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A New Livestream Retail Analytics Framework to Assess the Sales Impact of Emotional Displays

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Abstract

At the intersection of technology and marketing, this study develops a framework to unobtrusively detect salespeople's faces and simultaneously extract six emotions: happiness, sadness, surprise, anger, fear, and disgust. The authors analyze 99,451 sales pitches on a livestream retailing platform and match them with actual sales transactions. Results reveal that each emotional display, including happiness, uniformly exhibits a negative U-shaped effect on sales over time. The maximum sales resistance appears in the middle rather than at the beginning or end of sales pitches. Taken together, the results show that in one-to-many screen-mediated communications, salespeople should sell with a straight face. In addition, the authors derive closed-form formulae for the optimal allocation of the presence of a face and emotional displays over the presentation span. In contrast to the U-shaped effects, the optimal face presence wanes at the start, gradually builds to a crescendo, and eventually ebbs. Finally, the study shows how to objectively rank salespeople and circumvent biases in performance appraisals, thereby making novel contributions to people analytics. This research integrates new types of data and methods, key theoretical insights, and important managerial implications to inform the expanding opportunity that livestream e-commerce presents to marketers to create, communicate, deliver, and capture value.

Keywords

deep learning, emotions, face detection, livestream e-commerce, salesperson effectiveness

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Livestream retailing augments traditional go-to-market strategies by reaching consumers via screen-mediated sales presentations for a variety of products. Amazon Live, Facebook Live, Taobao Live, and QVC serve as prominent exemplars. This type of retailing blends technology and marketing: the technology integrates video stream broadcast platforms, electronic payment systems, and forward and reverse logistics for efficient delivery and hassle-free returns, and the marketing combines entertainment and retailing, enhances reach via influencer marketing, shortens the purchase journey to the duration of the sales presentation, and permits value capture via innovative payment plans. In a typical video sales pitch, a host (salesperson) nudges a prospective customer through the purchase funnel by building awareness of an item's features, benefits, price, and discounts, as well as instilling urgency to buy. For example, on Taobao Live, which reaches over 37 million Chinese viewers monthly, top influencer Wei Ya helped Procter & Gamble accelerate its customers' journey from awareness to purchase and Tesla generate customer leads (Greenwald 2020).

The continuous stream of sales presentation videos can be captured using advanced computing capabilities (Oblander

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et al. 2020; Wedel and Kannan 2016). Using video footage, marketing scientists can apply artificial intelligence technologies to automatically detect a salesperson's face in each frame, extract emotional expressions, and relate them to actual customers' behavioral data —all unobtrusively at a large scale— to generate novel insights (Marinova, Singh, and Singh 2018), thereby augmenting the sparse knowledge on the business impact of emotional displays.

Recent studies have investigated the effects of emotional displays on various marketing metrics. For example, Teixeira, Wedel, and Pieters (2012) offer the first study to automatically extract the emotions of joy and surprise that viewers experience when watching television commercials and then relate these emotions to attention and ad avoidance behavior. Similarly, Liu et al. (2018) examine the impact of emotional displays on sales using the Facial Action Coding System (Ekman and Friesen 1978) to categorize a set of emotions (e.g., happiness, surprise, disgust) based on facial expressions of viewers watching movie trailers, compute the average watching intention for each movie trailer, and relate it to box-office revenues. They find that viewers' emotional displays of happiness positively influence both watching intentions and box-office revenues. However, although Liu et al. (2018) incorporate prospective consumers' emotional displays into their study, the role of emotional displays on the seller side of the exchange dyad remains an unexplored cue that shapes consumers' purchases. Indeed, in their survey of the literature on emotions, Bagozzi, Gopinath, and Nyer (1999, p. 184) emphasize that "much of what we do know is confined to consumer behavior, as opposed to the behavior of salespeople or marketing managers."

To our knowledge, the current study is the first to assess the sales impact of product, price, sales force, advertising, and promotion in the presence of a salesperson's face and emotional displays. Specifically, we address the following knowledge gaps:

1. Do salespeople's emotions in livestream presentations impact sales? If so, to what extent?
2. How do the effects of emotions vary over an item's presentation span?
3. What is the optimal allocation of face presence and emotions over the presentation span?

To answer these and related questions, we collaborate with a livestream retailer that broadcasts television shows 24 hours each day of the week, deploys salespeople to deliver live sales presentations of hedonic products, receives payments by credit cards, and ships orders by mail. A typical show lasts one hour and presents about eight items. We analyze the video data consisting of 62.32 million frames over two years. To put this scale in perspective, this footage exceeds two million 30-second TV ads. Then, we apply two machine-learning algorithms: real-time face detection (Viola and Jones 2001) and real-time emotion classification (Arriaga, Plöger, and Valdenegro 2017). Specifically, the face detection algorithm discovers the presence or absence of a face in every frame of the video, while the emotions classifier (based on a convolutional neural network with rectified linear unit activation) assigns probabilities to the facial expressions in each frame with a face. Thus, we unobtrusively extract the display of emotions of each salesperson in one-to-many screen-mediated marketing communications in consumer markets.

Next, across 99,451 sales pitches, we match the salespeople's six emotional displays —happiness, sadness, surprise, anger, fear, and disgust— to how long each item was shown, the product category to which it belongs, the number of units sold, the price charged, and whether shipping fees were waived. Finally, we extend marketing mix models on two frontiers: the inclusion of emotional displays and salespeople's effectiveness. We emphasize that the literature on marketing mix models is vast, as is the literature on emotions; however, they do not overlap. This study bridges the two distinct domains.

Our analysis of large-scale video data shows that salespeople's emotions negatively impact sales across all six emotions, including happiness. The magnitude of sales decline across all the emotions is .47%, which is more than double the free-shipping effect (.20%). Happiness constitutes more than one-third of the total sales decline. Thus, we uncover a new maxim: sell with a straight face (i.e., reduce facial expressions).

