baek et al., 2012; Chua & Banerjee, 2015), review consistency (e.g., Baek et al., 2012; Ludwig et al., 2013), and time lapsed (e.g., Moore, 2015; Zhou & Guo, 2017).

More recent literature has investigated the influence of reviewer connectedness (e.g., Zhou & Guo, 2017), review consistency (e.g., Ludwig et al., 2013), readability (e.g., Agnihotri & Bhattacharya, 2016; Fresneda & Gefen, 2019), order effect (e.g., Zhou & Guo, 2017) and emotions (e.g., Lee et al., 2017) on review helpfulness. Recent work has established that narrativity within online reviews can markedly influence consumer persuasion (Van Laer, Edson Escalas, Ludwig, & Van Den Hende, 2019), and that the extent to which a review tells a story, significantly impacts the perceived helpfulness of the information (Van Laer et al., 2019).

In addition to the lack of clarity around *which* factors have an impact on perceived helpfulness, there are also contradictory findings with

Table 1
Summary of prior studies investigating review helpfulness.

Study	Persuasive Factor	Measure	Study	Context	Operationalization of Helpfulness
Reviewer related factors	Reviewer expertise	Total number of reviews, reviewers age, number of followers, source/reviewer credibility, reviewer experience, reviewer reputation	Agnihotri and Bhattacharya (2016), Baek et al. (2012), Cheng and Ho (2015), Chua and Banerjee (2015), Ghose and Ipeirotis (2011), Pan and Zhang (2011), Zhou and Guo (2017)	Amazon (search & experience goods) Amazon (search & experience goods) iPeen.com.tw (restaurant review) Amazon (books) Amazon (electronic goods) Amazon (experimental & utilitarian products) Yelp (restaurants)	Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes Helpfulness vote ratio Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes
	Reviewer connectedness	Number of review friends (online attractiveness)	Zhou and Guo (2017)	Yelp (restaurants)	Helpfulness votes
	Reviewer disclosure	Age, name, nickname, hobbies	Forman et al. (2008), Ghose and Ipeirotis (2011)	Amazon (books) Amazon (electronic goods)	Helpfulness vote ratio Helpfulness vote ratio
Review related factors	Review length	Review length, review depth, word count, review elaborateness, review quantity	Baek et al. (2012), Chua and Banerjee (2015), Fang, Ye, Kucukusta, and Law (2016), Fresneda and Gefen (2019), Ludwig et al. (2013), Mudambi and Schuff (2010), Pan and Zhang (2011), Salehan and Kim (2016), Zhou and Guo (2017)	Amazon (search & experience goods) Amazon (books) TripAdvisor Amazon (appliances & supplies) Amazon (books) Amazon (search & experience goods) Amazon (experimental & utilitarian products) Amazon (technology products) Yelp (restaurants)	Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes Helpfulness vote ratio Helpfulness vote ratio Helpfulness vote ratio Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes
	Review rating	Star rating, recommendation rating, rating extremity	Baek et al. (2012), Chua and Banerjee (2015), Ghose and Ipeirotis (2011), Ludwig et al. (2013), Moore (2015), Mudambi and Schuff (2010), Pan and Zhang (2011)	Amazon (search & experience goods) Amazon (books) Amazon (electronic goods) Amazon (books) Amazon (utilitarian & hedonic products) Amazon (search & experience goods) Amazon (experimental & utilitarian products)	Helpfulness vote ratio Helpfulness vote ratio Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes Helpfulness vote ratio Helpfulness vote ratio
	Review valence	Sentimental tone of the content in the review, review valence, review sidedness, positive/ negative affective content, sentiment score	Agnihotri and Bhattacharya (2016), Baek et al. (2012), Fang et al. (2016), Forman et al. (2008), Fresneda and Gefen (2019), Lee et al. (2017), Ludwig et al. (2013), Moore (2015), Salehan and Kim (2016), Zhou and Guo (2017)	Amazon (search & experience goods) Amazon (search & experience goods) TripAdvisor Amazon (books) Amazon (appliances & supplies) TripAdvisor (Hotels) Amazon (books) Amazon (utilitarian & hedonic products) Amazon (technology products) Yelp (restaurants)	Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes Helpfulness vote ratio Helpfulness vote ratio Helpfulness votes Helpfulness vote ratio Helpful votes Helpfulness vote ratio Helpfulness votes
	Argument quality	Argument quality, argument strength, recommendation framing, information uniqueness, objective/subjective statements	Cheng and Ho (2015), Fresneda and Gefen (2019), Ghose and Ipeirotis (2011)	iPeen.com.tw (restaurant review) Amazon (appliances & supplies) Amazon (electronic goods)	Helpfulness votes Helpfulness vote ratio Helpfulness vote ratio
	Readability	Readability, eloquence, number of spelling errors, easy reading text	Agnihotri and Bhattacharya (2016), Fang et al. (2016), Fresneda and Gefen (2019), Ghose and Ipeirotis (2011)	Amazon (search & experience goods) TripAdvisor Amazon (appliances	Helpfulness vote ratio Helpfulness votes Helpfulness votes ratio Helpfulness vote ratio

(*continued on next page*)

Table 1 (*continued*)

Study	Persuasive Factor	Measure	Study	Context	Operationalization of Helpfulness
				& supplies) Amazon (electronic goods)	
	Review consistency	Review recommendation consistency, rating inconsistency, quality rating variation	Baek et al. (2012), Ludwig et al. (2013)	Amazon (search & experience goods) Amazon (books)	Helpfulness vote ratio Helpfulness vote ratio
	Emotions	Intensity of emotional expressions	Lee et al. (2017)	TripAdvisor (Hotels)	Helpfulness votes
	Narrativity	Narrative content, discourse, transportation, and persuasion	Van Laer et al. (2019)	TripAdvisor/ experiment	Likert-type scale
	Order effect	Order of a review	Zhou and Guo (2017)	Yelp (restaurants)	Helpfulness votes
	Time lapsed	Length of time lapsed from the posted review, days between post-date of focal review and post-date of first review, posting date, time distance, age of review	Fang et al. (2016), Moore (2015), Zhou and Guo (2017)	TripAdvisor Amazon (utilitarian v hedonic products) Yelp (restaurants)	Helpfulness votes Helpfulness votes Helpfulness votes

Note: Helpfulness vote ratio (the proportion of helpful votes in total votes).

regards to *how* aspects of each factor affect the level of perceived helpfulness. Extant research indicates that the most common theories used to explain the persuasive role of message content and review presentation on behavioural intentions, are dual processing theories (Chang et al., 2015).

2.3. Dual processing theories

Literature around the dual processing approach to information adoption encompasses three prominent theories: the Elaboration Likelihood Model (ELM), the Heuristic Systematic Model (HSM), and the Dual-Process Theory (DPT), all of which examine the role played by both the content and context of the message (Chang et al., 2015). Dual processing theories consider how different types of influences, such as argument strength, valance polarity or recommendation rating, affect the persuasiveness of received information (Cheung, Luo, Sia, & Chen, 2009; Wang, Wang, & Tang, 2019). Notably, the ELM, initially created by Petty and Cacioppo (1986), theorises that people process persuasive information by either a central route or a peripheral route, based on their ability and motivation (Cheung et al., 2009). Scrutiny of the information is conducted via the central route, while environmental cues of the message are used to determine whether to accept or not accept a message via the peripheral route. Similar to the ELM, the HSM, developed by Chaiken and Eagly (1989) also utilises two routes of information processing, one heuristic and the other systematic, to determine message persuasiveness. Heuristic processing applies cues or short cuts to evaluate a message, whereas systematic processing methodically evaluates the quality of the message.

