ORIGINAL ARTICLE

Mining brand value propositions on Twitter: exploring the link between marketer-generated content and eWOM outcomes

Mostafa Alwash[1] · **Bastin Tony Roy Savarimuthu[2]** · **Mathew Parackal[3]**

Abstract

Content marketing has become a mainstream channel for brands to engage the market with value propositions. Through content, brands control, instigate and co-create value with its target audience. However, the nature of value propositions embedded within the cycle of content co-creation and their impact on eWOM outcomes has received scant attention from an empirical perspective. In this paper, we propose a value proposition-based framework around content marketing using established business perspectives. We employ bidirectional Twitter data from brands and customers to unearth descriptive, diagnostic and predictive insights into value propositions. Using a sample of marketer- and user-generated data from 10 Coffee ($n_{(MGC)} = 290$, $n_{(UGC)} = 8811$) and Car brands ($n_{(MGC)} = 635$, $n_{(UGC)} = 7035$) in 2018, a taxonomy of value propositions based on the literature was proposed and validated. The results of our study identify (a) descriptive insights explaining differentiation of brand value propositions, (b) diagnostic insights relating to consumer sentiments in response to the value proposition mix and (c) predictive insights of models predicting brand-specific values' influencing Like, Share, Comment and Positive/Negative valence. Our results show that an effective social media marketing strategy selectively uses elements of the marketing mix (i.e. 4 P's) within value propositions to attract favourable eWOM outcomes.

Keywords Brand communications · Marketer-generated content · Value propositions · Customer engagement · eWOM outcomes

1 Introduction

The locus of control in digital media has shifted meaning making from marketer to consumer (Deighton and Kornfeld 2008). Today brands as luxurious as Gucci and transnational as Starbucks (Taecharungroj 2017) use social media to build a narrative (i.e. using content) to nurture relationships on the digital marketing stage. The effort of which has proven

to have significant business consequences (e.g. reputation, acquisition, retention, sales) on consumer behaviour (Godey et al. 2016). For example, in 2012 the marketing team at the McDonalds Corporation asked its customers to share positive stories using the hashtag #McDStories, the tactic backfired and provoked negative eWOM for the brand (Pfeffer et al. 2014). This analogy illustrates how brands can frame the meaning behind a message (i.e. with good intentions) but ultimately have little control over the audiences' actions, highlighting a real-world digital dilemma for marketing practitioners. A consequence of the establishment of social media, there is a shift towards relationship-oriented approaches that integrate and reinforce the content created by the customer into the offerings of a brand. This approach develops a co-created story (Singh and Sonnenburg 2012) which is fostered by the brand and driven by the audience via their engagement on the business's e-channel.

Content marketing is considered as a cornerstone to a brand's marketing mix, with most brands utilising this approach to build relationships (Mangold and Faulds 2009). This form of marketing has been defined as the

✉ Mostafa Alwash
    malwash@gmail.com

    Bastin Tony Roy Savarimuthu
    tony.savarimuthu@otago.ac.nz

    Mathew Parackal
    mathew.parackal@otago.ac.nz

1   Department of Informatics, University of Oslo, Oslo,
    Norway

2   Department of Information Science, University of Otago,
    Dunedin, New Zealand

3   Department of Marketing, University of Otago, Dunedin,
    New Zealand

'*creation of valuable, relevant and compelling content*' (Pulizzi 2012) and facilitates co-creation between the brand and consumer by anchoring meaning within a message (i.e. content). Businesses consciously (via social media marketing plan) or unconsciously (via ad hoc decisions) design *market-shaping content* (Nenonen et al. 2020) which sends an expectation to customers on the benefits (i.e. value propositions on offer) the community can expect of the brand. Customers on their own accord interpret meaning from content; this content from the managers' point of view (i.e. antecedents) can be seen as having value propositions (at some level of abstraction) embedded (e.g. using offerings such as brand products, promotions or services) in order to drive business objectives (Customer Engagement (CE) in the form of eWOM outcomes).

As of yet, the pursuit of understanding the granularity and plurality of value propositions has seen slow progress (Goldring 2017) and this ambiguity in grounding is due to the historically conceptual nature of value propositions within the literature (exemplified in Clarke III 2001; Yrjölä et al. 2018). For digital marketers, this is particularly troubling because 'value propositions drive value co-creation' (Vargo 2011), and hence, there exists an empirical research gap in the compartmentalisation of value propositions within social media marketing.

The relationship between value propositions and eWOM outcomes in our view lacks proper investigation due to underdeveloped *bridging research* (Brodie et al. 2011a, b). In increasingly dynamic digital markets, the parsing of value propositions has only recently seen developments from the bottom up (i.e. practice to theory). Prior works in grounding value propositions have explored data collected based on surveys and polls (Beatty et al. 1985; Heinonen et al. 2014), ignoring information-rich social media sources such as content from Twitter and Facebook. Moreover, the link between *empirically sourced value propositions* in the context of content marketing and eWOM outcomes has seldom been investigated.

This work aims to bridge this gap on value propositions by mining marketing messages. Towards this end, this work posits that marketing messages contain a marketing mix of value propositions which can further development within marketing segmentation; in addition, we argue that value propositions embedded in social media messages (e.g. tweets) influence eWOM outcomes. To operationalise this preposition, this work studies the relationships between the value propositions embedded in brand posts (the antecedents) and feedback via eWOM metrics (consequents) collected from Twitter brand followers. This work scrutinises these relationships using a proposed value taxonomy (15 value dimensions identified in this work) which discovers the impact of value propositions on Likes, Shares, Comments via predictive modelling. Our results

highlight how extracting value propositions from within marketing tweets can help in understanding the relationship between marketer-generated content (MGC) and eWOM outcomes. Our findings have implications for both research and practice (e.g. formulating data-driven social media strategies using samples of content co-creation) which, respectively, adds to the body of knowledge within marketing (MacInnis 2011) corresponding to identifying, delineating, differentiating and advocating contributions which we discuss below.

With the aim of identifying conceptual contributions, this research helps to inform insights and theory-building on the acquisition of value propositions from a bottom-up perspective (i.e. text analytics) using the two-way medium of Twitter as a stage for investigating content co-creation. On delineating conceptual contributions, this work demonstrates a statistical workflow between the antecedents of brand value propositions on social media and the consequents of eWOM outcomes, explaining relationships that give control to the brand manager. For differentiating conceptual contributions, this research develops a construct (value taxonomy of value propositions) that transforms unstructured text into semantically labelled marketing logic (e.g. product, price, promotion) which can form a representative basis of value propositions in social media marketing. Lastly, on advocating conceptual contributions, this work aims to bolster the importance of mining content marketing (e.g. Twitter business pages) for the discovery of empirical patterns by adopting a co-creation perspective that uses the lens of value propositions to structure marketing messages.

The structure of the paper is as follows: first, we present the related literature on social media marketing in relation to co-creation and discuss the background of value propositions. Second, we present our four research questions (RQs) which investigates the inquiry of value propositions within social media. Third, we provide the research methodology, results and discussion for the Delphi and longitudinal studies examined within this paper. Fourth, based on the findings of the research, we present and highlight the critical implications of identifying value propositions in relation to eWOM outcomes and discuss how mid-range theory as presented in this paper can provide insight into a brand's actions on social media business pages. This paper concludes by reviewing the principal contributions of the research, followed by an overview of the key findings discovered in relation to the research gap addressed by this work.

1.1 Background on co-creation

The co-creation of value is centred on mutually beneficial relationships, effective communication and favourable experience (Grönroos 2004). In the context of social media, co-creation is encapsulated in the dyadic communication

between brands and consumers. Marketers use the abstraction of branded content to centre (i.e. proxy the conceptual) value co-creation process for both the brand and the community, as it drives online community practices which generates value for participants (Schau et al. 2009; Laroche et al. 2012). Value is no longer in the hands of marketers but co-created from the beneficiary. Hence, in the co-creation paradigm, the marketer is limited into the consumer's experience by *offering value propositions* (i.e. statements of benefit). In this perspective, the consumer co-creates a contextual experience (embedded in the social context (Heinonen et al. 2013) of content) and in participation with a brand's social media e-channel (i.e. Facebook and Twitter). Meanwhile, the brand strategically maximises the exposure of market-facing value propositions available to the market.

The seminal works in the field of co-creation (Prahalad and Ramaswamy 2000; Vargo and Lusch 2004; Payne et al. 2008; Grönroos and Voima 2013) establish a concrete foundation on which conceptual understanding has flourished (Galvagno and Dalli 2014); however, the use of co-creation within empirical contexts such as in social media has seen a bifurcation of research streams.

For example, the work of Skålén et al. (2015) examined the collaborative e-channel of Alfa Romeo and identified how interacting, identity and organising practices influence value co-creation (Skålén et al. 2015). Notably, this work is one in a series of works that approach co-creation using the qualitative method of netnography (Sindhwani and Ahuja 2014; Sorensen et al. 2017; Fujita et al. 2019). In a similar manner, several works have also conducted an analysis of brand engagement data using interviews and surveys of customers (Kao et al. 2016; Choi et al. 2016a, b; Zhang et al. 2020; Cheung et al. 2021); however, the scalability of these techniques has been highlighted as a limitation (Bharti et al. 2014).

The literature on co-creation has also seen works that introduce frameworks to enrich perspectives within theory (Ramaswamy and Ozcan 2018; Merz et al. 2018), and these have been critically important as they help break down high levels of abstraction related to theory and develop empirical-to-conceptual bridging (Ge and Gretzel 2018) which is seldom investigated within the literature. Furthermore, researchers have also adopted mixed-method approaches (Kunja and Acharyulu 2018), such as the work of Choi et al. (2016a, b) wherein observations of digital marketing from channel is scrutinised using structural equation modelling in order to predict purchase intention.

The research stream most pertinent to this work is that of the quantitative approaches to co-creation within social media. As relationships (i.e. social media messages with standardised attributes such as text, likes and shares) within the brand's online audience grows, business pages in the public domain (Trusov et al. 2009) offer huge potential in

understanding the dyadic sentiment from marketing stakeholders. Work by De Vries et al. (2012) examined international brands on Facebook and uncovered predictive models which explain the statistical relationship between determinants (e.g. vividness, interactivity in marketing messages) and eWOM outcomes such as liking and sharing behaviour for the brand. In research by Cvijikj and Michahelles (2013), scholars traced the content of online brands and examined the relationship between factors of content marketing (i.e. media type, content type, posting day/time) and consequents in the form of likes, comments, shares and interaction duration. Research on the platform of Twitter has also provided quantitative contributions, with the study of Hodeghatta and Sahney (2016) exploring the conversation and sharing phenomena within the entertainment (i.e. movie) industry. In addition, the work of Okazaki et al. (2020) looked into how network analysis can be applied to Twitter to evaluate the 'connectedness' of consumers with marketing messages.

Twitter has increasingly become a customer service platform (Gallaugher and Ransbotham 2010) for businesses that seek to foster a feedback loop with online audiences (Lusch and Vargo 2009). More specifically for researchers, eWOM outcomes for messages posted (e.g. likes, shares, comments) have become a standardised way of gauging customer engagement (Van Doorn et al. 2010) in co-created digital marketing. A key paper in this area is that of (Goh et al. 2013) which shaped the distinction within the literature between the actor-specific spheres of influence in the dyadic relationship (i.e. the *stimuli* and *feedback*). Stimuli in this context refer to brand-driven content, termed as marketer-generated content (MGC), while feedback for online participants is considered as user-generated content (UGC).