Furthermore, the level of the optimal face presence reduces over the initial 10% span, then gradually increases as the presentation progresses, and subsequently tapers down in the last 15% span. Finally, most marketing mix models ignore the role of the sales force (e.g., Ataman, Mela, and Van Heerde 2008; Naik, Raman, and Winer 2005), and when they do include it (e.g., Gatignon and Hanssens 1987), the sales force variable is operationalized at an aggregate level (e.g., number of salespeople, number of calls). Consequently, companies are limited in their insights into an *individual* salesperson's effectiveness. By contrast, the proposed framework uses person-specific dummy variables to estimate individual salesperson's impact, yielding valuable information on salespeople's performance, which circumvents managers' cognitive biases (e.g., homophily) in recognizing excellence and identifying candidates for retraining, thus contributing to people analytics in a sales setting. Next, we describe the conceptual background needed to interpret the empirical results.

Conceptual Background

Facial expressions are social displays that a sender strategically deploys to elicit a desired response from a receiver (Crivelli and Fridlund 2018; Fridlund 1994). In other words, facial expressions are "declarations that signify our trajectory in a given social interaction, that is … what we would like the other to do" (Fridlund 1994, p. 130). They are social communicative moves that serve as "tools for social influence" (Crivelli and Fridlund 2018, p. 393).

A sender may mask true intentions. The onus is, therefore, on the receiver to decipher the sender's intent. The Emotions as Social Information (EASI) model (Van Kleef 2009, 2016;

Table 1. The Implications of a Sender's Strategic Social Communicative Moves.

Seller's Facial Expression[a, b]	Seller's Intent[a]	Consumers' Inference about Seller	Consumer Action Tendency	Illustration of Consumer Action Tendency
Happiness (smile)	Influence consumer to affiliate	A seller's happiness may be taken as a sign that the seller is gaining in the negotiation at the target's expense (Van Kleef et al. 2010).	Move against	An entrepreneur displaying a broad (slight) smile in a profile photo on a website is likely to receive less (more) financial backing for a crowdfunded project (Wang et al. 2017).
Sadness (pouting)	Influence consumer to provide support	A seller's sadness may be taken as a sign that the seller is recruiting succor (Scarantino 2017a) and trying to get consumers to lower their guard.	Move away or against	A service provider displaying intense sadness during a cell phone purchase is likely to result in the customer registering lower satisfaction with the product received and service (Cheshin, Amin, and Van Kleef 2018).
Surprise (startled)	Influence consumer to engage	A seller's surprise may be taken as a sign that the seller is trying to garner attention/liking in an attempt to make them more amenable to persuasion.	Move toward or away	A host on livestream video displaying surprise to customers is likely to garner greater interest in an offering. Alternatively, the surprise may serve as an unwelcome distraction and cause the customer to lose interest in the item.
Anger (scowling)	Influence consumer to submit	A seller's anger may be taken as a sign that the seller is losing in the negotiation and engaging in aggressive action to reassert dominance (Fridlund 1994).	Move toward or away	A manager displaying anger in response to employees' competence-based violations diminishes perceptions of leader effectiveness (Wang et al. 2018).
Fear (gasping)	Influence consumer to help and protect	A seller's fear may be taken as a sign that the agent is recruiting empathy and trying to get consumers to lower their guard.	Move away or against	A fear appeal in a television ad (e.g., Nationwide Insurance's "Make Safe Happen" 2015 Super Bowl Ad featuring a young boy who is no longer alive) led to negative social media posts and reduced liking of the ad (Bharadwaj, Ballings, and Naik 2020).
Disgust (nose wrinkling)	Influence consumer to reject current situation	A seller's disgust may be taken as a sign that the seller is seeking to violate behavioral norms in the negotiation (Heerdink et al. 2019).	Move away or against	A third-party observer of scenario featuring disgust (vs. neutral expression) finds that it triggers inferences that a norm has been violated (Heerdink et al. 2019).

[a]Crivelli and Fridlund (2018).
[b]Van Kleef et al. (2010).

Van Kleef et al. 2010) asserts that buyers scrutinize the seller's expressions in commercial exchanges in an attempt to discern the seller's strategic intentions. For example, Wang et al. (2017) show that sellers sporting a broad smile during an encounter are perceived as less competent and that perceived incompetence is more likely to be evident among prevention-focused customers and in high-risk consumption settings. Furthermore, their field study in a crowdfunding context reveals that a project creator with a broad smile is perceived as less competent, which reduces the total amount of money pledged for a project, the total number of large-scale donations made by backers, and the average amount of money pledged per backer. Similarly, Cheshin, Amit, and Van Kleef (2018) find that displays of intense happiness (e.g., a broad smile) by customer-facing employees can undermine trust and reduce satisfaction with the product.

Scarantino (2017a, 2017b, 2018) provides a theoretical explanation for *why* receivers are likely to draw certain inferences with respect to a sender's facial expression, and the EASI model offers clues on *how* receivers are likely to react to the cue. Salespeople's expressions elicit customers' inferences about sellers' characteristics such as competence, trustworthiness, and persuasive intent. Such inferences, in turn, impact customers' purchasing behaviors. Drawing on extant theory, Table 1 presents the seller's facial expressions, intent, consumers' inferences about sellers, and consumers' action tendency with examples. According to Van Kleef et al. (2010), consumers' action tendencies are to (1) *move toward* (i.e., consumers experience a positive emotional reaction toward the influence attempt and thereby seek to cooperate with the seller); (2) *move away* (i.e., consumers experience a slightly negative emotional reaction toward the influence attempt and thereby seek to temporarily ignore or avoid the sender); or (3) *move against* (i.e., consumers experience a highly negative emotional reaction toward the influence attempt and thereby seek to terminate the interaction). Thus, Table 1 explains how salespeople's emotional displays trigger buyers' inferences in one-to-many broadcast communications.

