Interesting numbers: an ethnographic account of quantification, marketing analytics and facial coding data

Abstract

This paper asks why facial coding, a method for understanding emotions that was rejected by mainstream psychology for over century, has emerged as a popular method in contemporary marketing. Reading ethnographic, historic and technical datasets, the paper argues that facial coding works because it shifts the task of quantification from humans to computers. This grants facial coding an appearance of objectivity that allows marketing practitioners to open up new ways of understanding, talking about and acting in markets that go beyond the data itself. Informed by science and technology studies (STS), the paper offers the concept of *interesting numbers* to illuminate these contradictory tendencies in the quantification of consumer behaviours. It alerts us to the importance of the agents and forms of quantification in selling a measure to marketers. In short, the paper shows that, when it comes to marketing measures, the numbers count.

Keywords: facial recognition data; market shaping; sociology of translation; marketing measures

Introduction

From keyed sales coupons to neuromarketing, marketers have long used technologies and scientific methods to organise markets. Facial coding is the latest example of this trend. Many leading brands test their marketing communications using this approach. Since 2015 Unilever, for example, has used facial coding to test every ad for all their brands. Yet, curiously, facial coding is an incredibly old method that dates back to Charles Darwin (1872) and has been utilised in anthropology and psychology since the 1970s (Ekman and Friesen 1978). Indeed, Bettman (1979), former editor of the *Journal of Consumer Research*, recommended facial coding as robust method for understanding consumer emotions nearly 30 years ago. So why it is only in the last few years that marketing practitioners have paid attention?

We know that quantitative representations of consumers rarely reveal the underlying nature of consumers' behaviours. Instead, they are useful because they allow marketers to understand, discuss and act in new ways. Starting from this idea, this paper analyses what marketing researchers do with facial coding data through an ethnography of a global marketing company. It shows how marketing researchers interpret facial coding data using familiar concepts, lay understandings and their belief in the objectivity of computational analysis, big data and machine learning. Deploying these different perspectives, marketers shift between prediction and description and make claims based on, but not always supported by, the data. In short, assumptions about objectivity of facial coding provide marketers a license to give new subjective meanings to it.

To make sense of these observations, the paper uses the notions of translation and interests developed in STS to describe facial coding data as an *interesting number*. This concept emphasises that what is *interesting* about quantitative representations emerges from the *interests* of the people using them – that is, their material, cultural and ideological values and commitments – such that 'to understand what counts' in marketing practice, 'we have to be clear who it counts for' (Cluley, 2020: 48). Combining conceptualisations from existing literature with insights derived from empirical materials, the paper outlines three forms of interest (*directing*, *imputed* and *transformed*) that are aligned through facial coding data. Here, the concept of *interesting numbers* also encourages us to think about what is *interesting* about a particular form of quantitative representation. The paper argues that forms of quantification provoke different marketing actions just as different ways of describing consumers influence subsequent actions. Accordingly, the paper concludes that facial coding has risen to prominence not because of *what* it represents, which is similar to other measures, but because of *how* it represents it. Facial coding shifts the work of quantification to computers, creates new ways of visualizing consumers' emotions and reveals temporal trends not possible with many other forms of quantifying consumer emotions. The wider point of this analysis is, then, to show that quantifications are not equal.

Theoretical motivation: translation, interests and quantification

Two areas of marketing theory have concerned themselves with quantitative representations of consumers. A marketing management literature develops, popularises and tests particular marketing measures and a critical literature explores their utility, history and meaning. Within the latter, a sociological literature suggests that few marketing measures accurately represent the things marketers care about (Avis et al, 2014; Schwartzkopf, 2015; Zwick and Bradshaw, 2016). Rather, they shape chaotic markets according to the underlying ideology and politics of marketing practice. It is to this literature that this study turns for inspiration. This section outlines the background and key ideas that motivate the paper.

Translation

Emerging from the sociology of science, the sociology of translation directs our attention to the ways in which knowledge claims from one domain gain value in another. In perhaps the most influential contribution here, Callon (1984) defines translation as a four-stage process whereby actors first categorise or frame a situation (problematisation). Based on this, others are recruited to think in terms of the problematisation through devices and artefacts such as slideshow presentations and academic papers (interessement). As they are recruited, the original definition of the situation as well as the status and relations between interested actors are locked in place (enrolment). Finally, if sufficient actors are enrolled, a network capable of acting in concert emerges (mobilisation).

Seen in this way, a scientific fact is understood as 'a product of the interaction between a large number of diverse actors' who are mobilised to support it (Callon 1990: 132). This includes human and non-humans such as measuring instruments, microscopes and recording equipment. These ideas have 'inspired marketing researchers to adopt a "flat ontology" and explore the agentic qualities of humans, objects and technologies' within marketing practice (Cluley, 2018: 289). For example, Schneider and Woolgar (2012) explore the agentic qualities of neuromarketing machines; Cluley and Nixon (2019) examine the layering of ontologies that transform a phone box into an advertising media; Muniesa and Trébuchet-Breitwiller (2014) describe the translation of human subjects into measuring devices in marketing research.