Although an abundant number of research streams have emerged regarding content co-creation in social media, few works (Denktaş and Sürücü 2019) have also addressed the role of value propositions and this is disconcerting as value propositions frame the context of customer exchange and act as a marketing façade which reinforces the entire co-creation process for participants (Grönroos 2008b). A value proposition has been defined as 'a statement of the functional, emotional, and self-expressive benefits delivered by the brand' (Aaker 2012), and others have described it as 'an actor's invitations for other actors to engage' (Chandler and Lusch 2015). The principle that value propositions are a communicative tool (Ballantyne and Varey 2006; Ballantyne et al. 2011) and a 'value-supporting process' (Grönroos 2008a) is well documented within the marketing literature. What is less explored in marketing is the enumeration (i.e. shape) of value propositions within low levels of abstraction such as in content marketing (i.e. MGC).

Given conventional marketing thinking, it would be a sturdy assumption to argue the supposition that the fundamental elements of the marketing mix (4 P's) would play

a constructive role in the design of MGC (Mangold and Faulds 2009; Weinberg and Pehlivan 2011), as is apt in traditional practice (McCarthy 1960). UGC on the other hand has become highly conventionalised owing to the large platforms (e.g. Facebook, Twitter, YouTube, Instagram) using a threefold system of consumer eWOM modalities (Muntinga et al. 2011; Luarn et al. 2015) built on actions of Liking, Sharing and Commenting. Research has found that not all MGC sources produce the same effect on eWOM outcomes (Alboqami et al. 2015; Coelho et al. 2016). Therefore, it has become a growing area of interest to research and understand the kind of stimuli that yields *shallow* (e.g. superficial metrics such as the number of likes, shares and comments) and *deep* (sentiment-based count of valence in comments) engagement (Lagun and Lalmas 2016), a perspective which is provided in this paper. Shallow engagement is defined as vanity metrics that are produced via engagement and are unprocessed, closed formats of feedback within social media. Deep engagement on the other hand presents opportunities to further segment customer engagement by employing semantic analysis of UGC (e.g. finding the sentiment of an MGC thread). For instance, marketing researchers can use deep engagement to target embedded sentiments in order to help explain how value propositions embedded in marketing communications (i.e. MGC) can generate positive and negative discussions in the online community (Park and Lee 2009; Lee and Youn 2009; Roy et al. 2019). In deep engagement, much more focus is given to the context coming from the consumer (in the form of rich open-ended contextual comments) which is lost in shallow metrics such as Likes. Sentiments as a form of deep engagement are an important research angle as it directly impacts participation in value co-creation and trust with the brand (Seifert and Kwon 2019; Hollebeek and Macky 2019). In this study, we provide a quantitative perspective by examining how the originating antecedent of value propositions embedded in MGC shapes the co-created story as seen through the outputs of eWOM outcomes.

1.2 Research questions

In this section, we introduce the research questions (RQs) which progressively narrows our research inquiry and scopes our objective of producing descriptive, diagnostic and predictive insights regarding value propositions in social media. The origins of these RQs are based on the empirical research gap (i.e. shortage of grounding) of value propositions highlighted in the background of this work and of contributing to the existing understanding and development of CE (Brodie et al. 2011a, b) within the social media marketing literature. In this paper, we shed light on the types of value propositions (i.e. stimuli) embedded within co-created brand

communications, understand how sentiments (i.e. feedback) are perceived in relation to brand value propositions and lastly combine these insights to construct actionable predictive models of eWOM outcomes (i.e. Like, Share, Comment, +/− valence).

The first RQ that we introduce seeks to investigate the dimensions (value propositions) of the value taxonomy embedded in brand messages (i.e. MGC). It asks:

RQ1: How do brands differentiate themselves using value propositions on Twitter?

Answering the question above is important to establish a baseline to differentiate brands using value propositions in a top-down (brand-focused) fashion. In doing so, we gain an understanding of 'what' strategic appeals are currently being used by brands in practice.

The second RQ seeks to follow on from marketing stimuli to investigate the diagnostic context of marketing feedback (i.e. UGC) in a bottom-up (customer-focused) fashion. It drills down analytics by grouping descriptive value propositions (structured in RQ1) with consumer sentiments, thus exposing the diagnostic view of value propositions from the consumer's point of view. It asks:

RQ2: What is the nature of community feedback to brand value propositions on Twitter?

Beyond the marketers' perspective, as posited by the previous questions, community perspective is significant because consumers subjectively associate sentiments with differentiated content and communicate their responses using modalities such as Likes, Shares and open-ended Comments (i.e. UGC). The second inquiry explains 'how' online consumers react in response to brand value propositions by considering subjective consumer sentiments.

The last RQs (RQ3 and RQ4) demonstrate the practical utility of scrutinising the link between value propositions embedded in MGC and eWOM outcomes by developing statistical relationships between stimuli (MGC) and feedback (shallow CE expressed as the number of Likes, Shares, Comments and deep CE as net sums of positive and negative valence within UGC), and these RQs ask:

RQ3: Which brand value propositions predict shallow CE on Twitter?

RQ4: Which brand value propositions predict deep CE on Twitter?

Our objectives in RQ3–4 is to explain 'why' certain statistical relationships between brand value propositions and eWOM outcomes occur. We build predictive intelligence by
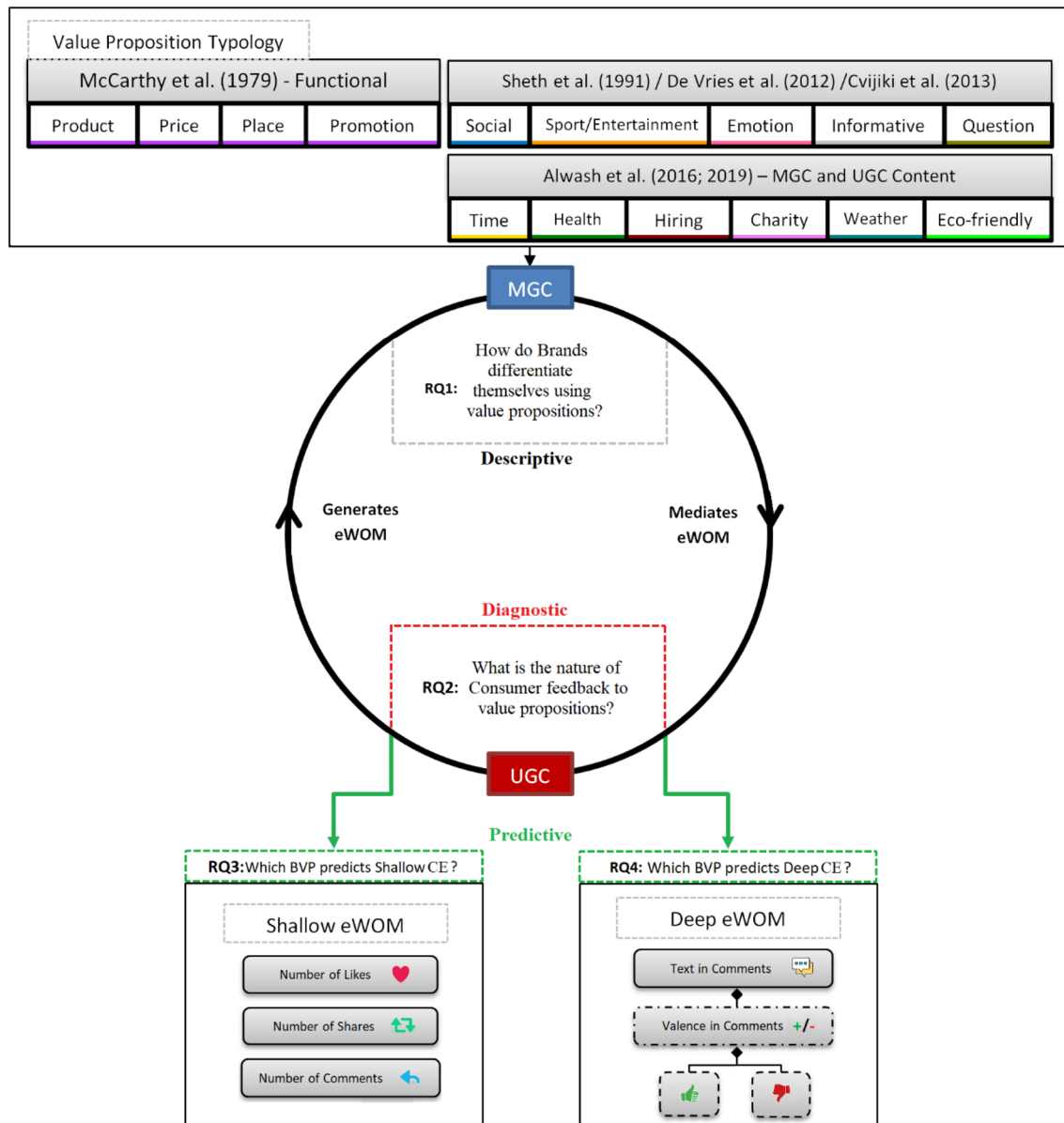
Fig. 1 Content co-creation feedback loop

using brand-specific datasets of one-to-many linked dialogues between marketer and consumers, providing a data-driven model which supports decision-making centred on embedded value propositions. This allows for the identification of marketing insights (i.e. predictive variables) from within unstructured content that otherwise would remain hidden. The RQs illustrated in Fig. 1 are shown using a feedback loop and this is fitting as the co-creation of content is a cyclic process. At the top portion of the dyadic interaction is MGC which seeds the production of eWOM and organises threads of discourse. Additionally, MGC contain types of marketing stimuli (i.e. independent variables considered in this study which are discussed in the following section) that target the audience of the brand. Conversely eWOM outcomes such as UGC at the

bottom portion of the feedback loop depict the kind of actions and modalities the consumer can perform in response (e.g. communicate negative sentiments, share MGC to their social network). Lastly, there also exists a directional and predictive relationship between the types of stimuli communicated and the forms of CE produced (i.e. shallow or deep CE). We therefore collectively test the value taxonomy as being applied (i.e. operationalised) within two contexts of use (i.e. MGC and UGC) within content marketing.

In the following section, we provide an overview of the construction and validation of a value taxonomy developed to classify value propositions in social media (Study 1) and then follow on by applying this framework to longitudinal samples of observational content co-creation (Study 2).

2 Study 1: developing a typology of value propositions

The purpose of this study is to provide construct validity for a framework used to classify value propositions in marketing messages (i.e. MGC). For this purpose, the qualitative Delphi method was used as high levels of consensus were required of the framework when disambiguating value propositions from marketing messages. The aim of the study is to ascertain whether a panel of experts can objectively come to a consensus based on open coding using 15 value propositions from a proposed taxonomy.

2.1 Study 1: method

We employed a two-round Delphi study comprising of 10 interdisciplinary experts in which each independent expert was tasked with using the proposed value taxonomy to encode samples of branded messages ($n = 20$) across two rounds (the first blind and the second with solicited feedback). The 10 academic experts (Male $= 7$, Female $= 3$) all held the PhD accreditation and were from the Department of Marketing ($n = 5$) and Information Science ($n = 5$). The Delphi panel spanned a wide range of cultural backgrounds (8 different countries) and years of expertise in their respective field (mean $= 11$ years). The technical background of expertise was as follows: customer experience (2 cases), entrepreneurship education, marketing (2 cases), software engineering, computer science, information systems and data science (2 cases).