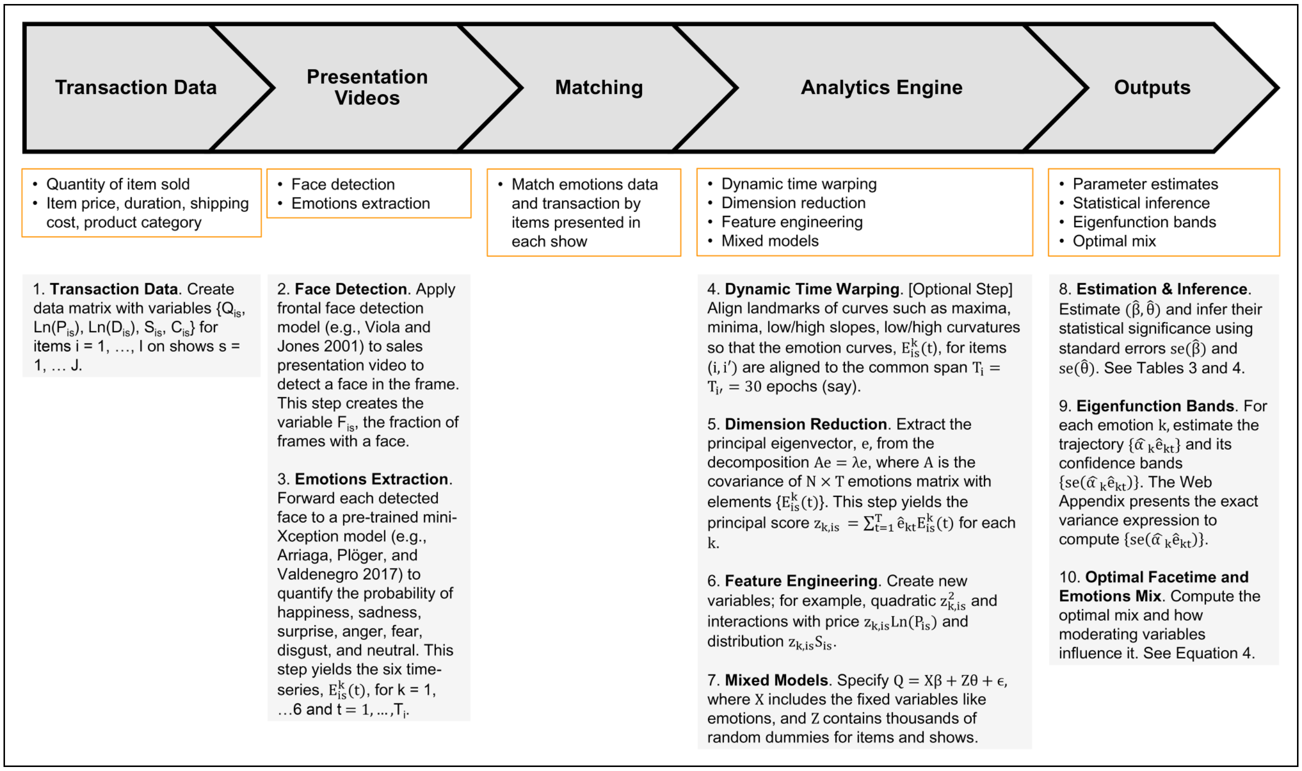

Figure 1. Livestream retail analytics framework.

More specifically, Table 1 provides theoretical bases to interpret our empirical results. First, positive facial expression (i.e., happiness) invokes the action tendency to move against. In a competitive buyer–seller exchange setting, a seller's happiness expression engenders consumers' inference that the seller is gaining an advantage, thereby reducing the seller's trustworthiness as well as consumers' purchasing tendency (Van Kleef 2009, 2016; Van Kleef et al. 2010) — a finding consistent with Wang et al. (2017) that a seller's broad smile results in the inference of low competence and the action tendency of reduced buying activity. Second, negative facial expressions (i.e., sadness, anger, fear, and disgust) invoke the action tendency to move away. For instance, a seller's sadness expression in a selling context invokes the consumers' inference of garnering empathy as an attempt to lower their guard, which can be off-putting to consumers, who might then either ignore or avoid the seller. Consistent with this expectation, Cheshin, Amin, and Van Kleef (2018) show that the display of sadness by frontline employees undermines trust and lowers satisfaction. Last, surprise can be either a positive or negative facial expression: consumers can infer that the seller is trying to garner attention, which invokes the action tendency to either move toward or move against, depending on whether consumers believe the expression is appropriate.

Livestream Retail Analytics Framework

The proposed framework circumvents limitations such as simulated interactions in laboratory studies, survey-based studies relying on self-reports, manual observation and coding of facial displays, small sample sizes, limited set of emotional displays, and lack of business metrics as the response variable. For example, Hennig-Thurau et al. (2006) investigate the impact of service representatives' happiness expressions on subjects in lab settings (using trained student actors). Gountas, Ewing, and Gountas (2007) conduct surveys with airline passengers' assessments of flight attendants, and Kadic-Maglajlic et al. (2017) rely on surveys completed by sales managers self-reporting their own ability to perceive their salespeople's emotions. Pugh (2001) manually evaluates a small sample of bank employees' smiles in salesperson–customer service encounters. These studies lack the full spectrum of emotional displays and sales performance as the response. Hu et al. (2021), a notable exception, seek to understand the content effects on sales. Specifically, they analyze a small sample of 275 sales pitches from Home Shopping Network and incorporate minute-by-minute cumulative sales; however, they ignore the role of facial expressions. To circumvent the aforementioned limitations, we develop a framework that unobtrusively collects nonsimulated market interactions, does not rely on self-reports, does not require manual observation or coding of facial displays, involves a large sample size, covers a broad spectrum of six emotional displays, and, most importantly, uses sales transactions as the response variable. Figure 1 presents the ten-step framework to capture and analyze the structured and unstructured data from livestream retailing.

Data Capture

The first two pennants in Figure 1 list three steps that pertain to data capture. Transaction data contain structured information such as quantity of items sold, prices of items, duration of display, shipping cost, and product category. Video footage of salespeople's presentations offers the unstructured data. We process the video footage as follows. Each video frame is a colored image with a resolution of 480×360 pixels. For every second of the video footage, we select a frame, convert it to grayscale, and present it to a pretrained OpenCV frontal face detection model based on the Haar cascade algorithm (Viola and Jones 2001). For each detected face, the grayscale frame bounded by the face's region of interest is forwarded to an emotion classification model to infer the emotional state of the salesperson by producing probabilities for happiness, sadness, surprise, anger, fear, and disgust. We classify emotional displays using a pretrained mini-Xception model developed by Arriaga, Plöger, and Valdenegro (2017). Thus, we unobtrusively extract data on whether a face exists in 62.32 million frames and the probabilities of emotional displays. The third pennant in Figure 1 uses time stamps (i.e., the start and end times of item displays) to compute the display duration. We match 25,565 distinct items across 6,065 shows to the accounting data on orders placed, selling prices, and free shipping waivers.