Deutsch and Gerard (1955) DPT is a psychological theory based on the receiver's personal evaluation of the received information, consequently relevant elements of received information such as the content, source, and receiver, are important sources of influence (Chang et al., 2015). When adapted to the online environment, DPT proposes online consumer review characteristics can effectively be classified into informational influences, centred on the content of the reviews, and normative influences which relate to the context of the review (Cheung et al., 2009; Filieri, 2015). Furthermore, both informational and normative factors work together to influence the reader's information evaluation (Chang et al., 2015).

The DPT "considers how different types of influences (normative factors and informational factors) affect the persuasiveness of on-line consumer reviews" (Cheung et al., 2009, p. 13), whereas the ELM and HSM essentially explore how different *depths* of message processing undertaken, affect persuasive communication. For this reason, the DPT guides this study as it aims to determine what *types* of informational and normative factors influence the persuasiveness or perceived helpfulness of online reviews, resulting in "Likes" from reviewees. Additionally, elements of the DPT are more applicable to this research since restaurant reviewees are processing the information provided from a dedicated OOP through both central and peripheral routes simultaneously. Readers are potential restaurant patrons and are therefore scrutinizing the reviews for recommendations (central route), however, the reviewee is also influenced by the "Likes" the review has received (peripheral route).

Accordingly, the aim of this study is to investigate the relevance of "Likes" as an indicator of helpfulness using a large sample of reviews from Zomato, an OOP with a reputation for providing informative and reliable restaurant reviews. By applying the DPT to this research, it is expected that the normative determinant of '*review star rating*', and the informational factors '*argument quality*' and '*recommendation framing*', will influence the perceived helpfulness of online restaurant reviews. This will be demonstrated by the application of "Likes" to indicate acceptance of the information in the review as helpful. As consumers perceive reviews as more helpful in the presence of positive reinforcement from other consumers (Risselada et al., 2018), the more "Likes" a review receives the greater the *social impact* of the review.

3. Research proposition development

3.1. Review star rating

A star rating, also referred to as a recommendation rating, is a valenced numerical rating generated by the reviewer and given to an online review to reflect the reviewer's overall satisfaction with the product or service (Ahmad, 2017; Pentina et al., 2018). A distinctive feature of reviews on the Zomato OOP is the 1 to 5 star rating given to the restaurant to indicate the customers recommendation based on their usage experience. Based on prior research, typically a low star rating represents dissatisfaction or a negative view of the product or service experience, whereas a high star rating denotes a satisfactory experience and therefore, a more positive opinion of the product or service (Ahmad, 2017; Ghasemaghaei et al., 2018; Pentina et al., 2018). The use of star ratings as a measure of valence polarity in online review research is common practice (Ahmad, 2017; Ghasemaghaei et al., 2018; Pentina et al., 2018).

There are, however, significant contradictions pertaining to the way in which star ratings influence perceived helpfulness. To illustrate, several studies indicate consumers perceive reviews with low star ratings (negative) to be more helpful than high star ratings (positive) (Eslami et al., 2018; Lee et al., 2017). Whereas, in direct contrast to these findings, Pan and Zhang (2011) observed a positivity bias in the relationship between review valence (star rating) and helpfulness, emphasising that positivity levels are heightened for experience goods. Correspondingly, Pentina et al. (2018, p. 130) advocate that "negative reviews may be considered less credible, trustworthy, and helpful in the experiential services context". Another view is that both positive and negative extreme ratings (e.g., from eBay sellers) are more helpful than moderate ratings (Pavlou & Dimoka, 2006). A finding also supported by Forman et al. (2008) who state extreme ratings, in their case for book reviews, are found to be more useful than moderate ratings.

In direct contrast to both Pavlou and Dimoka (2006) and Forman et al. (2008), Mudambi and Schuff (2010) propose experience product reviews with either extremely high or extremely low star ratings are associated with lower levels of helpfulness than reviews with moderate star ratings. This finding supported by Ren and Hong (2019), indicates there is an inverted 'U-shaped' relationship between valence and perceived helpfulness. Specifically, as valence reaches a moderate level of either a negative or positive star rating, perceived helpfulness is heightened (Ren & Hong, 2019). Furthermore, Mudambi and Schuff (2010, p. 189) suggest "consumers are more open to moderate ratings of experience goods as they could represent a more objective assessment". This opinion is supported by Salehan and Kim (2016, p. 36) who state, "reviews that lean toward either positive or negative may be perceived by consumers as biased and consequently less helpful". Ren and Hong (2019) further reinforce the findings of Mudambi and Schuff (2010) agreeing that extreme views are less helpful than moderate reviews (specifically for experience goods) providing empirical evidence that product type moderates the effect of valence polarity on helpfulness. According to Ren and Hong (2019) prior studies have failed to take into account the significance of the product type when investigating the impact of persuasive influences on perceived helpfulness, attributing this lack of differentiation to the inconsistent findings in the literature. This leads us to the following proposition.

Proposition #1: Star ratings given to online restaurant reviews have an inverted 'U-shaped' relationship with perceived helpfulness of the review.

3.2. Recommendation framing

Although both star ratings and recommendation framing relate to the valence of the review, recommendation framing refers to the linguistic content of the review or the tone of the message, as opposed to star ratings which provide numerical evidence of the reviewers overall level of satisfaction with the product or service. To clarify, positively framed reviews emphasise the strengths or positive aspects of the product or service, while negatively framed reviews stress the weaknesses or problems with the product or service (Chang et al., 2015; Cheung et al., 2009; Lee et al., 2017; Pentina et al., 2018). When reviewees evaluate the helpfulness of an online review, the sentimental tone expressed within the review has a significant impact on the perception of helpfulness (Cheung et al., 2009; Lee et al., 2017; Pentina et al., 2018). This is irrespective of whether the information is positively or negatively framed (Ahmad, 2017; Chang et al., 2015). However, prior research indicates there are mixed findings pertaining to how sentiment is framed in an online review and the level of perceived helpfulness.

These inconsistencies in the literature can be attributed to differences in the source of the review, or the product category under review (Mudambi & Schuff, 2010; Ren & Hong, 2019). For example, an increase in fake online reviews has led to a lack of confidence in the credibility of online reviews posted on company controlled websites or forums. Consequently, consumers are turning to more reliable platforms, such as OOPs, as the source credibility is already established, negating the risks associated with unreliable or fake reviews (Agnihotri & Bhattacharya, 2016). The type of product under review also moderates the effect of sentimental tone on perceived helpfulness (Mudambi & Schuff, 2010; Ren & Hong, 2019). To demonstrate, Sparks and Browning (2011) suggest positively framed information in travel reviews (an experience product) exercise a far stronger influence on helpfulness, than negatively framed information. Whereas Cheung et al. (2009) found that negatively framed messages, on a discussion forum pertaining to an array of products and services, are perceived as more credible than positively framed messages for search products. Agnihotri and Bhattacharya (2016) posit that the relationship between sentimental tone and helpfulness for both search and experience products is non-linear. Therefore, whether the content of a review is predominantly positive or negative, the perceived helpfulness of the review diminishes in cases of extreme sentimental tone (Salehan & Kim, 2016).