In round one, an experimental dataset of 20 coffee brand tweets was provided to each panellist via an online survey tool which also included a guideline document containing definitions and examples of each dimension within the taxonomy. Panellists were informed that classifications of value propositions should only be seeded from words propositioned within the brand tweet and that a tweet may contain multiple value propositions. Following round one, round two aimed at gaining complete consensus between classifications, and this was resolved using agree/disagree decisions made by the experts. Lastly, experts in addition to the 15 dimensions of the value taxonomy could also encode ad hoc custom value propositions that they perceived to be embedded. If enough consensus on this 'Other' proposition exists, then it would be included within the value taxonomy. The final open coding results were evaluated using inter-rater reliability (IRR) and Cohen's kappa statistic.

We introduced a literature-inspired taxonomy of 15 value propositions (see Table 1) as our research construct

which integrates prior conceptualisations of values embedded in the marketing literature. These dimensions notably begin by integrating the 4 P's (dimensions 1–4) of the traditional marketing mix, namely *Product*, *Price*, *Place* and *Promotion* which have been historically significant within the marketing literature (Grönroos 1997; Van Waterschoot 2000; Constantinides 2006). Then, based on a comprehensive survey of the marketing typology literature, we found commonly cited consumer-side dimensions of value (dimensions 5–8), namely *social* value, *entertainment* value, *emotional* value and *informative* value (Sheth et al. 1991; Bagozzi et al. 1999; Ang and Low 2000; Sweeney and Soutar 2001; Petrick 2002; De Vries et al. 2012; Seraj 2012; Aaker 2012; Witkemper et al. 2012; Cvijikj and Michahelles 2013; Ashley and Tuten 2015). Additionally, works in social media content have consistently contained *question* and *time dimensions* to categorise informational content (dimensions 9–10) in online dialogues (Jansen et al. 2009; Harper et al. 2009; Efron and Winget 2010; Dacko 2012; Lee et al. 2018). Last, are the dimensions of *health*, *hiring*, *charity*, *weather* and *eco-friendliness* (dimensions 11–15) drawn from existing typology research in the social media literature (Lee 2008; Joos 2008; Brown and Vaughn 2011; Lovejoy and Saxton 2012; Coursaris et al. 2013; Kwok and Yu 2016).

Column 1 of Table 1 indicates the identifier of the value proposition dimension, while Column 2 shows the name of the dimension and Column 3 provides a definition of each dimension. Column 4 provides tweet examples where the dimension is encoded (see underlined features in Table 1) and Column 5 identifies the number of keywords associated with each dimension that was used in Study 2 of this research in which textual features automated the coding process of value propositions. For example, in the brand tweet '@dunkindonuts The Kit Kat Coolatta, equally as good in your left hand as your right. #InternationalLeftHandersDay,' based on references to two products embedded (e.g. Kit Kat, Coolatta), this tweet is coded as containing a product value proposition.

We utilise the value taxonomy first to address the accuracy of encoding value propositions in marketing messages (Study 1) and then proceed to apply it to the four RQs presented within the "Research questions" section (Study 2).

2.2 Study 1: results

The level of consensus from results (see Appendix for complete measures) produced by the Delphi panel in round one was an impressive 91%. Only three value proposition dimensions caused a mismatch in classifications, and these are in descending order of mismatch: Sport/Entertainment (60%),

Table 1 Value taxonomy, examples tweets and dimension-specific features

| #	Dimension	Definition	Example	Corpus keywords (Study 2)
1	Product	Tweet relates to named products, either tangible commodity or intangible service	@dunkindonuts The Kit Kat Coolatta, equally as good in your left hand as your right. #InternationalLeftHandersDay	1646
2	Price	Tweet relates to pricing (reference/actual) or method of purchase ($,£, Free, Sale, Mastercard)	@HyundaiUSA Woo! @usnews has ranked the #HyundaiKona as the BEST new #SUV under $20,000	294
3	Place	Tweet relates to location, distribution or place of access to the product/service (California, Texas, New York)	@TimHortons Kenya's only hockey team had nobody to play. So, we brought them to Canada for a game	1241
4	Promotion	Tweet relates to product/service promotional appeal (BOGO, free, save, % off)	@peetscoffee Happy #NationalCoffeeDay! Receive 25% off all beans in coffeebars and on http://Peets.com	259
5	Social	Tweet relates to association appeal (family, friends, school, office, church)	@VW I've got two boys and two girls so it'll eventually get passed down to them, owner John S. and his #MK2 #Jetta	742
6	Sport/Entertainment	Tweet relates to an entertainment appeal (NHL, NBA, FIFA)	@Ford Fall in #Texas means the @StateFairOfTX and FOOTBALL! Football Imagine rolling up to your tailgate in one of these bad boys. Who do you root for?	629
7	Emotion	Tweet relates to expressions of affective state in regards to a product/service/brand (love, hate, cry, ❤,)	@AudiOffical Indulge in something that provides you with pleasure, satisfaction and ease. We call this sheer luxury	1483
8	Informative	Tweet relates to informational resources (For more info, Introducing, Coming Soon)	@Starbucks We're excited to announce that we're expanding @Starbucks Delivers with @UberEats, available throughout the U.S. by early 2020! Learn more: http://sbux.co/2Qd5SbD	333
9	Question	Tweet relates to a direct question (?)	@peetscoffee Have you tried Kenya Nyeri yet? Grab a pound or two of this prized, plush single-origin coffee while you can! Available now in stores and online: http://bit.ly/KenyaNyeri	1
10	Time	Tweet relates to time, date or schedule (Day, January, 2018)	@BMW Timing is everything. The #BMWi3s takes only 42 min to 80% charge on quick charging stations	602
11	Health	Tweet relates to state of physical, mental and social well-being	@panerabread Smoothies so fresh, so clean. What's your fave?	190
12	Hiring	Tweet relates to career opportunities with the brand	@Starbucks We are proud to announce we have reached our goal of hiring 25,000 veterans and military spouses. These partners (employees) have made us a better company and inspired our new commitment to hire 5000 veterans and military spouses annually	54
13	Charity	Tweet relates to philanthropy with the brand (donate, philanthropy, charity)	@Starbucks We make a difference when we come together. Please join us in donating now to @RedCross to help those affected by #Hurricane-Florence	131
14	Weather	Tweet relates to weather conditions	@MercedesBenzUSA Sun, rain or snow, there's nowhere a G can't go. #GClass #MercedesBenz #MercedesJared Stern	340
15	Eco-friendly	Tweet relates to practice of environmental-friendliness (recyclable, biodegradable, ecological)	@Toyota See how one great idea cut chemical use by over 80%, reduced plastic waste AND improved quality… all at the same time: https://toyota.us/34WJ7gr	114
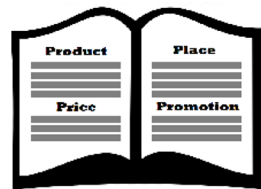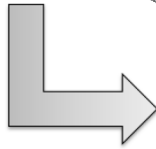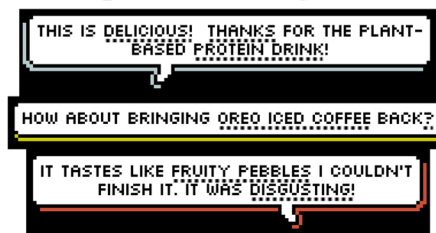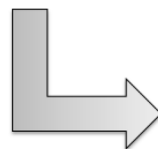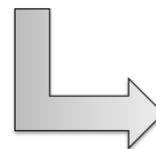
Fig. 2 Methodology workflow diagram

Emotion (71%) and Social (90%) propositions. Moreover, instances of the custom 'Other' dimension (e.g. Balance, Process, Instrument, Intrinsic, Ingredient, Individualisation, Performance, Technique, Evidence and Arrangement) were not shared between experts (i.e. used exclusively) and hence were dropped for greater consensus in round two. Following the process of providing feedback on the matches/mismatches of experts, all mismatches were resolved. This brought the final outcome of the Delphi panel to 96% on the task of classifying value propositions in content marketing and this is considered as an excellent level of consensus (Landis and Koch 1977). In the next subsection, we provide a discussion of the Delphi study conducted in this work.

2.3 Study 1: discussion

The finding of the Delphi study was a significant outcome that provided internal validity for the research construct moving forward. Moreover, the kappa measures from this study were in line with current works in the domain of social media (Ashley and Tuten 2015; Poba-Nzaou et al. 2016) providing confidence that the construct tested amongst experts was a reliable instrument. The completion

of study one provided the impetus to introduce two additions within study two. The first was developing an automated corpus to perform lexical coding in place of open coding and the second was to longitudinally scale sampling of content in regards to both MGC and UGC for both top car and coffee brands.

3 Study 2: modelling value propositions in content co-creation

The purpose of study two is to use the lens of value propositions to investigate the phenomena of content co-creation from both the brand and consumer's point of view. This involves combining both brand (MGC) and consumer (UGC) tweets, alongside eWOM outcomes to develop an understanding of the relationship between the two. We begin by outlining the research methodology, provide the findings of the study in relation to the posed RQs and discuss the outcomes of the longitudinal sampling.

Table 2 Digital marketing outcomes for top coffee and car brands

Brand	Domain	Brand Tweets	Comments per Tweet	Comments ($\bigcirc$)	Shares ($\uparrow\downarrow$)	Likes ($\heartsuit$)	Positive ($\mathring{\triangle}$)	Negative ($\mathring{\triangledown}$)
@Starbucks	Coffee	22	98.2	2161	26,539	99,856	659	338
@dunkindonuts		61	41.3	2519	11,909	41,495	571	395
@TimHortons		48	22.7	1092	9358	25,846	402	138
@panerabread		55	38.9	2139	6250	47,065	574	288
@CostaCoffee		13	48.2	627	1361	6368	201	68
@TheCoffeeBean		33	3.9	130	485	1995	49	15
@cariboucoffee		14	4.9	68	133	933	28	6
@peetscoffee		39	1.3	51	80	397	14	3
@BMW	Cars	110	19.5	2145	25,819	172,761	957	379
@AudiOffical		88	12.6	1111	8701	67,404	399	136
@Toyota		121	6.3	758	4695	19,849	289	169
@Honda		76	8	610	4013	17,251	248	220
@MercedezBenzUSA		40	5.8	232	3133	18,680	173	17
@Chrysler		85	4.1	348	2880	18,903	183	46
@Ford		17	49.4	840	2356	8943	251	276
@VW		32	4.8	153	770	3605	66	48
@MazdaUSA		21	7.2	152	743	2553	63	48
@HyundaiUSA		45	15.2	686	719	2265	215	131

3.1 Study 2: method

The design of study two comprises four parts as shown in Fig. 2. First, we discuss the data collection of this study. Second, we detail the development of a dictionary corpus to supervise classification of marketing messages. Third, we discuss the automatic coding technique of extracting value propositions from messages using lexical analysis, and fourth, we outline our quantitative analysis procedure which examines the relationships between extracted value propositions and eWOM outcomes.

3.1.1 Study 2: data collection

We utilised Twitter as the platform of choice as this has consistently been used within the corporate world (Culnan et al. 2010). We collected data using the Twitter API of 20 corporate brands for 3 months (August 1, 2018, to October 31, 2018). The brands belonged to two market domains, fast-moving consumer goods (FMCG) (coffee) and automobiles (cars), and these industries were selected due to their high engagement with consumers (Javornik and Mandelli 2012). The top brands in each domain were selected on the basis of market revenue for the 2018 period (i.e. how much share they accounted for in the market) and this was determined using publicly available brand rank lists of revenue available on www.statista.com. The Twitter handle of each brand was then identified and checked to ensure the use of the English language (as this was important for the English-based

corpus). The message posted by a brand (i.e. MGC) was identified using the Tweet ID, with all related community messages (feedback as UGC from customers) being linked using this parent Tweet ID. For each brand message (i.e. brand tweet), we collected the number of Likes, Shares and Comments it attracted from the community for statistical purposes. Also, within the Comments, we identified whether the sentiments expressed in UGC were positive or negative using lexical analysis (e.g. normalised using polarity-weighted keyword counts) discussed in the following subsection.