Analytics Pipeline

The fourth pennant in Figure 1 consists of dynamic time warping (step 4), dimension reduction (step 5), feature engineering (step 6), and mixed models (step 7). To understand dynamic time warping, let $E^k_{is}(t)$ denote the time pattern of the emotional display k, where $k = 1, \ldots, 6$ for an item i in show s. Data analysis commonly uses variable transformation such as squaring, which alters the magnitude of $E^k_{is}(t)$ but keeps its x values (time) unaltered. In contrast, we transform $E^k_{is}(t)$ by shifting, stretching, or shrinking the time argument, denoted by t in $E^k_{is}(t)$, but keeping its magnitude (y values) the same. This shifting, stretching, or shrinking applies to each item i in show s and emotion k. For example, Sin(t) and Cos(t) are different curves, yet if we replace t in Cos(t) by $(\frac{\pi}{2} - t)$, we shift the cosine curve along the time dimension to overlap it with the sine curve exactly. The function $\phi(t) = \frac{\pi}{2} - t$ is called a "warping" function that performs shifting; however, more generally, it can stretch or shrink time, differentially at various instants, to align curves more closely with each other with respect to their landmarks such as peaks, valleys, and inflection points. This process of dynamic time warping is also known as curve registration or landmark alignment. The resulting aligned curves serve as inputs for analysis rather than the raw curves $E^k_{is}(t)$. Subsequently, we present the empirical results with and without curve alignment to understand the benefits of this optional step.

Dimension reduction enables us to capture the dynamic effects of emotional displays on quantity sold. Specifically, for each item-show, the time t in $E^k_{is}(t)$ spans over 30 epochs, which are defined as 1/30th of the total duration of item i displayed in show s. Consequently, we have 180 additional variables (i.e., 30 epochs for six emotions). Furthermore, we generate an additional 180 variables by including its quadratic terms and yet another 360 variables by interacting them with price and promotion. To maintain parsimony and mitigate collinearity, we extract the principal component to capture "happiness" (say, when $k = 1$) via the principal scores $z_{kis} = \sum_{t=1}^{30} \hat{e}_{kt} E^k_{is}(t)$, where $\hat{e}_k = (\hat{e}_{k,1}, \hat{e}_{k,2}, \ldots, \hat{e}_{k,30})'$ is the principal eigenvector that reduces the dimensionality from 30 epochs to the scalar z_{kis}. Then, we regress the quantity sold Q_{is} on the principal scores z_{kis} to estimate the trajectory of sales impact of an emotional display together with its confidence intervals. For details, see the Web Appendix.

Feature engineering supplements the new features to represent the quadratic and interaction effects. To this end, we included z^2_{kis} for each emotion k and interaction terms such as $z_{kis} \times X_{is}$, where X_{is} denotes a moderating variable of interest (e.g., price). To generate the outputs listed in the fifth pennant in Figure 1, we formulate a set of mixed models.

Model Development

Figure 2 illustrates how marketing mix — product, price, sales force, display duration (advertising), and free shipping (promotion) — together with face presence and emotional displays (happiness, sadness, surprise, anger, fear, and disgust) affect the focal outcome representing customers' purchase behavior (i.e., sales). In Model 1, we formulate the marketing mix model with marketing mix variables, time effects, and random effects for items and shows. Model 2 extends Model 1 by incorporating the face presence and six emotional displays. Model 3 adds the quadratic effects of emotional displays. Model 4 further augments Model 3 with interactions of price and promotion with the emotional displays.

Model 1: Incorporating Salespeople and Time Effects in Marketing Mix Models

We investigate how the number of units of an item sold on a given show varies with the item's price, its duration of display, whether free shipping was waived, the product category to which it belongs, the salesperson who presented it, and the time effects (day effect, week effect, and year). The model specification is as follows:

$$\begin{aligned} \mathrm{Ln}(Q_{is}) = \beta_1 \mathrm{Ln}(P_{is}) + \beta_2 \mathrm{Ln}(D_{is}) + \beta_3 S_{is} + \beta_4 C_{is} \\ + \sum_{j=1}^{22} \lambda_j H_{js} + \tau' T_{is} + \mu_0 + \mu_{1i} + \mu_{2s} + \epsilon_{is}, \end{aligned} \quad (1)$$

where Q_{is} denotes the quantity sold of an item i in the show s with $(i, s) = 1, \cdots, N = 99,451$; P_{is} represents the item's price in dollars; D_{is} is the display duration in seconds; S_{is}