According to Purnawirawan, Eisend, De Pelsmacker, and Dens (2015) when consumers are searching for experiential products or services such as a restaurant, they are looking specifically for positive reviews, either to confirm their choice or to assist in the decision making process (Sen & Lerman, 2007). Reviewees will give more weight to positive than negative reviews since positive reviews are more consistent with their decision. Therefore, positive reviews will be considered more helpful than negative reviews and subsequently receive more "Likes" as a result. Thus, the following is proposed:

Proposition 2: Positive recommendation framing in online restaurant reviews will be associated with perceived helpfulness as indicated by "Likes" given to the review.

3.3. Argument quality

Argument quality relates to the strength of the information within the message and is one of the most extensively examined persuasive elements of online reviews (Ahmad, 2017; Cheung et al., 2009; Chua & Banerjee, 2015; Fresneda & Gefen, 2019; Liu et al., 2018; Malik & Hussain, 2018). Fresneda and Gefen (2019) suggest the perception of review helpfulness increases with the depth and quality of the information provided in the review. It is the substance of the text in an online review, as opposed to the quantity of information, that is key to perceived helpfulness (Malik & Hussain, 2018). There is general consensus throughout the literature regarding the significance of strong argument quality as a necessary condition to ensure review helpfulness (Ahmad, 2017; Fresneda & Gefen, 2019; Malik & Hussain, 2018). Furthermore, although the star rating (normative determinant) given to a review has the capacity to influence the perception of helpfulness, reviewees rely on strong argument quality (informational determinant) within the review to support their recommendation (Cheung et al., 2009). The extent to which a reviewee perceives the information within a review as convincing or helpful, will directly affect their subsequent behaviour, particularly in an online environment (Cheung et al., 2009). Therefore, in the context of online restaurant reviews it is posited that argument quality will influence the endorsement of "Likes" to indicate the perceived helpfulness of the information in the review. Consequently, it is proposed that:

Proposition #3: Strong argument quality in online restaurant reviews will be associated with perceived helpfulness as indicated by "Likes" given to the review.

DPT is valuable in explaining message effectiveness in situations of group discussions, such as online consumer reviews, where there is discussion content (informational factors) and numerical evaluations (normative factors) from within the community (Cheung et al., 2009; Filieri, 2015). Consequently, through a mixed methods approach the current research broadens past investigations to consider the influence of the review on the reviewees' processing of the review content (i.e., DPT) and their subsequent reaction ("Likes") to the review. Furthermore, the use of both content analysis and quantitative statistical analysis ensures breadth and depth of understanding and strengthens the contribution of this research.

4. Methodology

To enrich theorisation a mixed methods approach was employed using both qualitative and quantitative data collected from Zomato

(zomato.com/Dubai). The design utilised in this research is classified as concurrent triangulation (Creswell & Creswell, 2018; Östlund, Kidd, Wengström, & Rowa-Dewar, 2011), a mixed method designed to facilitate the integration of both qualitative and quantitative findings in one study. Using triangulation as a methodological metaphor can offer a better understanding of both subjective (informational) and objective (normative) aspects of the data (Östlund et al., 2011), providing insights beyond what can be explained by a single methodology (Pavlou & Dimoka, 2006). Thus, qualitative analysis was used to explore the proposed relationships, with quantitative analysis utilised to provide additional numerical information to interpret the qualitative data-based findings.

4.1. Data collection

A total of 58,468 individual customer reviews were retrieved from the Zomato platform including: the textual content of the review, the restaurant URL, the date and time the review was posted, the rating given to the restaurant, and the number of "Likes" given to the review. It should be noted that in this study, Zomato incorporates a "Like" function on its platform therefore, "Likes" were used as a heuristic cue to reflect a reviewee's acceptance of a review as helpful. Data were extracted via web-scraping technology and exported for quantitative data analysis to examine the textual content of the large unstructured dataset.

4.2. Variables

4.2.1. Operationalisation of key variables and measurements

Operationalisation of perceived helpfulness in the literature is primarily based on the ratio of helpful votes given to a review over the total number of helpfulness evaluations (Agnihotri & Bhattacharya, 2016; Baek et al., 2012), or simply the total number of helpful votes (Zhou & Guo, 2017; see Table 1). However, Fresneda and Gefen (2019) question the suitability of using helpfulness ratings to measure the value of an online review, suggesting that inconsistencies in research outcomes can be attributed to the use of such helpfulness measures. This is a view consistent with Hong et al. (2017, p. 4) who advocate that "helpfulness measures, namely the helpful vote ratio and the number of helpful votes, generally have conflicting findings on the same determinant factor of review helpfulness". This suggests a more autonomous measure of helpfulness will be more effective. In Cheng and Ho (2015) work, they operationalise the usefulness of restaurant reviews based on a point system. Reviewees award the review with a point to acknowledge their opinion of its perceived helpfulness, and there is no limit to the points a review can receive. Similarly, restaurant reviews on Zomato are assigned "Likes" to indicate helpfulness, with "Likes" from different reviewees accumulating. Therefore, rather than relying upon a forced response to a dichotomous question (Huang et al., 2015; Mudambi & Schuff, 2010) this study undertakes further investigation utilising "Likes" as a new measure of review helpfulness. Operational definitions and measurement methods for all key variables are provided in Table 2.

Table 2
Operational definition and measurement method of key variables.

Dual processing	Variable	Operational definition
Normative factor	Review star rating	The review star rating is defined as the valance polarity of the review. In this study a low rating (1–2.5 stars) indicates a negative view of the restaurant; a high rating (3.5–5 stars) reflects a positive view of the restaurant; and a three-star rating reflects a moderate view (Ahmad, 2017; Chang et al., 2015; Jia & Liu, 2018). Using this measurement, a rating of 1 star denotes an extreme negative rating and a rating of 5 stars represents an extreme positive rating (Ghasemaghaei et al. (2018).
Informational factors	Recommendation framing	Recommendation framing in this study is defined as the sentiment within the content of the review and whether it is predominantly of a positive nature (e.g., a praise message) or of a negative nature (e.g., a complaint message) (Chang et al., 2015; Lee et al., 2017; Pentina et al., 2018).
	Argument quality	Argument quality refers to the comprehensiveness of the information in the review. Providing understandable, relevant, and believable recommendations that match the star rating denotes high argument quality of the review content (Chang et al., 2015).
Outcome	**Variable**	**Operational definition**
Helpfulness ratings	Helpfulness	"Likes" given to an online restaurant review reflect the readers perception of helpfulness. As "Likes" increase, the perceived helpfulness of the review increases, and the level of social impact is heightened.