The two-way datasets gathered for this study comprised of coffee tweets ($n_{(MGC)} = 290$, $n_{(UGC)} = 8810$) and car tweets ($n_{(MGC)} = 635$, $n_{(UGC)} = 7035$). Of the top-10 brands considered in the FMCG domain, one brand (@McCafe) discontinued Twitter marketing and another brand (@AuBonPain) produced less than five tweets and thus were not considered for analysis. The parameters for study two are shown for each brand in Table 2 for every eWOM outcome studied.

3.1.2 Study 2: development of a dictionary corpus

As previously mentioned, we developed a technique that automatically extracted the structure of value propositions in marketing messages using a dictionary corpus (Pak and Paroubek 2010) and this has been made available.[1] The
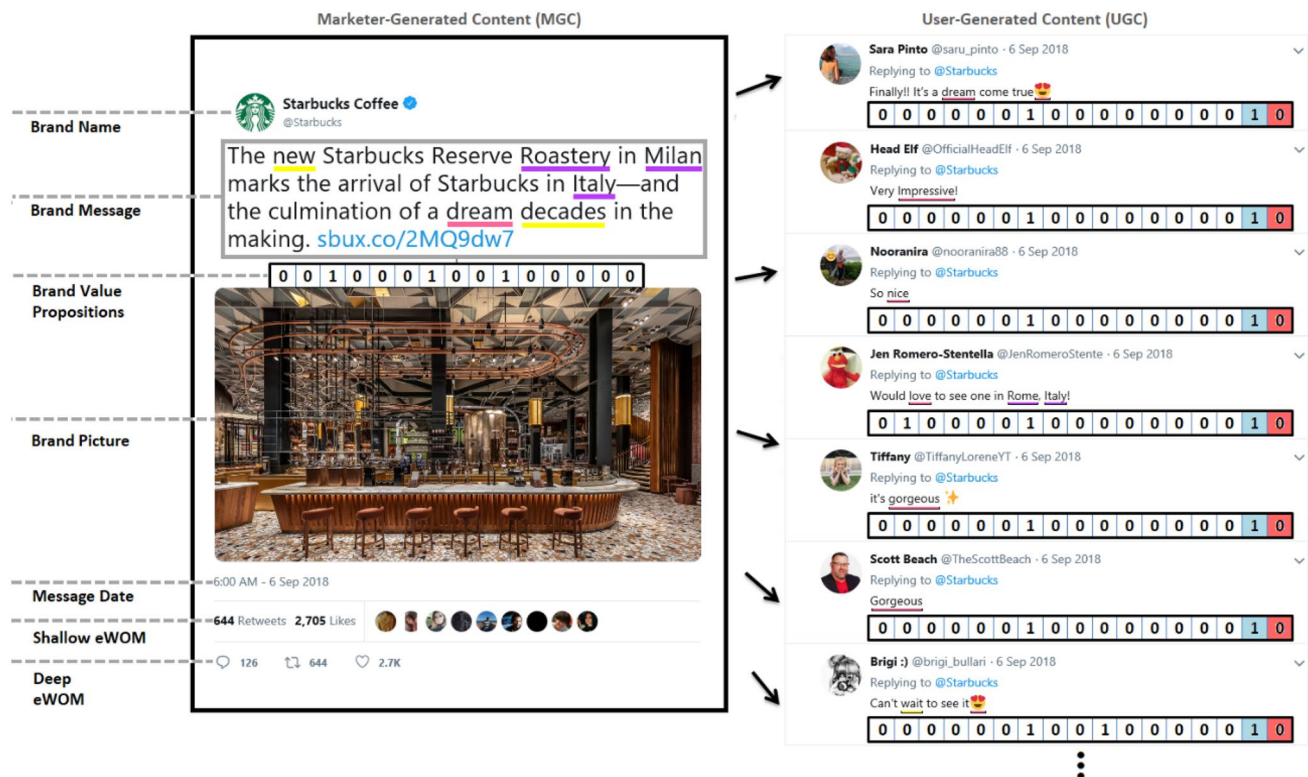
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[1] https://figshare.com/s/a2bb4108528f33e954bc.

Fig. 3 MGC and UGC examples for a tweet from Starbucks in 2018

bag-of-words (BOW) corpus which was developed comprised of 9700 keywords (shown previously as counts within Column 5 of Table 1) and these were used to identify 15 value proposition dimensions (and this is explained in detail in the next subsection). Sentiment analysis was applied to UGC comments received in response to every MGC message, UGC was additionally categorised into one of two categories (positive and negative) based on affect keywords of 659 positive and 975 negative keywords that were derived from LIWC's affect word bank. The corpus developed in this work is an extension to Linguistic Inquiry and Word Count (LIWC) (Tausczik and Pennebaker 2010) and utilises feature engineering (i.e. the process of turning raw data into marketing features) to enumerate labelled keywords from observational marketing data which automates the extraction of classifications (1 s and 0 s corresponding to whether a tweet contains a value proposition or sentiment) within marketing tweets.

This corpus comprising 15 value propositions and two sentiment categories was then used to supervise the classifications extracted within the next step of our methodology.

3.1.3 Study 2: lexical coding using the value taxonomy

The computational procedure to classify content-level semantics into value propositions used in this study is

known as lexical analysis (Gavard-Perret and Moscarola 1996; Dhaoui et al. 2017). This analysis 'offers a natural bridge between the in-depth coding of qualitative data and the statistical analysis of quantitative data by offering an automated means of coding' (Bolden and Moscarola 2000). The keywords within our corpus, defined as one of the 15 value propositions or sentiments, were transformed via lexical analysis into a binary vector of 1s and 0s where 1 corresponds to the presence and 0 the absence of a value proposition or sentiment. An illustration of this procedure is shown in Fig. 3 for Starbucks and Fig. 4 for BMW. These figures show that each marketing message is analysed based on the context of stimuli (MGC) provided within the marketer's content and feedback as it is received from the customers (UGC).

As shown in Fig. 3, the MGC example focuses on a *place* (i.e. with phrases such as Roastery, Milan, Italy, new, decades and dream), while the MGC example in Fig. 4 focuses on a *product* (the phrases of excitement, Sunday, 3series and Gran Turismo). These value propositions were encoded into individual vectors (1 s or 0 s for each of the 15 value propositions) below the sender's message (for MGC shown to the left and UGC shown to the right). All keywords in the corpus which correspond to a value proposition in tweets encode a 1 in the respective dimension in both Figs. 3 and 4, resulting in 3 out of 15 dimensions encoded for both MGC
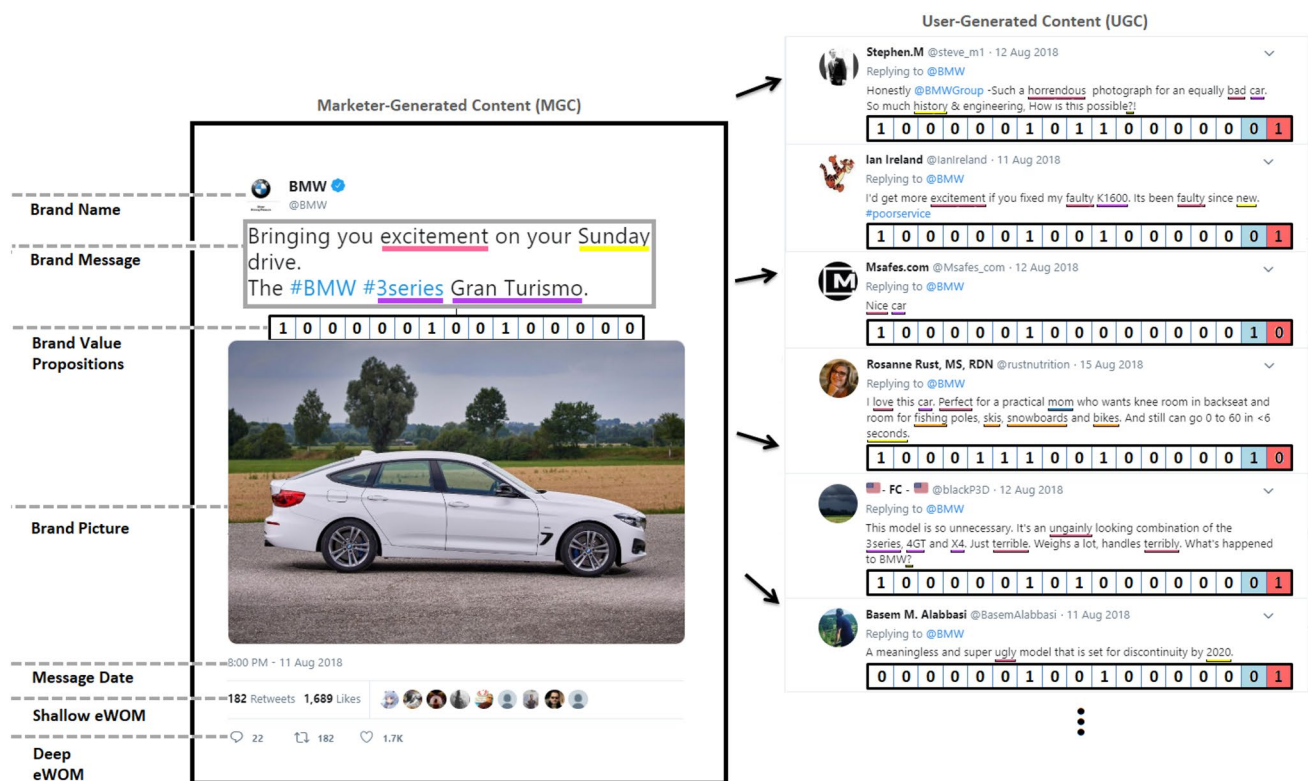
Fig. 4 MGC and UGC example for a tweet from BMW in 2018

examples. The responses to these brand messages (UGC) are shown on the right of the figure. It can be observed that the responses from the community reciprocate the original propositions in response tweets, but also contribute consumer sentiments (the last two binary digits in the encoding which is highlighted in blue and red which represent positive and negative sentiments, respectively). The two sentiment categories which were specifically targeted at encoding customer sentiment shown on the right of Figs. 3 and 4, were identified explicitly by keywords such as gorgeous, impressive, horrendous and faulty (with the first two depicting positive sentiment and the latter two depicting negative sentiment). These classifications of sentiment were then normalised into a polarity class (either positive or negative) based on the net number of +/− weighted keywords within a customer tweet. The sentiments expressed in comments of a particular brand tweet were then computed based on the sum of the largest occurrences of positivity or negativity expressed. For Starbucks, the overall sentiment in comments received is positive (7 positive, 0 negative), and for BMW, it is negative (2 positive, 4 negative).

In the following section, we discuss how the data encoded based on lexical analysis was provided as an input to predictive models which examined the statistical relationship between value propositions and eWOM outcomes.