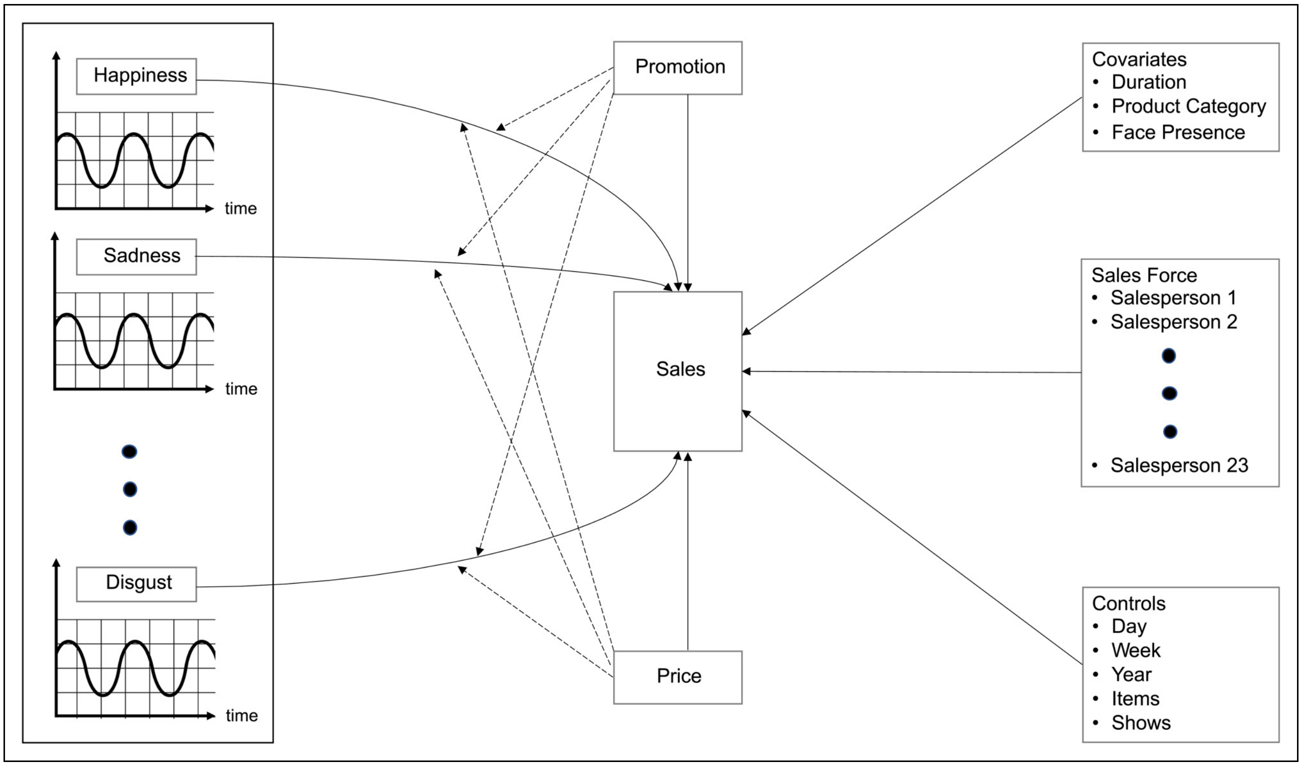

Figure 2. Modeling framework.
Notes: Straight arrows denote linear effects, arcs represent curvilinear effects, and dashed arrows are moderating effects.

captures free shipping ($S_{is} = 1$) or not ($S_{is} = 0$); and $C_{is} = \{0, 1\}$ indicate one of the two types of products (whose names are not disclosed for confidentiality). These five variables represent the proxies for the traditional marketing mix variables: product, price, sales force, marketing communications (i.e., length of ad), and promotion (i.e., free shipping). Given the log-log specification, the parameters (β_1, β_2) respectively yield the price and duration elasticity, which quantifies the percentage sales impact associated with a 1% increase in price or duration. The parameters (β_3, β_4) measure the percentage change in sales due to free shipping and product category. In addition, H_s is a 22×1 dummy vector, with unity for the element j and zero elsewhere, that identifies individual salesperson j hosting the show s. The corresponding λ_j furnishes the sales lift due to various salespeople, $j = 1, \ldots, 22$, relative to the baseline salesperson 23. A single salesperson owns the entire show in our data. The parameters (μ_0, μ_{1i}, μ_{2s}, ϵ_{is}) represent the fixed intercept, random intercept for items, random intercept for shows, and the usual zero mean and constant variance normal error term, respectively. The random effects parsimoniously reflect the variability about the intercept μ_0 due to heterogeneous impact of items and shows.

Time flows across 62.32 million seconds of the video footage in our analysis, and it exhibits periodicity for the seconds across days and for the days across weeks. To clarify, consider time in seconds since midnight. A total of 86,400 seconds elapse by the midnight of the next day, and then the clock resets to zero (00:00:00 hours). At 23:59:59 hours, the elapsed time is 86,399 seconds, and it is 5 seconds at 00:00:05 hour. Although the instants 23:59:59 and 00:00:05 differ by just 6 seconds, these two instants would be represented as if they are 86,394 seconds apart under a linear scale. Thus, to account for periodicity of the days and weeks, sine and cosine terms should be used as follows. Let t_{is} represent the seconds of a day when an item i in show s is displayed, where the full day of 86,400 seconds equals 360° or 2π radians. Then the two periodic regressors for the day effect are $D_{is} = \left(\mathrm{Sin}\left[\frac{2\pi t_{is}}{86400}\right],\ \mathrm{Cos}\left[\frac{2\pi t_{is}}{86400}\right]\right)'$. Similarly, let d_{is} represent the day of a week when an item i in show s is displayed, where the full week equals seven days. Then the two periodic regressors for the week effect are $W_{is} = \left(\mathrm{Sin}\left[\frac{2\pi d_{is}}{7}\right],\ \mathrm{Cos}\left[\frac{2\pi d_{is}}{7}\right]\right)'$. Because calendar years are not periodic, unlike seconds or days, let the dummy variable Y_{is} indicate the years. Thus, $T_{is} = (Y_{is}, W'_{is}, D'_{is})'$ in Equation 1 includes these five regressors with the conformable parameter vector τ that constitutes the year effect, the week effect, and the day effect on item sales.

Model 2: Incorporating the Presence of Face and Emotional Displays

The proposed livestream retail analytics framework provides the fraction of the frames containing a face when item i was displayed in show s, which we denote by F_{is}. In addition, when item i was displayed in show s, it furnishes the principal score z_{kis} for happiness (z_{1is}), sadness (z_{2is}), surprise (z_{3is}), anger (z_{4is}), fear (z_{5is}), and disgust (z_{6is}). Incorporating them in Model 2, we extend the right-hand side (RHS) of Model 1 as follows:

$$\begin{aligned}\mathrm{Ln}(Q_{is}) &= \alpha_0 F_{is} + \alpha_1 z_{1is} + \alpha_2 z_{2is} + \alpha_3 z_{3is} + \alpha_4 z_{4is} \\ &\quad + \alpha_5 z_{5is} + \alpha_6 z_{6is} + \mathrm{RHS(Model\ 1)}, \end{aligned} \tag{2}$$

where α_k are the effects of face presence and six emotional displays on sales. Because the score $z_{kis} = \sum_{t=1}^{30} \hat{e}_{kt} E_{is}^{k}(t)$, the sales impact $\hat{\alpha}_k \hat{e}_{kt}$ exhibits the trajectory over $t = 1, \ldots, 30$ epochs.