4.3. Qualitative analysis using Leximancer

Leximancer, an automated computer-driven lexical analysis program, was chosen to analyse the big, qualitative dataset with minimal intervention by the researcher. This approach allowed for an objective exploration of the data by considering blocks of the text to identify prominent concepts and themes within the data (Leximancer, 2017). Leximancer has been prolifically used by researchers working with big, qualitative data, ranging from investigations into online brand advocacy found within online community forum discussions (Wilk, Soutar, & Harrigan, 2019), interviews with sport management experts (Sotiriadou, Brouwers, & Le, 2014), tracking the history of cross-cultural psychology journal articles (Cretchley, Rooney, & Gallois, 2010), to sustainable supply chain news articles analysis (Kim & Kim, 2017). As highlighted by Wilk et al. (2019), Leximancer minimises researcher's bias in analysing qualitative data, however, a researcher's input is invaluable to the interpretation of the results produced by the program. Notably, the program's algorithm is based upon an iterative process of seeding word definitions from frequencies and co-occurrences of words (called concepts) within blocks of text (Smith & Humphreys, 2006; Sotiriadou et al., 2014). Leximancer groups key concepts into themes and this grouping is based on some commonality or connectedness such as contextual similarity, whereby the concepts appear close to each other on the Concept Map (Cretchley et al., 2010; Leximancer, 2017). The themes are named after the most prominent concept, which is marked on the Concept Map with a large dot. The size of the themes represents the concepts' co-occurrence with other concepts and the themes are heat-mapped from hottest to coolest (i.e., red is the 'hottest' or most prominent theme and purple is the 'coolest' or least connected theme) (Wilk et al., 2019). An Insight Dashboard report supports the visual Concept Map. In the report, concepts and tags are divided into dependent variables (categories) and independent variables (attributes) (Leximancer, 2017). Relative frequencies for each combination of categories and attributes are listed in the report and a Prominence Score (PS) is calculated. Prominence is defined as the joint probability divided by (the product of the marginal probabilities), where a score of > 1.0 for prominence indicates that the co-occurrence happens more often than chance (i.e., the items are not independent) (Leximancer, 2017). In calculating the PS, the algorithm combines the strength and frequency scores using Bayesian statistics, as PSs are absolute measures of correlation between category and attribute (Leximancer, 2017). An Insight Dashboard Report provides Prominence Scores 'PS' for concepts and compound concepts, where PS of 1 or more is considered sufficient to identify unique and important characteristics and, for compound concepts, a PS of 3 or more can be satisfactory (Wilk et al., 2019).

The aim of the Leximancer analysis was to provide a 'visual analysis' by allowing the program to objectively explore the big data to identify which restaurant reviews' characteristics are persuasive (i.e., argument quality) and, as a result, elicit perceived helpfulness, as well as, to better understand recommendation framing. This type of analysis also enabled the identification of the social impact of the review, by relating the number of "Likes" given to the reviews. Some Leximancer settings had been adjusted to suit the nature of the data which was being explored. As an example, the default 2-sentence block setting was increased to 4 sentences, in order to accommodate fragmented communication style that is often found in reviews and, more broadly, in online communication. For example, "IMO (in my opinion)." would typically be considered a sentence by the program. The Stop-Word list was also updated to include many words which the program typically automatically excludes from plotting on the Concept Map. Words such as 'good', 'great' and 'never' were re-instated back into the analysis and hence removed from the Stop-Word list, as they were considered essential evidence words in meaning attribution (Smith & Humphreys, 2006). Researchers use tags to better understand their datasets (e.g., Wilk et al., 2019) and such tags were seeded in this study to assist the exploration of the differences between restaurant reviews by "Likes" and Review Rating. The "Likes" and "no Likes" tags were seeded by selecting these variables from the MS Excel dataset, to appear as tags in the Leximancer analysis in the 'Mapping Concepts' setting. Furthermore, positive sentiment was seeded as a compound concept in the 'User Defined Concepts' setting, to include positive words evident in the reviews' content and included: 'amazing', 'best', 'delicious', 'great', 'loved', 'perfect', 'awesome', 'beautiful', 'enjoyed', 'excellent', 'fantastic', 'wonderful' and 'yummy'. Additionally, negative sentiment was seeded as a compound concept in the 'User Defined Concepts' setting and included the following words emergent from the reviews' content: 'disappointed', 'disappointing', 'never', 'bad' and 'worst'.

5. Data analysis and results

5.1. Quantitative data analysis and results – Stage 1

Descriptive statistics calculated indicate that of the total reviews in the sample (n = 58,468), the majority at 73% (n = 42,839) conveyed positive sentiment (rating of 3.5–5) about their restaurant dining experience, 17% (N = 9,694) expressed negative sentiment (rating of 1–2.5), and only 10% (n = 5,935) were neutral (rating of 3). With a Mean of 3.66 (*SD* = 1.08) the average star rating given to a restaurant review is moderate to positive. This finding is consistent with prior research (Baek et al., 2012; Huang et al., 2015). Further statistical analysis revealed that reviews with moderate ratings leaning towards positive sentiment (rating of 3.5–4) at 62% (n = 21,368) also attracted the most "Likes". To examine the statistical significance of valence on perceived helpfulness, t-tests were performed indicating positive reviews received a statistically significant higher number of "Likes" (M = 1.7, SD = 2.5) per review than negative reviews (M = 0.88, SD = 1.7), t −29.8 (p = .000).

The descriptive analysis also revealed that of 34% (n = 11,651) of "Likes" were awarded to reviews with extreme ratings, whether positively or negatively framed (1 or 5). Furthermore, when "Likes" were given to reviews with extreme ratings, very positive reviews (rating of 5) received significantly more "Likes" (n = 10,704) than very negative reviews (n = 947). With a minimum of 1 and a maximum of 50 "Likes" given to a review, out of the reviews that did receive a helpfulness vote (a "Like"), the average number of "Likes" with a mean value of 1.53 (SD = 2.38) suggests that generally the majority of Zomato reviews only received between 1 or 2 "Likes".

5.2. Quantitative results

To examine the proposed 'U shape' between review star ratings and perceived helpfulness a quadratic regression was applied to the data. To test model fit, a linear regression was conducted with the inclusion of star ratings and star ratings squared as predictor variables, and the number of "Likes" (perceived helpfulness) as the outcome variable. The inclusion of the squared star rating resulted in a statistically significant R2 change of 0.021 (F = 1250, 58,465 df, p = .000) from the first model. Thus, by adding the quadratic variable (star rating squared) to the second model there is a statistically significant increase in the model's capacity to predict perceived helpfulness. This indicates a curvilinear relationship between restaurant review ratings and perceived helpfulness. Furthermore, the R2 value of 0.027 is statistically significant (F = 825,009, df = 58,465, p = .000) and implies that 2.7% of the variability in the outcome variable was accounted for by both predictor variables (star rating and star rating squared). As shown in Fig. 1, the quadratic relationship indicated the higher the rating given to the restaurant, the more "Likes" the review received up to a certain point, then the number of "Likes" decline at the extreme end of the rating scale. The unstandardized beta for the Rating variable is 1.386 and the unstandardized beta for its squared value is −0.192, both of which are statistically significant (p < .005). The positive coefficient for Rating and the negative coefficient for Rating supports the proposed (Proposition 1) curvilinear relationship between restaurant review ratings and the perceived helpfulness of the review. This result is consistent with Mudambi and Schuff (2010) who also found there is an "inverted-U" relationship between rating and helpfulness, where reviews with extremely high or low star ratings are associated with lower levels of helpfulness, than reviews with moderate star ratings. Thus, the current study extends Mudambi and Schuff's finding of an "inverted-U" relationship between rating and helpfulness to the context of experience-based services (restaurants), and not just experience goods.

5.3. Qualitative data analysis and results - stage 2

5.3.1. Leximancer results

5.3.1.1. Review star rating. Two Leximancer-driven analyses were performed on the Zomato dataset. The first Leximancer-driven analysis included all reviews with tags for all ratings (ratings of 1 through to 5), "no Likes", and "Like(s)" (see Fig. 2). Interestingly, it was revealed reviewees tend to give no "Likes" to reviews that are either very negative or very positive (i.e., either a 1, 2 or 5 rating being associated with the "no Likes" tag on the Concept Map); which may be interpreted as 'extreme' evaluations of restaurants. Thus, suggesting there is an association between the recommendation rating of the review and the "Likes" it receives. Further, reviewees give "Like(s)" to reviews which gave restaurants a favourable good or moderate rating (e.g., 3 or 4 rating being associated with the "Likes" tag on the Concept Map), which may be indicative of these reviews being more believable and authentic, and consequently, more helpful. These findings support the 'U shaped', curvilinear relationship between "Likes" and restaurant ratings (Review Ranking) that was found using quantitative methods discussed above, thus supporting Proposition 1.