Yet, Callon also directs us to the ways in which the four stages of translation organise and reorganise social worlds. He states that translation is ‘the mechanism by which the social and natural worlds progressively take form’ because it is through the process of translations that people ‘define and associate the different elements by which they build and explain their world’ (1984: 224). Interestingly, here, translations do not rely on the legitimacy of a problematisation in its original domain. A controversial claim can interest and enrol others in a different domain through explicit power or subtle attempts to shape descriptions (Latour 2002). When this happens, and a description mobilises action, it gains legitimacy - even its home domain. So, instead of thinking about the legitimacy as an input to a problematisation, this understanding sees it as the output of translation. Legitimacy emerges when ‘new acting capacities, new referential ventures and new empirical realities’ are opened up by a problematisation (Muniesa 2014: 93).

Interests

But acting capacities are not equal. To explain why a translation succeeds when others fail, it is instructive to consider translation alongside the interests of the actors involved. Whereas Callon’s definition of interessement directs us to the ways in which diverse actors are enrolled into a network through artefacts that frame a problem in a particular way, the concept of interests developed in the sociology of science refers to the material, cultural and ideological commitments of actors. These form the raw material worked on through translation but they also emerge and are transformed through it.

In establishing a scientific fact, for example, ‘extra-scientific factors’ such as rhetoric, prestige and aesthetics play just as much of a role as the underlying discovery (Collins and Evan, 2002: 239). These factors are important because they allow scientists to appeal to the pre-existing interests of their audiences. Indeed, for Law and Williams, when they disseminate their discoveries scientists act like ‘those who attempt to sell products in other areas of social life, scientists undertake a version of market research. They assess the likely value of their product to this group or that. They design the product in such a way that its value will be as clear as possible to potential users. They package and place it with the same considerations in mind’ (1982: 537).

However, translation is not simply a matter of packaging a problematisation according to other actors’ pre-existing interests. Actors within the same social world have different and, potentially, conflicting interests. To enrol a strong network capable of mobilisation, it is necessary to align divergent interests (Fujimura, 1987). Law and Williams explain: 'both persuasion and power depend, in the last instance, on the capacity of whoever seeks to control, to align his array with that of the hearer at valued points’ (1984: 554). The interests of the editor of scientific journal, for instance, are not to publish a particular paper but must be enrolled and mobilised into support for a given paper.

Here, Callon and Law (1982) distinguish between imputed interests that are mapped to make a problematisation interesting and the transformed interests that emerge through the process of translation. It is these which are mobilised in the new capacities, ventures and realities opened up by a translation. Distinguishing these different interests explains why some translations fail. Gaps between imputed and transformed interests allow counter-enrolment whereby an actor resists attempts to enrol them. For example, Cluley (2020) shows how economic commitments, cultural values, philosophies, and political ideologies, which emerged between marketers discussing the ‘Do Not Track’ initiative, allowed a small group of actors to resist the attempt to allow web-users to opt out of online tracking. In the process of their technical discussion, a range of conflicting values and interests emerged making consensus impossible.

This case alerts us to another form of interests considered in the sociology of science. MacKenzie (1981) argues that pre-existing or directing interests push actors towards a problematisation. These are methodologically needed to help us explain why translations begin. They ‘explain knowledge generation’ (Woolgar, 1981: 369). Moreover, just as gaps may emerge between imputed and transformed interests that allow for counter-enrolment, so too gaps may emerge between directing, imputed and transformed interests that help us to explain why some translations fail.

Quantification

These ideas have been applied to frame marketing as a practice that translates qualitative judgements into quantitative representation and values. Muniesa and Callon (2005) describe thise process of *calculation*, which they see as the core activity of consumer markets, as involving three translations. First, similar to the process of problematisation, an object of measurement is agreed upon by marketers. This is a qualitative judgement in which a group of actors accept that something is important. Second, the actors agree on some way to measure it. This is akin to interessement as it involves identifying appealing representational devices. Finally, following the notions of enrolment and mobilisation, the measurements produce new objects and acting capacities. Muniesa (2014) illustrates how these processes work on individual consumers when they participate in marketing research. He explains that research participants become measuring instruments as they moderate their qualitative experiences of trial products into terms that interest researchers. Similarly, Cochoy (2008) coins the neologism *qualculation* to illuminate how consumers mix qualitative judgements and quantitative measures in their shopping decisions.

Despite emphasising the connection between qualitative judgements and quantitative representations in these translations, Callon and Law state that this understanding of consumers and markets 'has nothing to do with quantification' (2005: 730). That is to say, the way of measuring consumer behaviours, and the ways these measures influence action, is not seen as stemming from the quantification of consumer behaviors *per se*. Rather, the qualitative judgement attached to a measure through the process of translation is what counts.

But quantification does have some effects. Away from consumer markets, Espeland and Lauder (2007) use the notion of *commensuration* to describe the work done by quantitative representations such as prices, cost-benefit ratios, survey responses and rankings. In each case, they contend, the agreement on a specific measurement 'shapes what we pay attention to, which things are connected to other things, and how we express sameness and difference' (2007: 16). Once selected, a measure reduced and simplifies the world into 'new, precise, and all-encompassing relationships' (2007: 17).