Model 3: Incorporating Quadratic Effects

The effects of emotional displays may wax and wane. For example, moderate happiness may be effective, but limited or excessive happiness display may not be. To investigate such intensity effects, we extend Model 2 by incorporating the quadratic effects of facetime and emotional displays. Then, Model 3 is given by

$$\begin{aligned}\mathrm{Ln}(Q_{is}) &= \alpha_0 F_{is} + \gamma_0 F_{is}^2 + \sum_{k=1}^{6} \alpha_k z_{kis} + \sum_{k=1}^{6} \gamma_k z_{kis}^2 \\ &\quad + \mathrm{RHS(Model\ 1)}, \end{aligned} \tag{3}$$

where $z_{kis} = \sum_{t=1}^{30} \hat{e}_{kt} E_{is}^{k}(t)$, and γ_k represent the quadratic effects for the face presence and emotional displays, respectively. Equation 3 also includes the simple effects of face presence (α_0) and emotions (α_k), the marketing mix effects, and salesperson's effectiveness, time, and fixed and random intercepts via Model 1.

Optimal allocation of face and emotions. We derive the optimal face presence and emotional displays over time in the Web Appendix, which shows that the optimal number of frames to devote to face presence and each emotion k in every epoch t is given by

$$F_t^* = \begin{cases} -\dfrac{\alpha_0 e_{0t}}{2\gamma_0} & \text{if } \alpha_0 e_{0t} > 0,\ \gamma_0 < 0, \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{and} \tag{4}$$

$$E_{kt}^* = \begin{cases} -\dfrac{\alpha_k e_{kt}}{2\gamma_k} & \text{if } \alpha_k e_{kt} > 0,\ \gamma_k < 0, \\ 0 & \text{otherwise.} \end{cases}$$

Thus, for every epoch t in the presentation span T, the optimal allocation of face presence is $\frac{F_t^*}{\sum_t F_t^*} = \frac{e_{0t}}{\sum_{t=1}^{T} e_{0t}}$; and the optimal allocation for each emotional display k is $\frac{E_{kt}^*}{\sum_t E_{kt}^*} = \frac{e_{kt}}{\sum_{t=1}^{T} e_{kt}}$. To gain intuition, observe that $F_t^* \propto e_{0t}$ and $E_t^* \propto e_{kt}$ in Equation 4, which reveals that face and emotions allocation are proportional to the eigenvector weights: the larger the weight, the greater the intensity of face presence or emotional expressions.

Model 4: Incorporating Interaction Effects

Various factors can moderate the impact of sellers' affective displays on customers' attitudinal and behavioral outcomes. For example, some studies investigate boundary conditions from perceivers' characteristics, such as emotional receptivity (Lee and Lim 2010) and epistemic motivation (Wang et al. 2017). Others examine the moderating roles of the selling context, such as store busyness (e.g., Grandey, Goldberg, and Pugh 2011). To complement, we explore the moderating role of factors under managers' control such as price and promotion. Specifically, we augment Model 3 as follows:

$$\mathrm{Ln}(Q_{is}) = \sum_{k=1}^{6} \delta_k z_{kis} P_{is} + \sum_{k=1}^{6} \omega_k z_{kis} S_{is} + \mathrm{RHS(Model\ 3)}. \tag{5}$$

In Equation 5, the free shipping effect equals $\beta_3 + \omega_k z_k$, which depends on the level of emotional display, z_k. Similarly, each emotion z_k moderates the price elasticity $\eta_k = \beta_1 + \delta_k z_k P$. The preceding discussion completes the inclusion of emotions in marketing mix models.

Empirical Analysis

Context

A livestream retailer, whose identity remains confidential, broadcasts shows 24 hours a day, seven days a week, on its own television channel and sells exclusive hedonic products in multiple product categories. The salesperson hosting the show presents information on products and encourages viewers to place orders by telephone. Each show lasts for 60 or 120 minutes, is planned weeks in advance, and contains live sales pitches of items (i.e., not scripted or prerecorded). Besides selling, the salespeople attempt to build parasocial relationships with viewers so that they feel a bond with virtual personalities analogous to those with television celebrities or news anchors (Stephens, Hill, and Bergman 1996).

Data

Our direct-to-consumer retailer sells items from two product categories using 23 hosts as salespeople. The salesperson pitches multiple items during a show, and the item appears throughout the presentation span. We observe 99,451 sales pitches at an item-show level on salespeople's presence of face, their facial expressions, item prices, duration of display, shipping fee waivers, and, most importantly, actual sales as the dependent variable. Table 2 presents the descriptive statistics, and Tables 3 and 4 contain the estimation results for Models 1–4 obtained via the R package lme4.

Results

Sales impact of face presence and emotional displays

Face presence. Li, Shi, and Wang (2019) apply convolutional neural networks to detect the presence of a person's

Table 2. Descriptive Statistics.