5.3.1.2. Argument quality. The most prominent compound concepts identified by Leximancer are presented in Table 3. These assist in interpreting the Concept Map to ascertain argument quality, by identifying which pairs of words feature most prominently within the given dataset. Evidently, reviews with "no Likes" were simple in nature and about 'order', 'delivery', and 'time', specifically, the reviewer's disappointment with these aspects of their restaurant experience. In comparison, reviews with "Like(s)" were more elaborate in nature, presented an opinion and a call-to-action, including: 'best' 'restaurant' 'Dubai' and

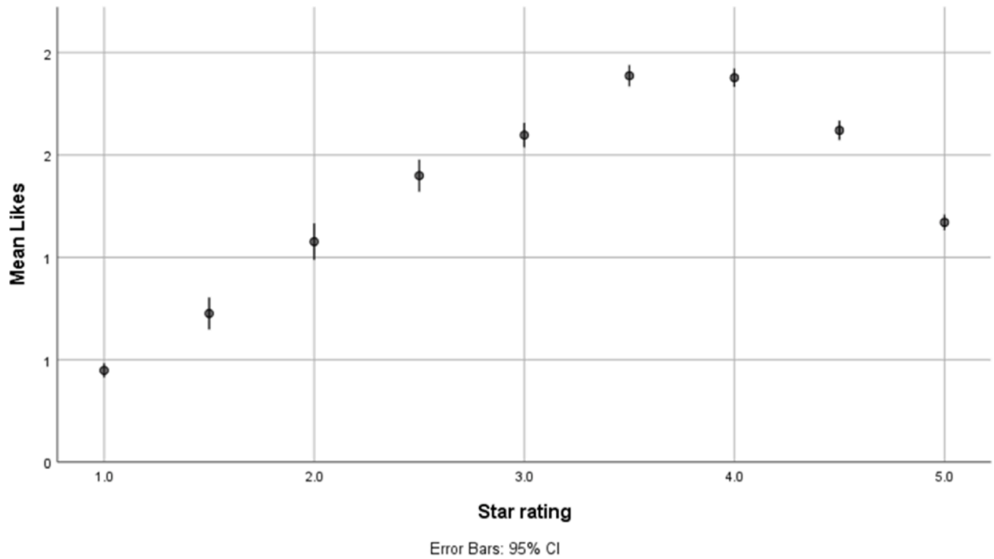

Fig. 1. Model free evidence of the relationship between restaurant and helpfulness ratings.

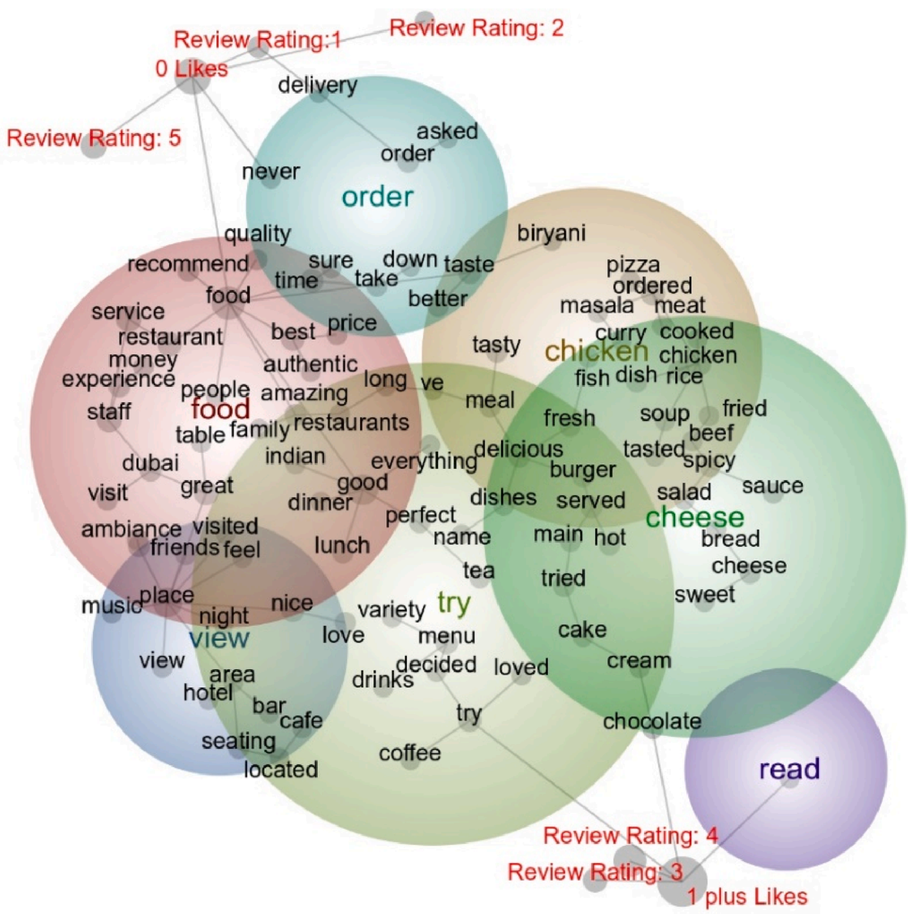

Fig. 2. All reviews segmented by rating, "no Likes" and "Like(s)".

'decided' to 'try', expressing the reviewer's satisfaction with the restaurant experience.

Upon closer inspection, reviews that received "no Likes" exhibited content of low argument quality (see Table 4, review # 3446 and review # 8). These reviews were quite narrow-focused, mostly about the food, service, price, or delivery, and included words describing the reviewer's level of satisfaction with the restaurant such as 'never' (negative sentiment) or 'good' (signifying moderate rather than extreme, positive sentiment).

For reviews that received "Like(s)", the content of the review was more elaborate and beyond just food-related discussion (i.e., strong argument quality), thereby providing support for Proposition 3. Reviews

Table 3
Comparison of top-ranking compound concepts between reviews with "no Likes" and "Like(s)" and positively and negatively framed reviews.

Compound concept "no Likes"	PS "no Likes"	Compound concept "Like (s)"	PS "Like (s)"
Order & delivery	11.1	Dubai & hotel	9.6
Order & asked	7.3	Restaurant & hotel	7.5
Order & take	6.9	Try & decided	6.7
Time & long	6.9	Menu & variety	5.3
Time & delivery	6.5	Dubai & best	4.9
Compound concept 'Positive Sentiment'	PS	Compound concept 'Negative Sentiment'	PS
'best & (in) Dubai'	48.3	'bad & experience'	307.3
'amazing & view'	37.5	'bad & service'	205.4
'best & restaurant'	29.0	'bad & delivery'	204.6
'delicious & soft'	27.9	'tasted & bad'	162.1

with "Like(s)", included insights into the 'place', enjoying eating out with 'friends', recommendation as the best 'place' in 'Dubai', comments around the 'menu' options, strong emotional words such as 'love', 'loved', 'delicious' and 'everything perfect'. These reviews were generally more comprehensive, included a wide variety of information about the restaurant and a more diverse positive sentiment vocabulary. Notably, these reviews included a call to action for the reader to 'try' or 'read' up about the restaurant (see Table 4, review # 10 and review # 58157).