While such explanations highlight the effect of quantification as a general practice, we know less about the ways that specific types of quantification operate. In comparison to the wealth of studies exploring the effects of qualitative frames of consumer behaviours (Cayla and Arnould, 2012; Callon., Méadel, and Rabeharisoa, 2002), visualisations (Pollock and D'Adderio, 2012) and the datafication of consumers (Cluley, 2020), we know little about the effects of, say, quantifying a qualitative judgement by a consumer through a Likert-scale rather than a ranking scale. Is it not possible that different quantifications appeal to and transform actors' interests in different ways? Do the numbers, to paraphrase Latour (1994), not add anything? Given the importance quantitative representations in contemporary markets related to big data, algorithms and data-driven marketing, thinking about quantification only in terms of qualification risks missing the active ways that markets are shaped through quantification. The motivating idea behind this paper is, accordingly, to consider the effects of specific forms of quantifying consumers in translating and aligning the interests of marketers.

Methods and Data

An ethnographic study was conducted in a marketing analytics and insight team at a global marketing organisation. The host organisation – anonymised as Super – started in the early 2000s and has grown to employ several hundred employees in dozens of offices worldwide. The firm offers a range of marketing-related services including bespoke ad testing, media buying and AdTech. Research activities are executed by their Analytics and Insight Team and are sold as standalone products, bundled with media buying and AdTech and used for business development and sales.

Entrée into Super took six months. It began with a chance meeting at an industry event between the lead author and Super's Analytics and Insight Director. This led to an email exchange and face-to-face meetings. Onsite fieldwork began in July 2016 after a non-disclosure agreement (NDA) was agreed between Super and the lead author's university legal team. Onsite participant observation lasted six months. The researcher worked in the Analytics and Insight Team as an unpaid, junior-level Insight Executive. Observations, notes and photographs were made onsite on a laptop. At the end of each day, a field dairy was written up. 23 in-depth ethnographic interviews were arranged to drive the interpretation. These were conducted between January and March 2017. During this time, observation and participation continued as the researcher monitored email lists, shared electronic drives and participated remote work and virtual meetings. In what follows, all data has been anonymised in accordance with the NDA.

Driven by the theoretical motivation described above, the fieldwork was analysed around a simple maxim: follow the data. This involved selecting an important form of quantitative data to follow. Facial coding data was selected due both to the level of access, novelty and the importance of this to Super and their clients. Marking the kind of *puzzling element* which ethnographers use to let the field direct their analysis (Arnould and Cayla, 2015) the author was asked to develop a literature review on facial coding methods as part of the entrée. Even though facial coding data was a core part of their offering, the Analytics and Insight Director recognised that they had limited knowledge of the underlying research behind their work.

Following the selection of facial coding data, fieldnotes and interview data were interrogated to identify how Super present facial coding data to their clients. This was augmented with an analysis of the production of the facial coding data covering computer science applications and psychological research to fully understand the process of quantification. Accordingly, an account of the ways Super interpret and present facial coding data is presented below. This is followed by a description of the quantification practices that capture and process visual data into facial codes and an exploration of the construction of facial codes themselves. These are then interpreted as a translation with an emphasis on the ways different interests explain the appeal of facial coding data to marketers.

From an advert to an expression

Evaluating an advert with a chart

Super's clients commission the Analytics and Insight Team to help them understand consumer reactions to their adverts. They test adverts using a range of research products including traditional survey measures, quasi-experiments and analysis of a proprietary database. For their facial coding product, Super recruit a sample of viewers from the client's target audience using an external sample provider; incentivise this sample to record themselves watching the test advert on an internet-connected computer with a webcam; and ask viewers to complete a survey on brand perception, purchase intention and self-reported emotional responses. The outputs of the webcam recordings are analysed to produce a time-series plot that shows the aggregate emotional responses for the sample across the duration of the test ad known as a "smile track". Image 1 offers a sketched representation of this output. It depicts a screenshot of an online meeting in which a smile track was discussed among the Analytics and Insight Team.

INSERT IMAGE 1 HERE

The Analytics and Insight Team emphasise that interpretation is the key part of their work. In the words of an Insight Executive, they 'give meaning to data'. Likewise, the Analytics and Insight Team Director explained: 'Anyone can look at a chart and say it's going up here or down there, explaining why, understanding what the data is telling you, that is not easy. That's what we do'. To manage the Team's interpretative work, the Analytics and Insight Team Director prioritises tasks using on online project management system on which he would post 'cards' for each live project. Each team member has primary responsibility for one product but they switch between tasks and products depending on workload. For this to happen, the Team works to a house style of interpretation through standardising practices and the automation of analysis tasks. The Director has editorial control over every report and, each day, the Team meet to discuss their progress, workload and key findings for each project.

The work of interpretation is done at a computer screen by a single analyst. It looks much like many other contemporary office jobs. It involves workers who drink coffee, listen to music on their headphones and flick between a variety of standard computer packages and web-browsers. Insight Executive (IE) had primary responsibility for facial coding data. He worked at his desk in Super's headquarters producing a "story" (IE interview) that could be fitted into a set of standard PowerPoint slides known as The Deck.