Variable	Description	Mean	SD	Range
Dependent Variable				
Quantity, Q_{is}	Number of items sold in a show	69.64	93.21	[1, 2024]
Marketing Mix				
Price, P_{is}	Price of the item	110.48	196.22	[6.29, 8,000]
Duration, D_{is}	Display duration in seconds	487.1	333.09	[61, 2,886]
Free shipping, S_{is}	Dummy variable for free shipping	.21	.29	{0,1}
Product category, C_{is}	Dummy variable for two categories	.04	.19	{0,1}
Emotional Displays				
Face Presence, F_{is}	Fraction of the frames with a face	.19	.12	[0, 1]
Happiness, E^1_{is}	Grand mean of probability of happiness display in all the frames with a face	.23	.21	[0, 1]
Sadness, E^2_{is}	Grand mean probability of sadness display in all the frames with a face	.10	.06	[0, .62]
Surprise, E^3_{is}	Grand mean probability of surprise display in all the frames with a face	.08	.12	[0, .78]
Anger, E^4_{is}	Grand mean probability of anger display in all the frames with a face	.09	.07	[0, .76]
Fear, E^5_{is}	Grand mean probability of fear display in all the frames with a face	.11	.06	[0, .58]
Disgust, E^6_{is}	Grand mean probability of disgust display in all the frames with a face	.02	.03	[0, .52]
Sales Force				
Salesperson 1, H_1	Dummy variable for Salesperson 1	.004	.065	{0,1}
Salesperson 2, H_2	Dummy variable for Salesperson 2	.004	.065	{0,1}
Salesperson 3, H_3	Dummy variable for Salesperson 3	.034	.182	{0,1}
Salesperson 4, H_4	Dummy variable for Salesperson 4	.002	.044	{0,1}
Salesperson 5, H_5	Dummy variable for Salesperson 5	.047	.212	{0,1}
Salesperson 6, H_6	Dummy variable for Salesperson 6	.036	.187	{0,1}
Salesperson 7, H_7	Dummy variable for Salesperson 7	.072	.258	{0,1}
Salesperson 8, H_8	Dummy variable for Salesperson 8	.079	.270	{0,1}
Salesperson 9, H_9	Dummy variable for Salesperson 9	.008	.091	{0,1}
Salesperson 10, H_{10}	Dummy variable for Salesperson 10	.000	.020	{0,1}
Salesperson 11, H_{11}	Dummy variable for Salesperson 11	.078	.268	{0,1}
Salesperson 12, H_{12}	Dummy variable for Salesperson 12	.082	.274	{0,1}
Salesperson 13, H_{13}	Dummy variable for Salesperson 13	.012	.108	{0,1}
Salesperson 14, H_{14}	Dummy variable for Salesperson 14	.126	.332	{0,1}
Salesperson 15, H_{15}	Dummy variable for Salesperson 15	.055	.228	{0,1}
Salesperson 16, H_{16}	Dummy variable for Salesperson 16	.054	.226	{0,1}
Salesperson 17, H_{17}	Dummy variable for Salesperson 17	.070	.255	{0,1}
Salesperson 18, H_{18}	Dummy variable for Salesperson 18	.052	.223	{0,1}
Salesperson 19, H_{19}	Dummy variable for Salesperson 19	.028	.166	{0,1}
Salesperson 20, H_{20}	Dummy variable for Salesperson 20	.041	.198	{0,1}
Salesperson 21, H_{21}	Dummy variable for Salesperson 21	.002	.039	{0,1}
Salesperson 22, H_{22}	Dummy variable for Salesperson 22	.040	.196	{0,1}
Salesperson 23, H_{23}	Dummy variable for Salesperson 23	.072	.259	{0,1}
Time Effects				
Year, Y_{is}	Year of the display (annual)	2018	.50	[2017, 2019]
Day of week, W_{is}	Day of the display (weekly)	3.98	2.0	[1, 7]
Time of day, D_{is}	Seconds since midnight	41508	25614	[3.16, 86400]

face in a Kickstarter crowdfunding video and show empirically that the presence of a human face makes a difference in shaping the desired funding outcomes. But does it impact sales? If so, to what extent? Our study answers these questions. The estimate of .338 in Table 4 (Model 2) means that sales increase by .34% when a face is present, an effect common to all the hosts. For a specific salesperson, say salesperson 15, the impact of sales pitch is $(.338 + .418) = .756$, which means sales increase by .76%. This magnitude explains why the livestream retailer prefers live broadcasts even when items could have been posted on the internet in a faceless manner.

Emotional displays. Table 4 for Model 2 partially presents the sales impact of happiness, sadness, anger, fear, and disgust. The estimates $\hat{\alpha}_k$ for happiness (–.033), sadness (–.003), surprise (–.001), anger (–.033), fear (–.005), and disgust (–.012) are uniformly negative and statistically significant for all emotions except surprise. Thus, we conclude that emotional displays decrease sales.

Table 3. Sales Impact of Marketing Mix, Sales Force, and Time Effects.

	Model 1		Model 2		Model 3		Model 4	
	Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.
Marketing Mix								
Ln(Price), β_1	–.756	–142.28	–.765	–148.54	–.769	–151.28	–.769	–150.43
Ln(Duration), β_2	.552	127.77	.626	132.10	.671	136.02	.671	135.98
Free shipping, β_3	.218	20.36	.198	18.78	.190	18.20	.189	17.97
Product category, β_4	.414	5.91	.386	5.47	.360	5.11	.357	5.07
Sales Force								
Salesperson 15, λ_{15}	.438	14.92	.418	13.82	.427	14.19	.426	14.16
Salesperson 20, λ_{20}	.412	6.59	.398	6.18	.385	6.01	.385	6.01
Salesperson 18, λ_{18}	.351	11.37	.388	12.20	.358	11.32	.358	11.34
Salesperson 12, λ_{12}	.313	11.61	.237	8.50	.238	8.57	.237	8.57
Salesperson 8, λ_8	.311	11.01	.264	9.04	.232	7.97	.231	7.96
Salesperson 7, λ_7	.288	9.92	.321	10.69	.299	10.01	.300	10.04
Salesperson 11, λ_{11}	.270	9.40	.262	8.83	.241	8.16	.241	8.18
Salesperson 19, λ_{19}	.255	6.48	.299	7.35	.267	6.60	.267	6.60
Salesperson 22, λ_{22}	.249	7.34	.308	8.81	.303	8.70	.303	8.71
Salesperson 3, λ_3	.227	6.07	.145	3.75	.173	4.49	.173	4.52
Salesperson 17, λ_{17}	.169	5.57	.171	5.45	.146	4.70	.147	4.73
Salesperson 21, λ_{21}	.140	.84	.085	.49	.098	.57	.096	.56
Salesperson 6, λ_6	.083	2.37	.075	2.07	.092	2.55	.090	2.52
Salesperson 16, λ_{16}	–.036	–1.15	.064	1.95	.055	1.68	.054	1.68
Salesperson 5, λ_5	–.099	–2.95	–.103	–2.97	–.057	–1.67	–.058	–1.67
Salesperson 13, λ_{13}	–.168	–3.04	–.200	–3.50	–.187	–3.29	–.187	–3.30
Salesperson 23, λ_{23}	–.183	–6.11	–.122	–3.93	–.090	–2.92	–.090	–2.92
Salesperson 14, λ_{14}	–.212	–7.90	–.237	–8.57	–.201	–7.27	–.200	–7.25
Salesperson 2, λ_2	–.312	–3.17	–.186	–1.83	–.179	–1.77	–.181	–1.80
Salesperson 1, λ_1	–.488	–6.17	–.495	–6.08	–.496	–6.14	–.496	–6.14
Salesperson 4, λ_4	–.539	–4.22	–.662	–5.02	–.663	–5.06	–.662	–5.05
Salesperson 10, λ_{10}	–.679	–2.25	–.697	–2.23	–.690	–2.22	–.688	–2.22
Salesperson 9, λ_9	–.790	–11.16	–.735	–10.03	–.749	–10.29	–.749	–10.29
Time Effects								
Year Effect, τ_1	–.204	–16.81	–.180	–14.63	–.167	–13.60	–.167	–13.63
Week Effect (Sin), τ_2	–.113	–13.38	–.115	–13.48	–.112	–13.24	–.112	–13.22
Week Effect (Cos), τ_3	.096	11.44	.099	11.67	.105	12.36	.105	12.37
Day Effect (Sin), τ_4	–.292	–32.77	–.302	–33.52	–.314	–34.95	–.314	–34.97
Day Effect (Cos), τ_5	–.541	–57.35	–.563	–58.98	–.569	–59.95	–.570	–59.99
Intercept	414.298	16.94	347.097	13.78	320.512	12.80	321.780	12.86
VIF Median (Max)	1.443 (5.110)		1.304 (5.172)		1.604 (9.721)		1.616 (9.724)	
Distinct Items	25,565		25,565		25,565		25,565	
Unique Shows	6,065		6,065		6,065		6,065	