3.1.4 Study 2: quantitative analysis procedure

The data encodings obtained using the lexical coding approach for the MGC and UGC (as described above) are used to present the descriptive *value signatures* of each brand (in RQ1 results) and used to structure the diagnostic analysis of value propositions (in RQ2 results) from the context of consumers. Furthermore, the encoded data was combined based on conversational contexts (i.e. via Tweet ID) to create regression models to predict five eWOM outcomes. The independent variables for these models were the 15 value propositions from the value taxonomy (i.e. 15 independent variables), and the dependent variables were content-level eWOM outcomes (i.e. Likes, Shares and Comments shown in the bottom left of Figs. 3 and 4 and the net sum of positive and negative sentiment per brand post shown to the right of Figs. 3 and 4). Regression analysis was employed as this has been a reliable statistical method (Draper and Harry 1998) to explain the impact of changing stimuli on targeted outcomes. In the next section, we provide the quantitative results pertaining to descriptive, diagnostic and predictive outcomes for our study.
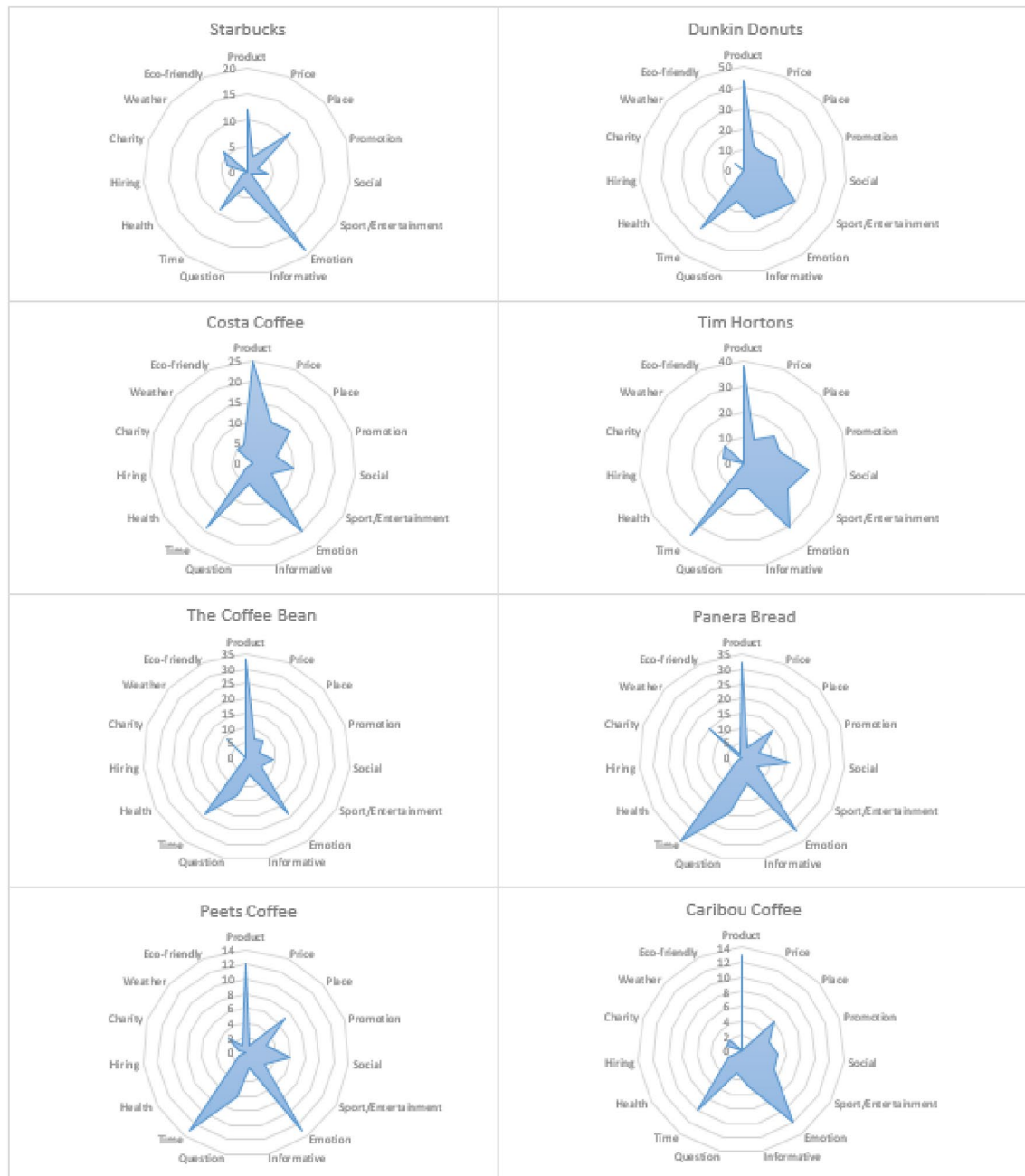
Fig. 5 Top-8 coffee brand value signatures

3.2 Study 2: results

In this section, we outline the brand-specific findings for RQs 1–4 by detailing the descriptive, diagnostic and predictive insights of value propositions in content marketing.

RQ1: How do brands differentiate themselves using value propositions on Twitter?

The findings for RQ1 examined 8 coffee brands and 10 car brands in order to identify the orientation of value propositions for each respective brand. We define the descriptive representation of value propositions embedded in marketing communications as a brand's *value signature*. The value signatures of top brands are shown in Figs. 5 and 6 in the form of radar charts for coffee and car domains, respectively. These figures present the measure of each dimension of value propositions (i.e. counts of a particular value dimension in the twitter dataset) in the
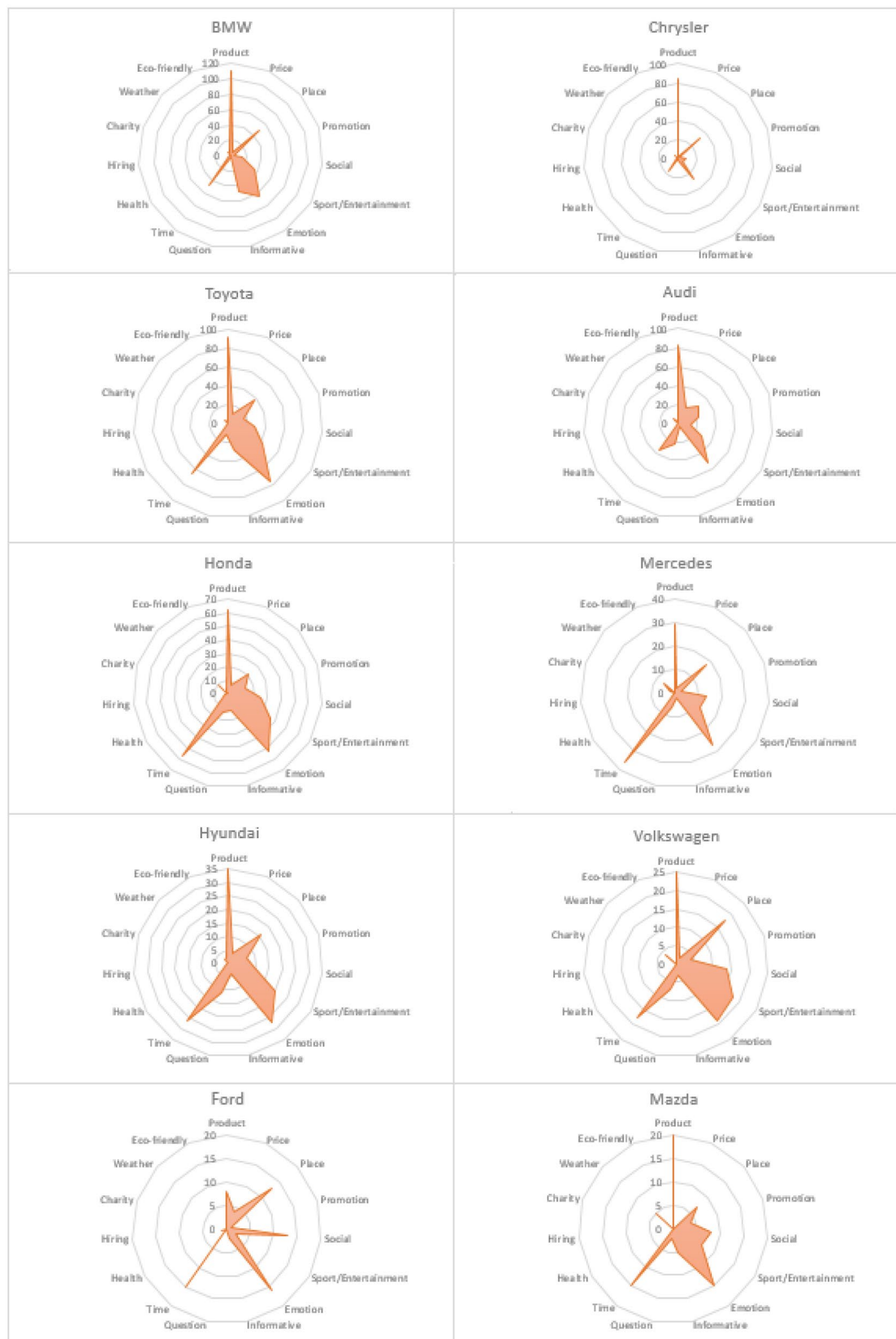
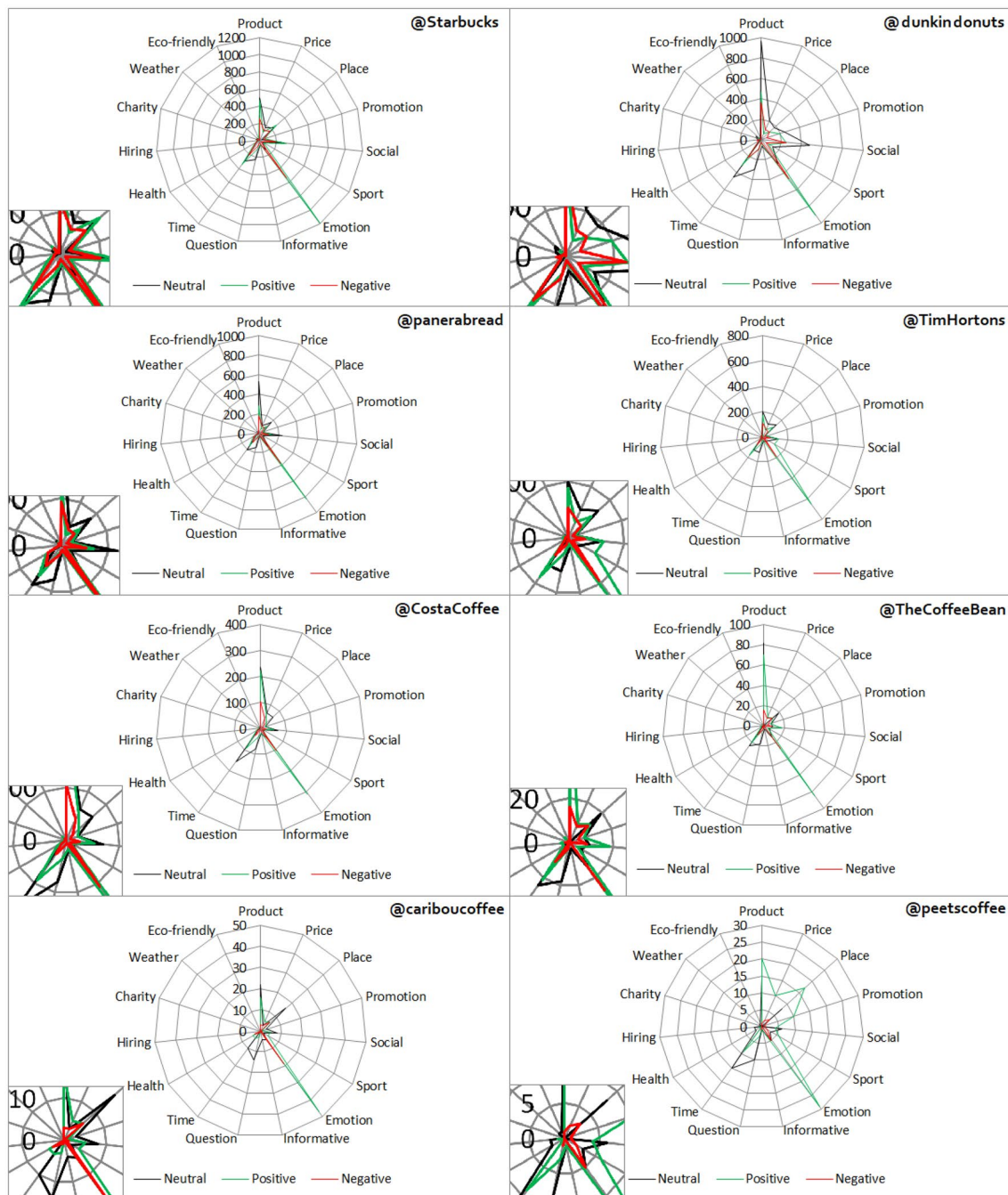**Fig. 6** Top-10 car brand value signatures