5.3.1.3. Recommendation framing. In exploring recommendation framing and helpfulness, the second Leximancer analysis (see Fig. 3) supported that, overall, positively framed reviews (positive sentiment) resulted in "Likes", whereas negatively framed reviews (negative sentiment) did not. On the Concept Map, the negative sentiment theme was associated with the "no Likes" tag, whereas the positive sentiment theme was associated with the "Likes" tag. Comparison of top ranking compound concepts (see Table 3) revealed what reviewees liked and did not like about the restaurants they were reviewing. To illustrate, a positive review using affirming words such as: *"…this is the best restaurant in Dubai…"* would generate more "Likes" than a negative review using dissuading words such as: *"…we've had such a bad experience at this restaurant…"*. Interestingly, positively framed reviews also tended to be more elaborate than negatively framed reviews, in line with discussion of findings associated within Fig. 2 above.

These findings suggest that, despite extreme positive restaurant reviews being associated with "no Likes", overall, positive recommendation framing (positive sentiment) in restaurant reviews is associated with perceived helpfulness as it generates more "Likes" than negatively framed reviews. These findings provide support for Proposition 2.

5.3.1.4. Extreme positive ratings. Extreme positive review ratings involved only those reviews which the reviewer gave a '5 star rating'. Notably, reviews which received "no Likes" focused mostly on 'food' and 'delivery', how 'good' the 'quality' was, 'great' 'service', and 'amazing' 'food' (Table 4, review # 20). These reviews were quite narrow-focused in nature (low argument quality), whereas reviews with "Like(s)" were more elaborate and included suggestions about 'experience', the 'place', with 'friends' and 'family', stronger positive-emotion words such as 'love', 'loved' and 'recommend', as well as 'everything' 'perfect', and discussion around 'try' and 'read' (strong argument quality). These findings provide further support for Proposition 2 and reinforce Proposition 3 suggesting that positively framed reviews with strong argument quality are associated with perceived helpfulness (see Table 4, review # 8087).

5.3.1.5. Extreme negative ratings. Extreme negative ratings were those reviews for which the reviewer gave a 1 star rating. An analysis of these

Table 4
Review content examples.

Review	Content
# 3446	*Great place and good food quality but delivery time takes too long. (Received '0' "Likes")*
# 8	*Good south Indian food with reasonable prices. Good taste, good seating arrangement and good service. I think no better keralian restaurant than this in terms of quality and prices.* (Received '0' "Likes").
# 10	*…I thought to give this place a try and I must say I am not disappointed at all with the food and service here, if you are nearby, do try this place. Ambiance is more of mix of colors; they have used green color with brown, which highlights the decor. They have private seating and corporate seating as well, which I found very innovative. Service is prompt and staff is helpful and polite. Other thing impressed me here is the menu; menu is mix of many must have Indian dishes, also some unique dishes. So in every dish it focuses on authenticity and very Indian touch, so even if the innovation is done with names".* (Received '32' "Likes").
# 58,157	*Having their Kifaya pastry was such a splendid experience. This soft and moist cake was light green in colour and topped with fruits. Definitely recommended.* (Received '17' "Likes").
# 20	*Awesome Hyderabadi Dum Biriyani… Placed an order and delivered on the said 15 mins.* (Received '0' "Likes").
# 8087	*Went there with a group of friends for dinner on Thursday night. We took the set menu. However, most of us were vegetarians and few Vegan as well. The interiors of this place are very royal and so is the service…made us feel very special with their extremely warm service. Chef Pradeep Khullar also catered to Vegan dishes even though it was not on the menu…. The main course and the desserts made our complete meal. The entire experience was memorable. A must visit place!* (Received '13' "Likes").
# 12	*Order came wrong, chicken is not that good when compared to other restaurants that offer the same meals with same price, coleslaw is just beyond terrible and fries are somehow dry and not good … fast delivery and terrible experience.* (Received '0' "Likes").
# 3588	*Horrible experience! I should have taken the empty tables and chairs on a Thursday night as a warning sign. They couldn't even get the most basic of dishes right and I won't be coming back to see what their main dishes would be like… When I wanted to ask for the bill, two of them acknowledged me yet no one attended to me. Would not recommend and will definitely not be coming back.* (Received '2' "Likes").

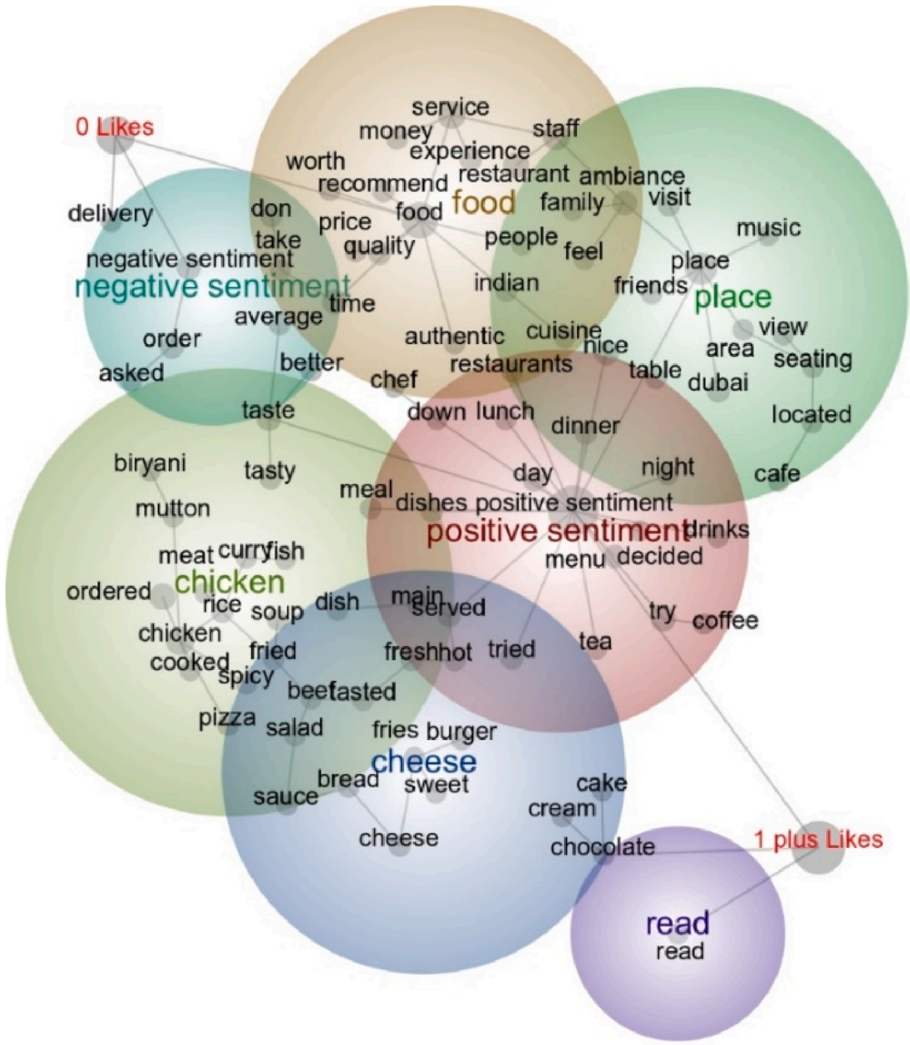

Fig. 3. All reviews segmented by positive sentiment, negative sentiment, “Likes” and “no Likes”.

negative ratings confirmed that reviews which received “no Likes” focused mostly on ‘food’ and ‘delivery’, with ‘worst’, ‘horrible’, ‘bad and ‘pathetic’ used to describe the food and delivery (i.e., low argument quality). Thus, providing further support for Propositions 2 and 3, that negative recommendation framing and low argument quality is perceived to be less helpful (“no Likes”) (see Table 4, review # 12).