IE worked with smile tracks to produce comparisons that he could narrate - or 'stories', as he called them. First, he compared emotional responses chronologically across the duration of an ad. For example, if a smile track rose, he assumed that respondents found whatever was happening on screen at that point funny in comparison to what was happening before it. Second, he disaggregated the data on a chart. He would compare emotional responses of different gender and age groups within the target market. This activity was built into a bespoke digital dashboard that produced these comparisons with a few clicks on a mouse. Finally, IE created differences by comparing a chart to others from Super's database. Comparison cases were chosen by intuition. IE reported that 'most Indian consumers smile more' and 'people just don't get excited about banks'. Again, this activity was so routinised that the ability to select comparison ads and brands was built into Super's dashboard.

Notably, IE ignored other data sources when creating a story. He had access to a range of emotional expressions including *surprise*, *concentration*, *shock* and *dislike*, each of which had their own time series “tracks” available in the dashboard. When questioned why he did not look at these, he explained that, due to the need to turn reports around quickly, he focused on smile tracks. He stated that ‘most brands don’t want to create other emotions’, ‘most other emotions don’t really produce anything interesting’, and ‘a smile is more obvious, it’s harder for it to mean anything else’. In other words, by focusing just on smiles IE was able to further standardise the adverts he analysed. It made his work easier and helped him tell a story he assumed the clients wanted to hear. Indeed, IE always had one eye on his client. He judged the potential stories in terms of their perceived relevance to clients – often in consultation with the Director, Team and other contacts in the company such as Sales.

IE’s interpretations were also shaped by a standard PowerPoint slideshow template called The Deck. This was the primary way of reporting to clients. It demanded that all interpretations be phrased as short actionable statements such as “Go big or go home”; “Focus on relatable stories”, or “Don’t worry about skipping”. The Analytics and Insight Team Director reviewed all Decks to ensure they met this requirement. The Deck also demanded that IE include an image of the smile track and “verbatim” quotations from respondents on each slide. So, once IE had decided on the most compelling story for the client, he would interrogate qualitative datasets to identify supporting verbatims. These were described as ‘drivers of the viewers’ responses’ in The Deck even though, analytically, they were selected to confirm IE’s explanations.

IE worked in this way because of weaknesses in the qualitative data. Viewers are incentivised to complete a survey but not required to offer meaningful qualitative data. So, they tend to leave open text boxes blank or add a few cursory words. To illustrate this, IE brought up a copy of an Excel sheet of respondents' answers. They mentioned little of interest beyond a few observations of the characters or plot of an ad (e.g. "cookie-monster"), elements that might embarrass the client (e.g. "sexy girl") or issues that might undermine their methodology (e.g. "I saw this ad in another survey"). In fact, detailed responses to open-ended questions made IE suspicious of the data. He stated that 'there's no reason for people to leave long answers, so I don't trust them when they do'.

The Deck included standard methodology slides that reference classic and recent academic studies to demonstrate the importance of consumer emotions as drivers of brand value. They used terms from behavioural science around non-conscious mental processing and included buzzwords about machine learning and algorithms. In client presentations, these slides were used to justify the use of facial coding data over traditional advertising effectiveness measures or glossed over. This depended on the client. When presenting to American brands, the Analytics and Insight Team emphasised the scientific rigour of their analysis with a focus on the methodology slides. When presenting to UK and European clients the focused on their stories.

The emotion algorithm: producing the chart

The smile track is a key device at Super. It visualises consumer emotions in a standardised form and is used to give meaning to data when interpreting and presenting research. The visualisation is not, however, produced by Super. Rather, an external analytics company, anonymised an

Analytico, create these artefacts through proprietary software. They deliver smile tracks to Super through a digital dashboard.

Although Analytico's processes were confidential, this section describes the technological infrastructure through published computer science research which validates their approach. It relates to machine learning. For context, machine learning is a once obscure branch of computer science that is now in vogue thanks to the rise of big data. It involves using computers to extract mathematically significant patterns from known datasets in order to make predictions. One application for machine learning involves categorising the content of images. It has been used to code the emotional expressions displayed in webcam recordings of people watching advertisements (Szirtesa et al, 2017; Orozco et al, 2016; Saraswat et al 2015). Here, it is estimated that it would take human coder up to 6 hours to code one minute of video. Through machine learning, the same minute of video can be processed within seconds (McDuff et al 2015b). McDuff and Kaliouby (2017: 150) calculate that they were able reduce over 50 years of 'direct coding time' to 72 hours of computation processing.

The work of McDuff and colleagues offers an exemplary account of the application of facial coding for marketing. Their research is targeted to computer scientists and is supported by commercial partners who provide them with data, participants and technical support. Indeed, in their papers, marketing applications are used to justify the development of machine learning facial coding technologies. For instance, McDuff et al observe: 'Many companies now use this methodology to test their content, including MARS, Kellogg's, Unilever and CBS. Unilever now tests every ad the company develops with this technology (over 3000 ads annually)' (2015a: 516). McDuff and Kaliouby (2017: 148) similarly justify their work by stating that facial coding 'has become a common tool in market research'. These papers are, in this sense, reports about the use of facial coding by brands.