Fig. 7 Top-8 coffee community value signatures by sentiment

context of each brand. The visualisation depicts a semantic structure that is abstracted from unstructured Twitter data. The structures illustrate the value propositions across brands and enable differentiation based on the embedded nature of marketing messages. Furthermore, competitors within the market can be compared against each other such as Starbucks and Dunkin Donuts. Based on the value propositions in social media, it can be said that the coffee leaders are employing quite different marketing strategies

(i.e. using product, emotion and social propositions). For example, while Starbucks targets customers with messages of their premium products and emotional benefits, Dunkin Donuts communicates messages that emphasise promotions that relate to athletic events. Moreover, the nature of value propositions between market domains is also different. The coffee domain exhibits a dominant orientation to Product, Social and Emotion appeals, whereas the car
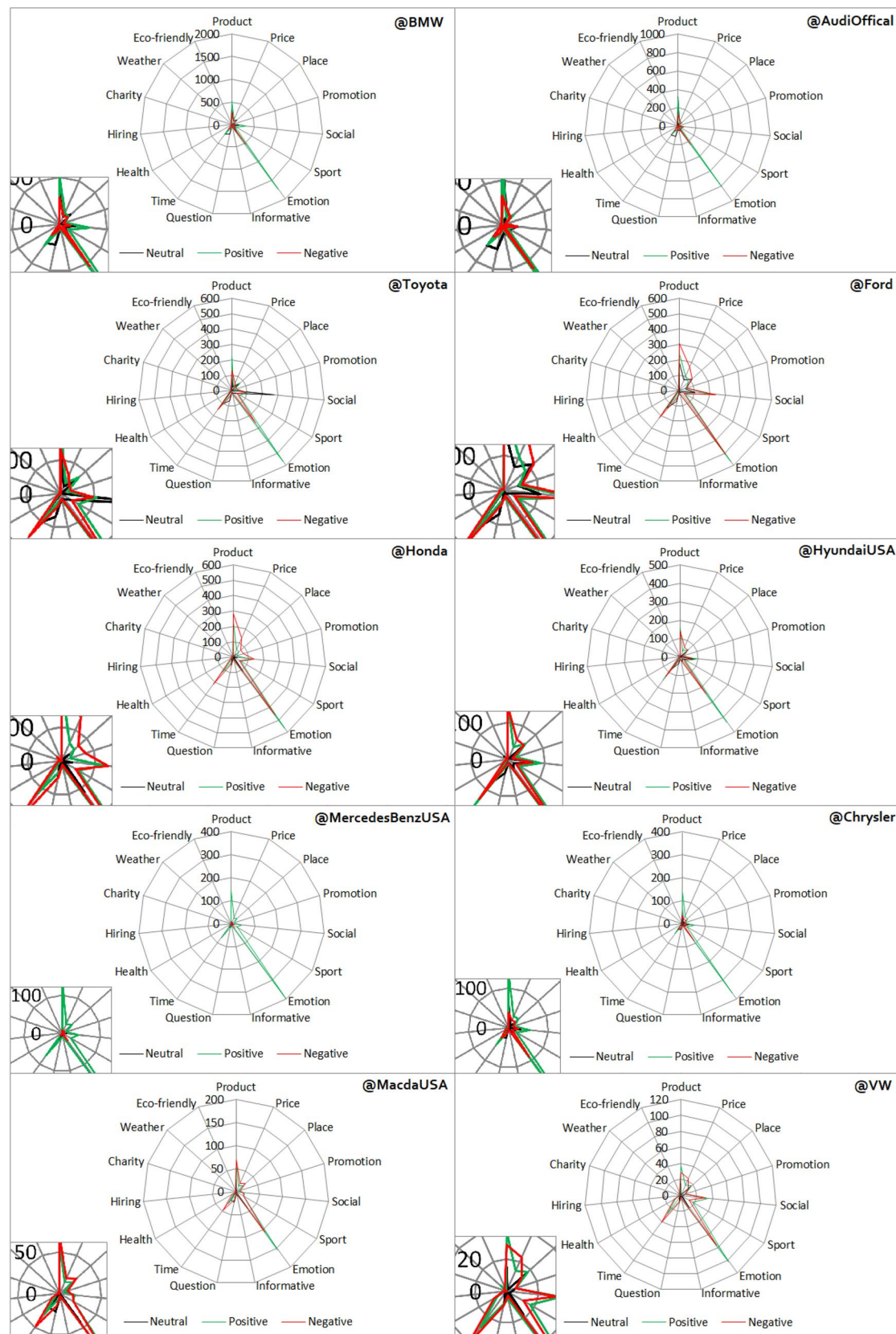
Fig. 8 Top-10 car community value signatures by sentiment

Table 3 Shallow regression models for top-8 coffee brands

Brand	Like	Share	Comment
Costa Coffee	Promotion*** (.570), Emotion** (.361), Informative** (.323)	Promotion*** (.436), Emotion** (.447), Informative* (.440)	Emotion* (.320), Informative*** (.509)
	$R^2 = .581$, R^2 (adj) .299, $F = 2.030$, df $= 13$, $p < 0.05$	$R^2 = .434$, R^2 (adj) .204, $F = 1.430$, df $= 13$, $p < 0.05$	$R^2 = .535$, R^2 (adj) .238, $F = 1.684$, df $= 11$, $p < 0.05$
Peet's Coffee	Charity* (.723)	Charity* (.709), Time* (.845)	Sport/Entertainment* (1.249), Time* (.907)
	$R^2 = .922$, R^2 (adj) .496, $F = 2.161$, df $= 11$, $p < 0.05$	$R^2 = .939$, R^2 (adj) .606, $F = 2.815$, df $= 11$, $p < 0.001$	$R^2 = .957$, R^2 (adj) .718, $F = 4.016$, df $= 11$, $p < 0.05$
Dunkin Donuts	Time* (.306)	Place* (.238)	Place* (.281)
	$R^2 = .185$, R^2 (adj) .128, $F = 1.014$, df $= 11$, $p < 0.05$	$R^2 = .187$, R^2 (adj) .135, $F = 1.026$, df $= 11$, $p < 0.05$	$R^2 = .166$, R^2 (adj) .096, $F = 0.947$, df $= 11$, $p < 0.05$
Panera Bread	Sport/Entertainment* (.362), Time* (−.303)	Sport/Entertainment* (.269)	Price*** (.269), Charity*** (.710)
	$R^2 = .281$, R^2 (adj) .133, $F = 1.115$, df $= 14$, $p < 0.05$	$R^2 = .259$, R^2 (adj) .098, $F = 1.000$, df $= 14$, $p < 0.05$	$R^2 = .841$, R^2 (adj) .785, $F = 15.100$, df $= 14$, $p < 0.001$
The Coffee Bean	Price*** (.618), Promotion* (−.647)	Price*** (.653), Promotion* (−.583)	Question** (.483)
	$R^2 = .422$, R^2 (adj) .195, $F = 1.583$, df $= 12$, $p < 0.05$	$R^2 = .338$, R^2 (adj) .173, $F = 1.108$, df $= 12$, $p < 0.05$	$R^2 = .259$, R^2 (adj) .142, $F = 0.947$, df $= 12$, $p < 0.05$
Tim Hortons	Sport/Entertainment* (.370), Emotion* (.340)	Sport/Entertainment* (.375), Emotion* (.300)	Emotion** (.498)
	$R^2 = .232$, R^2 (adj) .104, $F = 1.023$, df $= 12$, $p < 0.05$	$R^2 = .226$, R^2 (adj) .101, $F = .894$, df $= 12$, $p < 0.05$	$R^2 = .261$, R^2 (adj) .125, $F = 1.192$, df $= 12$, $p < 0.05$
Starbucks	–	–	Promotion* (.641)
	–	–	$R^2 = .622$, R^2 (adj) .327, $F = 1.013$, df $= 13$, $p < 0.05$
Caribou Coffee	–	–	–

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

domain focused primarily on Product, Sport/Entertainment and Emotion appeals.

RQ2: What is the nature of consumer feedback to value propositions on Twitter?

The second research inquiry RQ2 examined the feedback conveyed about value propositions by Twitter brand followers. Figures 7 and 8 show the counts of value propositions embedded in UGC and present the results of sentiments attached to value propositions conveyed in the marketing dialogue. The count of negativity and positivity for a given dimension is represented using red and green, respectively, while black denotes neutral occurrences. At the bottom left of each radar graph, is an enlarged version of the centre of each figure to show the leading propositions of positive and negative sentiment. Based on these diagnostic insights, brands can identify the type of sentiments associated with their strategic use of value propositions. For example, Starbucks in Fig. 7 shows that the Price proposition is more closely associated with negative sentiments (130 positive compared to 112 negative), while the Social proposition is more closely associated with

positive sentiments (317 positive compared to 195 negative). Comparisons between the two market domains found that the proportion of sentiments in the coffee domain was more favourable (73.25% positive, 26.5% negative) than the automobile domain (65.7% positive, 34.3% negative). This diagnostic view of value propositions can assist in uncovering the source of marketing communications (i.e. the value proposition) which seeds positive and negative discourse and allows brands to drive two-way content discourse. This also can provide brands with valuable information about what aspects will need to be improved to reduce negative sentiments.

RQ3: Which brand value propositions predict shallow CE on Twitter?