In comparison, and again confirming the previous analyses (see Table 4, review # 3588), reviews with “Like(s)” included stronger and more elaborate information such as ‘disappointed’ in the service and provided recommendations and reasons why not to visit (i.e., strong argument quality).

Table 5 summarises the research aims, propositions, procedures and findings of this study.

6. Discussion

For experience based services such as restaurant dining, consumers are increasingly reliant on online consumer generated reviews to influence their consumption behaviour, particularly due to their enhanced credibility as a believable information source (Cheng & Ho, 2015; Risselada et al., 2018). However, the proliferation of online reviews has made determining helpful reviews more problematic for the reviewee (Eslami et al., 2018; Mudambi & Schuff, 2010), making heuristic cues such as “Likes”, an efficient and informative shortcut (Jia & Liu, 2018; Risselada et al., 2018). Yet little is known about what constitutes a review that is helpful, as opposed to a review that is unhelpful.

By applying Dual Process Theory (Deutsch & Gerard, 1955) to the context of an online opinion platform (OOP), the current research explored the effect of informational (i.e., recommendation framing and argument quality) and normative influences (i.e., review star rating) on online restaurant reviews’ perceived helpfulness (i.e., a “Like”). More importantly, this study also explored what influences a review to be more helpful, as opposed to unhelpful.

From a theoretical perspective, the study supported both normative and informational factors having an influence on perceived helpfulness in an OOP. For example, the content analysis revealed reviewees predominantly applied a “Like” to reviews that gave restaurants a moderate to good recommendation rating (3–4 stars), a finding supported by the quantitative analysis with 62% of all “Likes” provided to upper middle range restaurant review ratings (3.5–4). This outcome is consistent with prior research (Baek et al., 2012; Mudambi & Schuff, 2010; Wang et al., 2019), and supported by Yin, Mitra, and Zhang (2016) who found that reviews with a higher average rating are more likely to receive helpfulness votes, and that a one star increase in the star rating given to a review increases the likelihood of a helpful vote by 17 percent. These findings contradict Lee et al. (2017), who found negative ratings more helpful than positive ratings, however, their sample was restricted to include only the reviews with extreme star ratings (i.e., extreme positive and extreme negative), subsequently negating the impact moderate valence may have on perceived helpfulness.

Table 5
Summary of research aims, propositions, procedure and findings.

Analysis Aim	Proposition	Procedure	Findings
To ascertain whether the normative determinant of '*review star rating*', will influence perceived helpfulness (through "Likes") of online restaurant reviews.	P1: Star ratings (valance polarity of the review) given to online restaurant reviews have an inverted 'U-shaped' relationship with perceived helpfulness of the review.	Regression Analysis	Curvilinear (inverted U-shaped) relationship between restaurant review ratings and perceived helpfulness.
		Leximancer Analysis (Concept Map)	Reviewees tend to give no "Likes" to reviews that are either very negative or very positive (i.e., either a 1, 2 or 5 rating being associated with the "no Likes" tag on the Concept Map, suggesting there is an association between the recommendation rating of the review and the "Likes" it receives. Reviewees give "Like(s)" to reviews which gave restaurants a favourable good or moderate rating (e.g., 3 or 4 rating being associated with the "Likes" tag on the Concept Map).
To identify whether the informational factor '*argument quality*' will influence perceived helpfulness (through "Likes") of online restaurant reviews.	P2: Positive recommendation framing (the sentiment within the content of the review) in online restaurant reviews will be associated with perceived helpfulness as indicated by "Likes" given to the review.	Leximancer Analysis (Insight Dashboard Report: Prominence Scores)	Reviews with "no Likes" were simple in nature and about 'order' 'delivery' and 'time', specifically, the reviewer's disappointment with these aspects of their restaurant experience. In comparison, reviews with "Like(s)" were more elaborate in nature, presented an opinion and a call-to-action, including: 'best' 'restaurant' 'Dubai' and 'decided' to 'try', expressing the reviewer's satisfaction with the restaurant experience.
To determine whether '*recommendation framing*' will influence perceived helpfulness (through "Likes") of online restaurant reviews.	P3: Strong argument quality (comprehensiveness of the information in the review) in online restaurant reviews will be associated with perceived helpfulness as indicated by "Likes" given to the review.	Leximancer Analysis (Concept Map & Insight Dashboard)	Positively framed reviews (positive sentiment) resulted in "Likes", whereas negatively framed reviews (negative sentiment) did not.

The current study also found that the normative cue of review star rating was only deemed helpful to a certain point (3–4 stars) before it became less helpful, implying that extreme ratings (1 or 5 stars) are less helpful than moderate reviews (Mudambi & Schuff, 2010; Ren & Hong, 2019). This finding is understandable given the increase in fake online reviews, that typically reflect extreme ratings, prompting scepticism and a lack of credibility (Agnihotri & Bhattacharya, 2016; Liljander, Gummerus, & Söderlund, 2015). The present study confirms that consumers cognitively process normative influences (review star ratings) as helpful only to a certain extent. Past a certain level, helpfulness of such reviews diminishes for consumers, possibly because suspicions are elevated regarding the authenticity of such reviews (Agnihotri & Bhattacharya, 2016).

Informational influences of both recommendation framing and argument quality were also found to influence perceived helpfulness. Reviews with "no Likes" (i.e., unhelpful) reflected low argument quality and were quite narrow focused. This finding was consistent across the content analysis for comparing helpful ("Likes") reviews with unhelpful ("no Likes") reviews and then more specifically, comparing extreme rating positive reviews and extreme rating negative reviews with both helpful ("Likes"), and unhelpful ("no Likes") reviews. Indicating that in all three instances, helpfulness ("Likes") was attributed to reviews of strong argument quality.

Positively framed comprehensive reviews were perceived to be more persuasive and helpful, prompting the reviewee to react with a "Like". This is consistent with Cheng and Ho (2015) who confirm the significance of argument quality on behavioural intentions, and Chua and Banerjee (2015) who found that more verbose language within a review suggests authenticity, therefore by providing reviewees with convincing recommendations, uncertainty is reduced.

6.1. Theoretical contribution

The current research extends extant literature by exploring actual, real content of online restaurant reviews in respect to perceived helpfulness, in order to delve beyond surface indicators of argument quality, such as word count and image count, (Cheng & Ho, 2015) to consider the manner in which the review is framed (informational influence), its argument quality (informational influence) and the recommendation rating (normative influence) provided. Further, the present study examined more explicitly the content and language used within the review to explore how these aspects influence perceived helpfulness via the reviewee applying a "Like". Reviews that were more elaborate, going beyond simply discussing the food elements to include emotion, recommendations to try and a call to action, resulted in "Likes". Thus, reviewees were more accepting of a review being helpful if the review reflected moderate restaurant star ratings, positive framing and strong argument quality with an emotional and experiential aspect extending beyond food. This reinforces the theory that when consumers read online restaurant reviews, they apply dual information processing of both normative and informational influences to assist with their decision making process.