In each case, the researchers follow a similar approach. First, they recruit participants who record themselves watching adverts. The researchers then extract facial movements from these videos using facial tracking software and apply a predictive algorithm to compute the likelihood that an image displays a particular emotional state. The algorithm scores the facial features identified in each frame of each video as a probability between 0-1 for a range of emotional states. These are then charted to produce 'a one-dimensional' track for each video showing movements in predicted emotional indicators such as eyebrow raises and disgust expressions (McDuff et al, 2015a: 514). The data that can be analysed in this way is vast. McDuff et al (2015a, 2014a) analyse 3,268 webcam videos with participants watching one of three adverts; McDuff et al (2015b) analyses 12,230 webcam videos with 1,223 participants watching 10 of 170 advertisements; and McDuff and Kaliouby (2017) analyse 2,186,207 videos from 500,170 unique participants.

In order to test the effectiveness of their predictive algorithms, McDuff and colleagues employ ground truth labelling. This means that a sample of their images were also coded by human judges and the results compared with the machine learning predictions. McDuff et al explain: 'A set of 247,167 frames were randomly selected for ground truth labelling. Three labellers labelled each video and the majority label was taken. Coders were instructed to label each frame as either representing a smile or non-smile' (2015a: 515). The human coders were recruited through crowdsourcing (McDuff et al 2015a) and Amazon's Mechanical Turk (McDuff et al, 2015b) and were not formally trained to executed facial coding. However, the results suggest that the predictive algorithm makes comparable judgements to those of untrained human coders.

To unlock further insights, and demonstrate the power of their approach, in each study, the researchers analyse facial coding data to identify general findings about advertising effectiveness. For instance, McDuff et al normalise advertisements into standard temporal units and average viewers' emotional responses to produce 'mean tracks' for different emotional expressions (2015b: 230). From this, they find that, at the aggregate level, there is a time period at the start of ads 'during which the distributions are very similar, up to 16 seconds … Suggesting it takes time for liking or disliking of an ad to become apparent' (McDuff et al, 2015a: 516). McDuff et al (2015b: 639) confirm the importance of such temporal trends and state that 'smile activity in the final 25% of the ads is the most strongly related to the liking reported after the ad'. So, by processing the data, they are able to create relationships and findings that were unknown or unobservable previously.

The computer science papers also establish the effects of their predictions on consumer behaviours. To do so, they correlate the presence of predicted emotions with self-report measures quantifying audience responses to the stimuli texts. For instance, McDuff et al (2015a) use three measures (*liking*, *familiarity* and *rewatchability*) and offer three responses to respondents –

essentially *yes*, *maybe* and *no*. McDuff et al (2015b) also incorporate an A/B Test. They include a pre-test survey measuring participants' existing brand purchase intentions using a 5-point Likert scale and compare this to post-view brand purchase intentions. These tests suggest that the emotions revealed through machine learning can predict brand-related outcomes.

However, there are limitations to automated facial coding and its applicability to marketing noted in these studies. First, not all web-users have or are willing to use a webcam to record their faces. In one study, 16,366 web users visited the study website but only 7,562 had a webcam and only 5,268 were willing to be recorded. Second, the facial feature trackers are not foolproof. Poor quality recordings, low-lighting, eye-glasses and facial hair can all affect their ability to identify a face in an image and to code it accurately. In one early study, only 3,268 of 5,268 videos were useable. Finally, the resulting videos often include little by way of emotional information. Typically, only around 17% of frames in useable videos demonstrate any emotional expression. These limitations have implications. Facial coding offers poor quality data on individual-level responses and must be aggregated to reveal any meaningful trends. McDuff et al (2014: 638) observe 'a large number of the false positive and false negatives occur when the viewers are relatively inexpressive'. Finally, because the machine learning algorithm learns from known data, it includes a number of biases. As such, McDuff and Kaliouby note that the 'data clearly shows that facial expressions should not be given equal weight when analyzing responses to content from different categories' (2017: 152). Computational techniques can help to standardise and represent emotional responses but the data they produce cannot be read uncritically.

Seeing emotions in expressions: standardising faces

A further step had to be taken before the computer scientists could apply their algorithms. Images of faces needed to be quantified and related to specific emotions. In this regard, the computer science literature references a specific coding scheme developed in cultural anthropology for this purpose known as Facial Action Coding Scheme or FACS (Ekman and Friesen, 1978). This section explains the underlying problematisations and knowledge claims made within cultural anthropology that first quantified emotions from images of people's faces.

The idea that emotional responses are reflected in facial expressions has a long history. Inspired by observations of his children, Darwin (1872) viewed emotions as distinct psychological states expressed outwardly. This distinguishes them from cognitions and attitudes which, largely, remain contained inside a person's head. Darwin believed that this was true of all animals. To support his claims, he conducted a study in which he presented photographs and wood engravings of human and animal faces to research participants and asked them which emotions they saw. His findings were disseminated in his 1872 book.