To answer RQ3 we constructed predictive models using multiple regression with the 15 value propositions as the independent variables and the three different eWOM metrics available on brand posts as dependent variables (i.e. number of Likes, Shares and Comments). Thus, for each brand, three models were constructed. The resulting models are presented in Tables 3 and 4 where Columns 2, 3 and 4

Table 4 Shallow regression models for top-10 car brands

Brand	Like	Share	Comment
BMW	Promotion** (− .231), Social* (− .200)	Social* (− .173), Sport/Entertainment* (.131)	–
	$R^2 = .218$, R^2 (adj) .142, $F = 2.258$, df = 12, $p < 0.01$	$R^2 = .128$, R^2 (adj) .084, $F = 1.187$, df = 12, $p < 0.05$	–
Chrysler	Place*** (− .505)	Place*** (− .404), Emotion* (.203), Weather* (.184)	Price* (.185)
	$R^2 = .431$, R^2 (adj) .336, $F = 4.537$, df = 12, $p < 0.001$	$R^2 = .316$, R^2 (adj) .207, $F = 2.775$, df = 12, $p < 0.001$	$R^2 = .123$, R^2 (adj) .078, $F = 0.962$, df = 12, $p < 0.05$
Honda	Product* (.201), Promotion** (.283), Social* (− .262), Sport/Entertainment** (.258), Weather* (.207)	Product* (.253), Promotion** (.299), Social* (− .243)	Product** (.359), Promotion** (.282), Question*** (.303)
	$R^2 = .377$, R^2 (adj) .234, $F = 2.633$, df = 14, $p < 0.001$	$R^2 = .345$, R^2 (adj) .205, $F = 2.296$, df = 14, $p < 0.01$	$R^2 = .232$, R^2 (adj) .185, $F = 1.759$, df = 14, $p < 0.05$
MazdaUSA	Promotion** (.680)	Promotion** (.753)	Promotion** (.821)
	$R^2 = .616$, R^2 (adj) .232, $F = 1.605$, df = 10, $p < 0.05$	$R^2 = .680$, R^2 (adj) .360, $F = 2.123$, df = 10, $p < 0.05$	$R^2 = .899$, R^2 (adj) .798, $F = 8.923$, df = 10, $p < 0.001$
Toyota	Product*** (− .387), Social* (− .202)	–	Product* (− .197)
	$R^2 = .231$, R^2 (adj) .175, $F = 2.196$, df = 15, $p < 0.001$	–	$R^2 = .153$, R^2 (adj) .102, $F = 1.211$, df = 15, $p < 0.05$
Volkswagen	Emotion* (− .391), Informative* (− .541), Question* (.280)	–	Question* (.331)
	$R^2 = .394$, R^2 (adj) .137, $F = 1.441$, df = 11, $p < 0.05$	–	$R^2 = .442$, R^2 (adj) .175, $F = 1.495$, df = 11, $p < 0.05$
AudiOffical	–	–	Sport/Entertainment* (.212), Question*** (.381)
	–	–	$R^2 = .196$, R^2 (adj) .149, $F = 1.525$, df = 12, $p < 0.05$
Ford	Time* (.486), Hiring* (.466)	Product* (.765)	–
	$R^2 = .684$, R^2 (adj) .268, $F = 1.308$, df = 10, $p < 0.05$	$R^2 = .623$, R^2 (adj) .359, $F = 1.103$, df = 10, $p < 0.05$	–
HyundaiUSA	–	Product* (.355), Time* (.306)	Question** (.473)
	–	$R^2 = .300$, R^2 (adj) .185, $F = 1.061$, df = 13, $p < 0.05$	$R^2 = .348$, R^2 (adj) .166, $F = 1.285$, df = 13, $p < 0.05$
MercedesBenzUSA	–	–	–

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

correspond to each of the models generated for the three dependent variables. The table contains two rows of results for each brand. The first row of each column identifies the brand-specific statistically significant variables obtained within regressions, with the standardised coefficients of these variables given in brackets. The second row presents the statistics associated with the regression equation including the adjusted R-squared values.

For example, the result for Costa Coffee shows that brand tweets that embed three propositions (Promotion, Emotion and Informative), accounted for 58% of the variability (R^2 value) in the number of Likes (dependent variable) produced. Across the three models for Costa Coffee, the explanatory power given by R^2 (adj) values range from 20 to 30%. In some cases of limited data, no significant models emerged for a brand (as indicated by a dash symbol). The results for the car domain are shown in Table 4. For example, it can be observed that for Ford, brand tweets embedded with Time and Hiring propositions accounted for 68% (R^2 value) in the Like dependent variable, with Product propositions accounting for 62% in the Share dependent variable. Across both models for Ford, the explanatory power given by R^2 (adj) ranged from 27 to 36%.

When comparing the models of the two domains, it can be observed that variables from the marketing mix (i.e. 4 P's) are embedded in a number of regression results within both the coffee domain and car domain. For coffee brands, the elements from the 4 P's is present in 5 of 8 coffee brands, with Product being in no models, Price in 3 models, Place in 2 models and Promotion in 5 models. For the car domain, the 4 P's is involved in 7 of 10 brands. Product is a predictive

Table 5 Deep regression models for top-8 coffee brands

Brand	Models based on positive (+) valence	Models based on negative (−) valence
Costa Coffee	Price* (.603), Place* (− .580), Emotion* (.355), Informative* (.485)	–
	$R^2 = .532$, R^2 (adj) .355, $F = 2.863$, df = 13, $p < 0.05$	–
Dunkin Donuts	Price*** (− .495), Place** (.341), Promotion* (.411)	–
	$R^2 = .315$, R^2 (adj) .161, $F = 2.049$, df = 11, $p < 0.05$	–
Tim Hortons	–	Place* (.277), Promotion* (.296), Emotion*** (.530)
	–	$R^2 = .302$, R^2 (adj) .143, $F = 1.362$, df = 12, $p < 0.05$
Panera Bread	Price*** (.611), Health*** (.351)	Health*** (.334), Charity* (− .339)
	$R^2 = .527$, R^2 (adj) .361, $F = 3.180$, df = 14, $p < 0.001$	$R^2 = .366$, R^2 (adj) .144, $F = 1.646$, df = 14, $p < 0.05$
Peet's Coffee	Charity** (1.053)	Promotion* (.569), Sport/Entertainment* (.644), Time* (.442), Charity* (.602)
	$R^2 = .926$, R^2 (adj) .847, $F = 7.540$, df = 11, $p < 0.05$	$R^2 = .935$, R^2 (adj) .894, $F = 17.190$, df = 11, $p < 0.001$
Starbucks	Informative* (.642)	–
	$R^2 = .752$, R^2 (adj) .350, $F = 1.871$, df = 11, $p < 0.05$	–
Caribou Coffee	–	–
The Coffee Bean	–	–

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 6 Deep regression models for top-10 car brands

Brand	Models based on Positive (+) valence	Models based on Negative (−) valence
BMW	Price* (.198)	Social* (− .244)
	$R^2 = .235$, R^2 (adj) .161, $F = 1.522$, df = 12, $p < 0.05$	$R^2 = .195$, R^2 (adj) .104, $F = 1.006$, df = 12, $p < 0.05$
Chrysler	Social* (− .223)	–
	$R^2 = .157$, R^2 (adj) .109, $F = 0.917$, df = 12, $p < 0.05$	–
Honda	Product*** (.392), Question* (.236)	–
	$R^2 = .271$, R^2 (adj) .159, $F = 1.842$, df = 14, $p < 0.05$	–
MazdaUSA	–	Place* (.727), Promotion*** (.491)
	–	$R^2 = .855$, R^2 (adj) .711, $F = 5.920$, df = 10, $p < 0.001$
Toyota	Price** (− .267)	–
	$R^2 = .241$, R^2 (adj) .189, $F = 1.749$, df = 15, $p < 0.05$	–
Volkswwagen	Question* (.397)	–
	$R^2 = .458$, R^2 (adj) .303, $F = 1.917$, df = 11, $p < 0.05$	–
AudiOffical	Question* (.211)	Emotion* (.284)
	$R^2 = .165$, R^2 (adj) .108, $F = 1.294$, df = 12, $p < 0.05$	$R^2 = .157$, R^2 (adj) .132, $F = 1.131$, df = 12, $p < 0.05$
Ford	Product* (1.086), Price* (− .657), Promotion* (.718), Emotion* (.649), Time* (.813)	Product* (1.124)
	$R^2 = .593$, R^2 (adj) .417, $F = 1.367$, df = 10, $p < 0.05$	$R^2 = .644$, R^2 (adj) .453, $F = 1.520$, df = 10, $p < 0.05$
HyundaiUSA	Question*** (.538), Time* (− .385)	Informative* (.363), Question*** (.566)
	$R^2 = .429$, R^2 (adj) .205, $F = 1.774$, df = 13, $p < 0.05$	$R^2 = .402$, R^2 (adj) .188, $F = 1.597$, df = 13, $p < 0.05$
MercedesBenzUSA	–	–

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

variable in 7 models, Price in 1 model, Place in 2 models and Promotion in 7 models.

These results indicate that the 4 P's are involved in a majority of eWOM modelling in both coffee and car domains, and thus, the 4 P's are important predictors of eWOM outcomes.

RQ4: Which brand value propositions predict deep CE on Twitter?

The multiple regression results for deep eWOM outcomes are provided in Tables 5 and 6. These findings indicate that different variables influence positive and negative sentiments expressed in UGC for the same brand. For example, for Panera Bread, Price and Health produced positive valence, and also Health and Charity produced negative valence. Notably, these variables are different from the ones identified for models constructed using shallow eWOM outcomes. For Panera Bread, the shallow eWOM models for Like and Share were mainly by Sport/Entertainment appeals. However, the variables influencing positive and negative valence in comments did not feature these. In the example of Costa Coffee, two of the predictors within shallow eWOM models (Emotion and Informative) also appear to influence positive valence; however, two additional variables (Price and Place) also emerge as predictive variables.

On comparing within and across the results in the coffee and car domain, similarities and differences can be identified based on brand value signatures (i.e. the abstractions generated using the value taxonomy). For coffee brands, the marketing mix emerged within the models for 5 out of 8 brands with Price, Place and Promotion predicting sentiment outcomes in 3 models each and the value proposition Product not predicting valence in any coffee brand. For car brands, the marketing mix variables re-emerge similar to the shallow eWOM outcomes, within 5 of 10 brands; however, it is the Product and Price which predicts deep eWOM in 3 models each, Promotion in 2 models and Place in 1 model. A noteworthy trend in the car brands is how commonly a Question appeal predicts sentiment-based engagement in the community (i.e. how the call to action explains sentiments used on its own (e.g. Volkswagen) or in conjunction with other propositions (e.g. Honda)). In addition, it is the car domain that contained larger volumes of marketing mix (i.e. product-oriented) appeals as compared to the marketing strategy of the coffee domain which contained more emotional appeals.

When comparing the impact of the same variable in influencing shallow vs. deep CE, we find that the *same variables* can be used to *predict different behaviours*. In the example of Ford, the presence of the Product in a marketing message influences the amount of retweeting (i.e. sharing of tweets) it receives (see Table 4). For predicting the deep eWOM metrics shown in Table 6, the same variable Product by Ford influences both positive and negative valence which is generated from the community. Positive discussions are influenced by the mention of Product appeals and other value propositions; however, negative discussions also arise *mainly because of the Product*. This shows how a predictive variable can positively affect both net positive and negative discourse. Thus, the empirical regression results suggest that there are differences in variables that can be used to predict shallow vs. deep eWOM outcomes. Next, we discuss the findings of modelling content co-creation and investigating value propositions using social media.

3.3 Study 2: discussion

The finding of the longitudinal study produced several statistically significant models across brands and market domains which identified the nature of the relationship between MGC and eWOM outcomes. Although existing works have delved into the strategic question of identifying differentiation based on value proposition offerings (Rintamäki et al. 2007), we have discovered this phenomenon using two-way observational data from content marketing. Specifically, we have segmented from within unstructured data, descriptive, diagnostic and predictive insights of value propositions within the dyadic cycle of content co-creation. As the uptake of social media for business awareness and engagement grows, so too does the need for an expanded analytical procedure in connecting marketing inputs to marketing outputs and this is what has been uncovered within this paper. In the next section, we expand on the research implications of this work by examining the conceptual and practical significance of the research and outline limitations as well as discuss future work.