This study contributes to contemporary research on review helpfulness by outlining the significance of strong argument quality, positive recommendation framing, and moderate star ratings as determinants of the perceived helpfulness of online restaurant reviews. More specifically, reviewees appear to seek out reviews which are positive in both normative and informational influences, which is logical given they are searching for a positive heuristic experience. Thus, reviewees consider positive reviews as helpful as they are looking for a restaurant that will provide them with a positive experience. This is as opposed to seeking out and deeming negative reviews as helpful, since the reviewee is not seeking a negative experience as the outcome in their decision process.

This study is also the first to explore the normative and informational influences of reviews not only in respect to helpfulness, but also unhelpfulness. Previous studies (Agnihotri & Bhattacharya, 2016; Baek et al., 2012; Lee et al., 2017) have centred their investigations exclusively on examining helpfulness of reviews. Even removing unhelpful votes from the sample to reflect only helpful reviews (Baek et al., 2012; Ren & Hong, 2019). Thus, they fail to comprehend what influences a review to be deemed unhelpful, which is important given past research has established helpful reviews to be more influential than unhelpful reviews on consumer behaviour (Ahmad, 2017). By utilising both quantitative and qualitative methods to examine real restaurant reviews on an OOP, the validity of the study's findings are enhanced. As supported by Östlund et al. (2011) this methodological approach can provide a more informed understanding of both subjective (informational) and objective (normative) aspects of the data. Furthermore, prior studies have either incorporated one methodological approach or when incorporating both quantitative and qualitative methods, have utilised interviews, experiments and/ or questionnaires, thus limiting the validity of the findings (Chang et al., 2015; Cheung, Lee, & Rabjohn, 2008; Filieri, 2015).

7. Managerial implications

Digital technological advancements impact how consumers communicate, therefore as online communication is continuously evolving, brands and social media platforms, such as OOPs, are being challenged to effectively react to these changes (Caid, 2020). Brand-related communication via user-generated content (UGC) is influential as it is perceived to be more authentic than brand-generated content (BGC) and has been shown to impact a prospective consumer's decision making process (Adjei, Noble, & Noble, 2010). This paper shows that OOP users find UGC, which gives moderate to positive review rating for a restaurant, more helpful than reviews that are negative or extremely positive. Thus, shedding new insights into how consumers communicate. OOP users engage more (give more "Likes") with reviews that are perceived more helpful and not extreme or forceful in nature. This has implications for brand managers, such as restaurant owners, to communicate in a similar way to their consumers; that is, less of a forceful 'sales pitch' manner and in a more informal way, when highlighting positive brand aspects, as this communication will resonate with their consumers more so than a hard sell (extreme positive framing).

Conversely, when brands, such as restaurants, encourage the giving of reviews by extant patrons (as is often the case when a consumer leaves a restaurant, they are often reminded by the restaurant manager to provide a review), the restaurant should highlight that they would appreciate *authentic*, real opinion giving, in the consumer's review (Agnihotri & Bhattacharya, 2016). As this research shows, moderate reviews are also seen as helpful to a prospective consumer.

Furthermore, OOP managers should offer a more diverse set of heuristic cues, beyond just the "Likes" button, to assist in the opinion giving and reacting (engagement) process. In its recent iOS update, Apple has broadened the range of emojis it offers its users, to include more elaborate, inclusive and diverse representation of their users' skin tone, gender and cultural background. For example, a thumb up is now offered to the Apple iPhone user in several different skin colour versions (Morrison, 2019). The diversity of visual, heuristic cues could venture beyond just a "Like" button to gauge helpfulness of a restaurant review and could include other reactions as seen on LinkedIn (hand clap, heart) (LinkedIn, 2020), to enable prospective consumers to better express their engagement with, and assessment of, the review given. Such a response by OOPs would further stimulate engagement with content, and with the platform itself, as it would broaden the freedom of expression and involvement by its OOP members.

Reviews that are posted on OOPs, such as Zomato, are already considered reliable, however, the linguistic style of the post and the route to persuasion makes a difference to how the review is perceived by consumers searching for information about a specific restaurant or selecting which restaurant out of many, to visit. For practitioners, the learnings from this study highlight the value in designing websites which facilitate reviewees being able to promote the helpfulness of a review (i.e., via a "Like" or some other similar cue) to enhance the social influence of the review. As helpful reviews can positively affect sales (Chen, 2013), if the reviewee can effortlessly filter through the numerous reviews to identify helpful reviews, it could assist in attracting new customers and generating sales. From the OOPs perspective, it is imperative that they can predict and draw attention to the most helpful reviews for their customers to save them time and improve their overall satisfaction and loyalty (Eslami et al., 2018). Further, the online platform could inform reviewers on how to write helpful reviews to stimulate reviewee acceptance of the review (i.e., a "Like"), by sharing some of the antecedents of a helpful review (e.g., use emotion, recommendations, call to action). Understanding the salient aspects of online reviews is paramount in today's competitive environment. From a management perspective, recognising the effects of linguistic style and textual content on consumer responses to online reviews (i.e., "Likes") will allow OOPs to foster an environment for effective and persuasive reviews.

Based on the findings from this research, OOPs need to ensure they include the functionality of a heuristic cue such as a "Like" on their platform so reviewees can indicate the perceived helpfulness of the review based on the review's persuasive attributes. A "Like" indicates the review is helpful, creates social impact and collectively, the greater the social impact of the reviews posted on an OOP, the more valuable the OOP becomes from the eyes of the prospective customer. As a result, the OOP becomes more active, users are more engaged, and the value of the OOP is heightened. Furthermore, information pertaining to the factors that influence message acceptance can be used by marketing practitioners to create persuasive promotional material, in order to influence consumer behaviour.

8. Limitations and future research

Although this study was based on a big data sample, it is limited by being centred on one OOP, Zomato – Dubai. Research across other platforms and countries is necessary, to assist with determining the generalisability of the results. Future studies should collect data from various countries across different OOPs (e.g., Yelp, TripAdvisor) to compare the findings, specifically, to ascertain whether there are different informational and normative factors in the review which are persuasive and helpful, resulting in social impact. The nature of the experience would also be interesting to explore to determine if the findings of the current study are generalisable across similar experience based services such as hotels and holidays.

This study used only the one computer-assisted qualitative data analysis software (CAQDAS) – Leximancer. However, it is acknowledged that other software, specifically probabilistic topic modelling algorithm-based, may provide new insights into the dataset (Colladon & Grippa, 2019). As noted by Blei (2012, p. 77). "Topic modeling algorithms are statistical methods that analyze the words of the original texts to discover the themes that run through them, how those themes are connected to each other, and how they change over time". It would be interesting to compare the results from Leximancer to those, for example, gained with Latent Dirichlet Allocation (LDA), which is the simplest topic model (Blei, 2012), to ascertain whether and how the algorithms these programs use, differ.

Another area for future research could extend the current study to consider whether the results would differ based on the quantity of reviewee acceptance (i.e., quantity of "Likes") of the review. It could be that as the quantity of acceptance increases, people are influenced more by others having already "accepted" the review, rather than the actual content of the review. The current study provides evidence of significant relationships and associations; however, causality is not established. This needs to be investigated further.

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