Despite its popularity and Darwin's credentials, for almost a century 'after Darwin wrote about expression, his views were rejected or simply ignored … Emotions are a fiction (they said) – an explanatory device used in some cultures to explain what they do; emotions have no biological or psychological reality' (Ekman 2009: xxiii). This changed in the 1970s with the validation of FACS. It was based on Darwin's ideas but standardised the process of coding images. As a result of this method, ‘[v]irtually no one in science today’ disagrees with Darwin’s core argument (Ekman 2009: xxiii).

FACS allows trained human coders to categorise recorded facial movements. It is based around Action Units (AUs) - a category still used in the computer science applications to extract facial movements for emotional analysis. AUs are movements on specific regions of a face that, once coded, can be combined to infer emotions, concentration and other forms of non-verbal communication. FACS, though, does not apply to the facial movements in an unmediated form. It creates structured data from a two-dimensional representation of facial movements such as a drawing, photograph or video.

FACS assumes that facial expressions are universal. But since its development it has created uncertainty here. Researchers now agree that different species reveal emotions in different ways. Indeed, we have seen the development of ChimpFACS as a standard way to measure the emotional expressions of chimpanzees. Similarly, while the FACS protocol is based on the idea that there are no cultural differences in facial actions, a range of researchers have sought to define culturally-specific emotions through FACS (Ekman and Friesen, 2003). Consequently, the list of accepted *universal emotional expressions* is now shorter than the list of potential emotional expressions that can be coded through FACS. They are happiness/joy, sadness, surprise, fear anger, disgust, contempt. The FACS system also assumes that facial expressions ‘that show feelings may be misinterpreted or missed entirely’ because the face is a multi-signal system and expresses multi-message signals (Ekman and Friesen, 2003: 5). As a signal system, the face provides three different types of signals. Static signals do not change or change incredibly slowly such as skin colour. Slow signals change over time such as wrinkles. Rapid signals are fast responses and include smiles and raising the eyebrows. FACS focuses on rapid signals(Ekman, 1993). So, the face does not reflect all emotions.

Further, FACS is founded on the idea that the face can express more than emotions and, therefore, cannot be coded in a straightforward way. Ekman and Friesen (2003: 11) tell us that the ‘face broadcasts messages about emotion, mood, attitudes, character, intelligence, attractiveness, age, sex, race, and probably other matters as well’. Emotional expressions may be linked with these signals but, in some cases, the messages may not involve any emotional component. Similarly, individual facial expressions may indicate multiple emotions at the same time. This is particularly true of smiles. While they are part of the facial expression of happiness, they ‘often occur when a person is not happy’ (Ekman and Friesen, 2003: 101). Moreover, the face does not always tell the truth. It 'conveys both true and false emotion messages. There are uncontrolled, involuntary, true expressions and also qualified, modulated, or false expressions, with lies of omission through innovation and lies of commission through simulation’ (Ekman and Friesen, 2003: 20). Taken together these assumptions mean that FACS should not applied uncritically. As Ekman and Friesen (2003: 20) put it: ‘It is not enough to determine what emotions are read from facial expressions. It is also crucial to discover whether the interpretations of the observers are correct or not’. For this reason, Ekman and colleagues advocate the use of trained human coders who can evaluate, explain and document their subjective judgements.

Explaining facial coding data

This section interprets the translation of consumer emotions in facial coding as a process involving qualification, quantification, and re-qualification. While each step can be set out in isolation, they should be considered in relationship with one each another. For the sake of analytic clarity, here they are discussed in turn.

Qualification

A qualification that underpins facial coding has a long-standing history within marketing theory and practice. It is supported by marketing theories of intermediate psychological effects. These theories suggest that persuasion works by creating psychological responses which lead to behavioural outcomes (for a review, see Cluley, 2017). These responses include cognitive and affective elements. Early 'information-processing' theories, for example, focused on the cognitive responses to marketing and explored issues such as consumer learning and information overload. Since the 1970s, marketing researchers identified the ways that affective processes moderate cognitive ones. That is, they argued that what people feel influences what they know. Some suggest that these approaches appeal to marketers because it is inherently easier to prompt a psychological response than a behavioural one. However, this means that facial coding data can draw on, rather than establish, a qualification of consumers that values on consumers emotions. This may explain references to behavioural science and psychology in marketing practice and the computer science literature. These are used to assert the importance of emotional responses and justify the application of machine learning to marketing.

Despite the novel algorithms and big data, then, this qualification means that facial coding data allows marketers to speak to their clients in a familiar way. It makes facial coding data commensurable with other forms of quantification which measure emotions. Facial coding data is, to paraphrase Latour (1994), a new bullet for an old gun. As such, if we want to explain why facial coding has become popular in contemporary marketing, we must look elsewhere than this original qualification.

Quantification

Few intermediate effects theories suggest that people are fully cognizant of their emotional responses nor able to verbalise them in a consistent and comparable way. Yet, traditionally consumer emotions have been quantified in marketing research via self-report measures. These ask research participants to score their own emotional responses to marketing communications, usually via Likert-type scales.