4 Implications

This paper investigated the relationships between the value taxonomy (of 15 value dimensions) and its impact on five eWOM outcomes (e.g. likes, shares, comments, +/− valence). By building predictive models, the result of our investigation has several implications for researchers and practitioners and these are outlined in the following subsections.

4.1 Conceptual implications

Our findings have three implications for the conceptualisation of theory. First, in RQ1, we designed a communication-grounded framework that demonstrated how marketing messages can be transformed into 15 value propositions. This first-order representation of value propositions at the micro-level extends current thinking of social media as resource-integrating spaces (Singaraju et al. 2016), supplementing the co-creation literature with a grounded conceptualisation that can help build perspective for the brand manager from the bottom up. For example, we transformed and visualised dormant data using the application of the value taxonomy to produce a *value signature*, and this, in turn, indicated how strategic propositions are heterogeneously conveyed by competing brands allowing for the discovery of creative strategies (Ashley and Tuten 2015) across marketing

brands. A second important insight of our work is within the area of brand management and marketing segmentation. The approach adopted in this work aligns with others who have adopted a taxonomy, typology or classification scheme (Coursaris et al. 2013; Ge and Gretzel 2018) to quantify characteristics of the domain. The unique contribution of this paper is in the validation, application and evaluation of the frameworks use for the collection of value propositions from content marketing, this, respectively, allows brand managers to take inventory of the meaning conveyed to their audience in a much more nuanced way.

Third, in RQ2, we unearthed value propositions within the context of consumer feedback by scrutinising UGC. Our findings show that both net positive and negative co-creation in content exists (Dolan et al. 2019) and this is associated with the antecedents of value propositions, this was additionally found to be different between brands. Also, the magnitude of negativity was higher in the Cars domain than the Coffee domain. This shows that there may be more opportunities for marketers to perform remedial actions (i.e. addressing negative comments) than others by categorising the sentiment and content coming from the community. Value propositions offer a useful lens for researchers to unearth specific variables (e.g. price) that need attention to prevent negative eWOM.

4.2 Practical implications

To the best of our knowledge, content in social media exchange has not been scrutinised systematically through the lens of value propositions (using a quantitative approach). Our work has four implications for practice.

First, our approach on unearthing value propositions can be of utility for organisations, as it provides a methodical approach to untangle value propositions from unstructured social media data. This understanding of the position and logic one conveys within the digital stage can to some degree provide a brand with awareness of the market and consumers.

Second, the *value signature* constructed using the value taxonomy (as shown in Figs. 5, 6) can be used to visualise and reflect on the value propositions that are being offered by a brand and to check for alignment against the brand's own values. As such, this will be an improvement over the current state in organisations where social media content strategy is not fully integrated within social media platforms, and value alignment checking is a laborious managerial task. Comparisons of value signatures of a brand against its competitors can be used for systematic benchmarking of branding and to learn from strategies of competitors that result in positive eWOM outcomes. For example, a brand such as BMW can examine the influence of divergent brands (e.g.

Tesla) and compare value offerings on Twitter to determine if immediate or mild action is required to shape engagement in a more progressive way. Additionally, the value signatures organised by sentiment (Figs. 7, 8) can be used to identify areas of concern, thus offering actionable insights for the organisation to consider.

Third, our results for RQ3 found that the traditional marketing mix variables (the 4 P's) were significant predictors of eWOM outcomes in many of the models. The findings support the notion that the marketing mix has evolved to be part of social media marketing practices (Pantano et al. 2019). This shows that marketers should actively consider solidifying their 4 P offerings in digital content marketing as these were found to be important factors for both customers and brands.

Fourth, our results in RQ3 and RQ4 show that different variables influence shallow vs. deep eWOM outcomes for brands. This suggests that the customers that engage with a brand differently (i.e. shallow vs. deep), may have different weights for different value propositions offered. This furthers understanding in targeted marketing as it shows that specific eWOM outcomes are influenced by differing factors.

4.3 Limitations and future work

The limitations of this research work include the dyadic context adopted by this study (i.e. the brand–consumer dyad) which investigates content marketing using value propositions that begins with the brand's point of view. This work did not consider consumer-to-consumer tweets as this was one-step removed from the marketing stimuli (i.e. content) and the corresponding feedback (i.e. those conversations which arise impromptu), which is outside the scope of this research. Moreover, another limitation of this work is the simplistic bag-of-words approach which was used for grounding value propositions; this contrasts with more complex methods (Han et al. 2014) which involve demographic segmentation or topic modelling. The methodological constraint of this study comprises of a supervised approach that requires phrases labelled into groups (e.g. Milkshake grouped into 'Product' dimension) to identify exact meanings. This is a manual process that is time-consuming and hence can pose a challenge when extending our approach to other domains. Another limitation present is that the primary unit of analysis in unstructured content was text-based tweets. Non-textual content formats such as images, audio or video tweets that were not considered could potentially provide further insights into value propositions. Having said that, the approach developed serves as a foundation for such

study (e.g. images in a tweet can be classified into the same dimension such as Product).

The directions for future work have two prongs. First, we aim to incorporate data mining techniques within a wider content marketing perspective which classifies multiple types of content (i.e. text, image, video) in brand communications into appropriate value dimensions. This objective could aid in improving the explanatory power in models and examine the nature of the information that is being conveyed by content type (i.e. text vs. images vs. video). Second, in addition to multi-content is the multi-channel practices used by a brand (e.g. value propositions embedded in Twitter, Facebook posts and websites). A holistic examination of digital marketing across different channels of a brand would need to integrate marketing analytics presented in this paper to better understand the impact of value propositions on customers and the resulting co-creation phenomena within content.

5 Conclusion

The principal contribution of this paper to the marketing and co-creation literature has been the introduction of a communication-grounded framework (i.e. value taxonomy) which enables the parsing of value propositions within content marketing. This work has addressed a significant research gap on quantifying brand value propositions in social media, and doing this has demonstrated how this representation can help predict eWOM outcomes (i.e. Like, Share, Comment, +/− valence). The key findings of this paper are that (a) differentiation of brand value propositions are conveyed in marketing messages, (b) consumer sentiments in response to the marketer's value proposition mix play an important role in shaping diagnostic insights for brand managers and (c) predictive modelling of value propositions offer a statistical means to deduce data-driven decision-making. In our view, the implication of this research lays the groundwork for more advanced study into brand value propositions on business pages. The direction for future research should focus on developing a clearer picture of co-creation within social media, one which strictly emphasises the value proposition as the driver of co-creation practices.

Appendix

This section contains additional material relating to the validation process undertaken using a Delphi method to test the value taxonomy used in this paper. The following are the summary results of the value taxonomy scrutinised by a Delphi panel of interdisciplinary experts in which each independent expert was tasked with using the proposed value taxonomy to encode samples of branded messages across two rounds (the first blind and the second with solicited feedback) and open coding between experts were matched.

The Delphi panel was constructed using 10 experts (Male = 7, Female = 3) with the PhD accreditation. The 10 academic experts were from the Department of Information Science ($n = 5$) and Marketing ($n = 5$). They spanned a wide range of cultural ethnicities (8 different countries) and years of expertise (mean = 11 years). Their background of expertise were in the areas of: customer experience (2 cases), entrepreneurship education, marketing (2 cases), software engineering, computer science, information systems and data science (2 cases). These Delphi panellists are referred to as panellists A–J. The first five experts [A, B, C, D, E] are from the marketing background, the second [F, G, H, I, J] are from Information Science. The experimental dataset was 20 brand tweets coded using an online-surveying tool (i.e. SurveyMonkey). To begin the Delphi study, the value taxonomy was made available to the panel in the form of a guideline document containing taxonomy dimension definitions and tweet examples of value dimensions seeded (i.e. grounded) in content (e.g. *The coziest of cups on the coldest of nights. #RedCups*). The panellists were told that classifications should be seeded from words propositioned within the brand tweet rather than an individual's familiarity, predisposition or stereotype. Also, a tweet can contain multiple value propositions and experts are expected to classify each value proposition embedded in the tweet. The panellists had input in two rounds of the study. In the first round, panellists used the taxonomy to classify 20 brand tweets in isolation. Then, each panellist was told the total agreements/disagreements (round two) and was shown the result of the agreement from the group and were asked whether they might change their position on those items they disagreed with as shown in the snippet below.

Tweet 2 – '**The upside-down #CaramelMacchiato — pairs well with frozen waffles and fantasy-based <u>tabletop games</u>.**'

There was 60% consensus that the tweet contains Sports/Entertainment information.

The tweet above contains 'Sport/Entertainment' information based on the underlined words? Yes/No.

This formed the second round. They also had the option

Table 7 Results of round one from the Delphi panel

Panel	Expert	κ coefficient (%)	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	DO
Round 1 (n=20)	A	87	18/18	2/2	3/3	2/2	2/3	0/1	3/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	1
	B	95	18/18	2/2	3/3	2/2	3/3	0/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	1
	C	91	18/18	2/2	3/3	2/2	3/3	0/1	4/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	1
	D	92	18/18	2/2	3/3	2/2	3/3	1/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	4
	E	88	18/18	2/2	3/3	2/2	3/3	1/1	7/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	8
	F	86	18/18	2/2	3/3	2/2	2/3	1/1	3/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	2
	G	96	18/18	2/2	3/3	2/2	3/3	1/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	1
	H	91	18/18	2/2	3/3	2/2	2/3	0/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	3
	I	89	18/18	2/2	3/3	2/2	3/3	1/1	4/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	4
	J	92	18/18	2/2	3/3	2/2	3/3	1/1	5/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0	3
Total	Delphi	91	100%	100%	100%	100%	90%	60%	71%	100%	100%	100%	100%	–	–	100%	–	28

Table 8 Results of round two from the Delphi panel

Panel	Expert	κ coefficient (%)	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
Round 2 (n=20)	A	94	18/18	2/2	3/3	2/2	2/3	1/1	5/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	B	98	18/18	2/2	3/3	2/2	3/3	0/1	7/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	C	94	18/18	2/2	3/3	2/2	3/3	0/1	5/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	D	98	18/18	2/2	3/3	2/2	3/3	1/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	E	100	18/18	2/2	3/3	2/2	3/3	1/1	7/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	F	94	18/18	2/2	3/3	2/2	2/3	1/1	5/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	G	98	18/18	2/2	3/3	2/2	3/3	1/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	H	96	18/18	2/2	3/3	2/2	3/3	0/1	6/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	I	94	18/18	2/2	3/3	2/2	3/3	1/1	4/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	J	96	18/18	2/2	3/3	2/2	3/3	1/1	5/7	4/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0
	Auto	92	18/18	2/2	3/3	2/2	2/3	1/1	5/7	3/4	1/1	10/10	1/1	0/0	0/0	2/2	0/0

to add more value propositions than the 15 that was provided in an open-ended dimension; however, no pattern of consistency was identified across experts (captured as 'DO' in results). The results of all of these were tallied in order to validate the results and compare for inter-rater reliability (IRR) differences. The final post-feedback open coding of results shown in Tables 7 and 8 from the sample identifies as having excellent agreement based on kappa static measure (Landis and Koch 1977) in the process of using the value taxonomy to classify value propositions in brand messages. The automated method presented in this paper was also compared to that of human coders with similar kappa measures produced; therefore the Delphi study shows that humans have consensus in using the value taxonomy to identify value propositions in marketing messages and that a computerised method can mimic the accuracy on the sample given in the task of coding marketing messages.

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