Facial coding is different. Following the validation of FACS, it involves trained human-coders quantifying visual representations of consumers emotions. It shifts the work of quantification away from the people experiencing the emotions. This has been extended through the computer science application of FACS. Here, humans have, at least in appearance, been removed from the measurement process altogether. In their place, quantification is performed by a computational infrastructure of web-cam videos, imagery processing and predictive algorithms and dashboards. Once a research participant has agreed to be involved, all they do is watch an advert. The rest of the process is automated.

In this sense, facial coding data differs from other forms of quantification which measure emotions in terms of the *agent* of quantification. This has two effects on the *form* of quantification. First, the use of computers makes it feasible to collect more data. Second, it allows more fine-grained forms of quantitative representation. Rather than quantifying emotions through whole numbers on Likert scales, computers can score each frame in a video as a float. Consumer emotions, consequently, become a continuous rather than categorical variable. This makes the smile track possible as each frame of a video can be scored individually. So, differences in quantification begin to explain the use of facial coding in marketing. While what it measures is the same as other forms of quantification, the way it represents consumer emotions allows marketers new ways to understand, discuss and act with consumers.

Requalification

A key requalification of facial coding data occurs when Analytics and Insight Team interprets and presents their interpretations to clients. This involves visual artefacts such as the smile track, verbatim quotes and The Deck. These allow the Team to construct and present an interpretations of facial coding data that make two further translations of the original qualification and quantification.

First, Super's requalification emphasises the agent and form of quantification. But it goes beyond them. References to the size of data, the objectivity of computer analysis and the law of large numbers appear when Super present to their clients. Buzzwords such as "big data", "machine learning” and “algorithms” are used to differentiate facial coding data from self-report measures. But, while they amplify the computational element of facial coding data, their interpretation performs a sleight of hand. The underlying algorithm that produces the smile track offers a prediction that an image includes facial movements that FACS categorises as a smile. When Super interpret a smile track, this prediction is used as a description of what has happened. They do not say that the data suggests consumers will smile, but that it shows they did smile. This is, of course, what traditional self-report measures represent. In other words, by emphasising the computationality of the data, the Analytics and Insight Team has a license to reframe the data in ways that make more intuitive sense to them and their clients.

Second, Super’s requalification focuses on happiness and pushes both other emotional expressions into the background. Here, the original qualification of intermediate effects is replaced by a single effect. Intriguingly, the explanation for this set out in the computer science papers is thathappiness predicts purchase intention. But this is not proved through behavioural data nor is the proof derived from computational analysis. Rather, it relies on Likert-type self-report measures. This means that flaws in self-report measures, which justify the move to machine learning, are ignored as self-report measures prove the validity of machine learning.

What we begin to see, then, is that facial coding data has value not simply because of the meaning attached to it an initial qualification. Rather, new meanings are attached to facial coding data during requalification. These are not only enacted between participants but derive from the agent and form of quantification. Specifically, the value of facial coding data derives from the way it shifts the work of quantification to computers, creates new ways of visual consumer emotions and reveals temporal trends not possible with many other forms of quantifying consumer emotions. These allow marketers to add interpretations to it.

Interesting numbers

Animating the translation of consumer emotions into facial coding data are sets of motivations and assumptions about others' motivations. To understand the appeal facial coding data, it is necessary to understand how these interests both shape and are shaped by the processes of translation. This section outlines how different interests manifest themselves through facial coding data. Some are based on direct observations. Others are speculative. In what follows, a selection of interests are offered to illustrate the importance of the material, cultural, political, philosophical, and ideological commitments of actors, others' beliefs about their interests, and the ways that facial coding data transforms and aligns the interests of clients, marketing researchers, computer scientists, research respondents and others.

Imputed interests

When actors begin the process of translation, they know at some point they will have to enrol others. This makes them act like marketers. They package their problematisation in ways they hope will appeal to others. Law and Callon label these assumptions about what other actors want as imputed interests. For example, Super's decision to offer a facial coding product was based on the firm's belief that such a product would interest their clients. Why? Because they assumed that their clients are interested in understanding consumer emotions using cutting-edge machine learning techniques. Further, they assumed that decision makers in client firms want Super to reduce uncertainty for them. Appeals to big data, machine learning and so on are attractive in this regard because they suggest that a measure is capable of driving decisions. Super also rely on imputed interests of specific clients when they requalify facial coding data. The Analytics and Insight Team have a clear idea what their clients want to know, what they will accept and where they can be challenged. Similarly, the application of facial coding to marketing in the computer science literature is based on a set of assumptions about the interests of brands. Many of the computer science papers begin with assertions about the need for marketers to understand consumer emotions and concerns about the cost and inaccuracy of existing self-report measures. These are rarely tested. Instead, the use of facial coding within marketing practice is presented as proof.

These are just a small selection of the imputed interests that play out in the case for illustration. The key point of imputed interests is not that they accurately describe others' interest but that they are the basis of actors attempt to interest and enrol them. In facial coding , the imputed interests seem quite similar. They closely aligned with the need to reduce uncertainty and provoke an emotional understanding of consumers. Because of this alignment, each assertion about what others want is supported by other assertions until they influence action, which then justifies the original problematisation. This suggests that facial coding is valued over other ways of quantifying consumer emptions not because it better aligns with marketers' actual interests but because it aligns better with imputed interests and, in the process, enrols other actors, such as editors of computer science journals, until these imputed interests come to life.

Directing interests

Imputed interests cover the material, cultural, political, philosophical, and ideological commitments that actors believe motivate others. They attract actors to a problematisation. But the actors are not empty vessels. They bring pre-existing interests they bring with them. These directing interests push actors towards a translation.

In this case, directing interests take three forms. First, there are directing interests that lead to a problematisation. For example, when Super developed a facial coding product, they were directed by their own business interests and desire to find a successful product to augment their offering. Second, there are directing interests that lead actors to impute others' interests. Again, Super's business interests led them to base decisions on their assumptions about the clients. Finally, there are directing interests that influence which forms of translation are selected in the attempt to enrol others among the choices that are available. For example, Super wanted standardise the process of interpretation. Super did not do this because they thought it was what their clients wanted but because it helped them to manage the process more efficiently. Facial coding was interesting here as it allowed them to focus on a single emotion and limited range of visualisations of data such as the smile track.

Transformed interests

Callon and Law's concept of transformed interests denotes interests that emerge through the processes of translation. For illustration, we can think of the motivations of individuals in the Analytics and Insight Team. The Insight Executives and Director came from a variety of educational backgrounds including business, social psychology, law and medieval studies. IE, discussed above, came from a literary background. None had an interest in facial coding prior to Super developing their facial coding product. But, after this, they developed an economic interest in facial coding data. That is, their desire to succeed at work transformed into an interest in facial coding data. Indeed, the fact that the Analytics and Insight Team were interested in knowing more about facial coding was what facilitated access for this ethnographic study.

Taken together, the concepts of imputed, directing and transformed interests help us to understand why facial coding data appeals to contemporary marketers - not only how it focuses their attention on particular values or manifests new ways of thinking, talking about and acting in markets. They key point here is that the valuation of consumer emotions and computer analysis relies on the imputed interests and directing interests of actors. Once, these qualifications have been quantified into new forms of representation, afforded by the form and agent of quantification, they enrol others into a network that aligns the interests actors brought with them, the interest others assume they hold and produces new interests.

To denote these relations, we can describe successful marketing measures such as facial coding data as *interesting numbers*. This concept denotes their ability to interest and, therefore, enrol a sufficient network of actors. It also suggests that certain numbers reflect marketers' imputed, directing and transformed interests and can be analysed to understand the underlying nature of contemporary marketing. Finally, it directs our attention to the ways that some quantitative representations of consumers interest actors because of the agent and form of quantification. In other words, it directs us to consider the affordances of different forms of quantification. The concept of interesting numbers emphasises that the form of quantification provokes marketing action - just as particular ways of framing markets influence subsequent actions.

Conclusions: Quantification and Marketing Science Fiction

The study explores the process of quantification that produce a marketing measure and shape how it is used in marketing practice. The key finding from this research is the importance of quantification. That is to say, what might seem like technical ways of counting consumers – such as the choice of using continuous or categorical variables – have profound effects on the ways marketers are able to structure, interpret and make sense of markets.

To get to this perspective, the study has interpreted the quantification of consumer responses through the sociology of translation. Here, it contributes to both recent marketing theory, the wider STS theory of calculation and current accounts of the organisation of markets. In each case, quantification tends to be seen as a consequence of some form of qualitative judgement. In STS, for example, calculation is viewed as something that 'has nothing to do with quantification' (Callon and Law, 2005: 730). However, it is not the case that once a qualitative judgement has been made about *what counts*, the issue of *how to count it* is simplified or inconsequential. Rather, once something has been qualified the issue of how to quantify it becomes even more important. These decisions shape re-qualification and interpretation practices.

The case explored here has a further consequence for understandings of contemporary marketing practice. It illustrates that computational methods have value not simply because they reveal new elements of consumer behavior nor because of their performative effects. Their value derives, at least in part, from the appearance of objectivity that is associated with them. Ironically, this allows marketers to make subjective claims that interest and to enrol others. It allows them, for example, to slip from prediction to description. Although this might seem like a misunderstanding, misapplication or misinterpretation, it is more instructive to think that this is what makes computational methods so interesting to marketers. They create translations that tangle together legitimate claims, errors and assumptions and open up space for interpretation that gives data new meaning. It suggests that the appeal of marketing science is the marketing science fictions it opens up. These literary practices are, if anything, gaining more power in contemporary marketing practice and deserve further study.

Indeed, a limitation of the current study is that it follows the data in one direction only. To fully understand the influence of interests and translations, it is essential that we follow data inside the marketing organisations who use marketing measures. This would help us to evidence the new acting capacities that are provoked by new forms of representing consumers. In short, it would show us what difference measures make. Do they, for example, open up new ways of relating to consumers or new values? In this study, there was a sense that, for many of the clients observed on the ground at Super, facial coding opened up interesting discussions but rarely altered their branding and marketing activities. The sentiment among the Analytics and Insight Team was that their marketing fictions were valued because they were comforting. They help marketers do what they were doing anyway.

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