We present the dynamic pattern of emotional displays with (see Figure 3) and without (see Figure 4) dynamic time warping. These dynamic patterns emerge from the elements of the eigenvector $\hat{e}_{kt}$ across the 30 epochs $t = 1, \ldots, 30$. For clarity, Figures 3 and 4 present the epochs on the unit interval. The elements of the eigenvector $\hat{e}_{kt}$, together with the estimates $\hat{\alpha}_k$, yield the total sales impact of emotions given by $\hat{a}_{kt} = \hat{\alpha}_k \hat{e}_{kt}$. Summing across all the epochs, the sales impact of emotional displays are as follows: happiness (–.18%), sadness (–.02%), surprise (–.004%), anger (–.18%), fear (–.03%), and disgust (–.06%). Happiness and anger induce the largest sales decline; surprise the smallest. Summing across these emotions, the magnitude of total sales decline (.47%) is more than twice the free-shipping effect (.198%). Happiness contributes more than one-third to the total sales decline.

What accounts for the negative sales impact? As discussed in the "Conceptual Background" section, sellers' emotional displays trigger buyers' inference and action tendencies. Specifically, Table 1 shows that positive facial expressions such as happiness negatively impact sales because consumers infer that the seller is gaining an advantage at their expense, thereby reducing sellers' trustworthiness and, in turn, buyers'

Table 4. Sales Impact of Face and Emotional Displays.

	Model 2		Model 3		Model 4	
	Estimate	t-values	Estimate	t-values	Estimate	t-values
Main Effects						
Face Presence, $\hat{\alpha}_0$	.338	12.66	3.138	43.35	3.140	43.37
Happiness, $\hat{\alpha}_1$	–.033	–40.39	–.025	–25.26	–.024	–20.23
Sadness, $\hat{\alpha}_2$	–.003	–3.56	–.001	–.90	.001	.62
Surprise, $\hat{\alpha}_3$	–.001	–1.07	.007	7.32	.008	7.09
Anger, $\hat{\alpha}_4$	–.033	–45.82	–.031	–29.70	–.031	–26.03
Fear, $\hat{\alpha}_5$	–.005	–6.58	–.003	–3.13	–.003	–2.92
Disgust, $\hat{\alpha}_6$	–.012	–16.63	–.011	–10.47	–.010	–8.52
Quadratic Effects (Estimate $\times$ 10^3)						
Face Presence, $\hat{\gamma}_0$			–4,641	–41.66	–4,644	–41.69
Happiness, $\hat{\gamma}_1$			–.769	–6.79	–.764	–6.73
Sadness, $\hat{\gamma}_2$			–.296	–4.31	–.303	–4.41
Surprise, $\hat{\gamma}_3$			–.613	–7.80	–.629	–7.99
Anger, $\hat{\gamma}_4$			.010	.17	.017	.28
Fear, $\hat{\gamma}_5$			–.442	–6.20	–.440	–6.17
Disgust, $\hat{\gamma}_6$			–.060	–1.93	–.061	–1.97
Moderation Effects (Estimate $\times$ 10^3)						
Happiness $\times$ Price, $\hat{\delta}_1$					–.009	–2.04
Sadness $\times$ Price, $\hat{\delta}_2$					–.012	–3.55
Surprise $\times$ Price, $\hat{\delta}_3$					–.012	–4.10
Anger $\times$ Price, $\hat{\delta}_4$					.005	1.27
Fear $\times$ Price, $\hat{\delta}_5$					.001	.32
Disgust $\times$ Price, $\hat{\delta}_6$					–.001	–.27
Happiness $\times$ Shipping, $\hat{\omega}_1$					2.248	.84
Sadness $\times$ Shipping, $\hat{\omega}_2$					–.411	–.18
Surprise $\times$ Shipping, $\hat{\omega}_3$					3.699	1.80
Anger $\times$ Shipping, $\hat{\omega}_4$					–1.671	–.76
Fear $\times$ Shipping, $\hat{\omega}_5$					1.144	.51
Disgust $\times$ Shipping, $\hat{\omega}_6$					–1.882	–.82

tendency to purchase (Van Kleef 2009, 2016; Van Kleef et al. 2010). This expectation corroborates Wang et al.'s (2017) findings, which show that a seller's broad smile results in a buyer's inference of a seller's low competence and reduces buying activity. A similar situation occurs with politicians sporting a "permasmile" (i.e., maintaining a smile for an extended period of time); they are not perceived as genuine, which induces distrust and leads to lost votes (Zetlin 2017). As for negative facial expressions (i.e., sadness, anger, fear, and disgust), they invoke the action tendency to move away, which corroborates Cheshin, Amit, and Van Kleef's (2018) finding that frontline employees' displays of sadness undermine trust and reduce satisfaction. Last, surprise can be either positive or negative, and it results in an insignificant effect on sales. Thus, this large-scale evidence supports recent studies (Cheshin, Amit, and Van Kleef 2018; Wang et al. 2017), and so we caution that emotional displays are bad for livestream retailing business.

Over an item's presentation span, the magnitude of sales impact $\hat{a}_{kt}$ builds up, attains a maximum in the middle, and recedes toward the end. Across the six emotions, this dynamic pattern holds uniformly. Are the U-shaped patterns significant? Using the expressions in the Web Appendix, we plot the confidence intervals in Figures 3 and 4. We conclude that because zero does not belong in it, except for surprise, the rest of the emotional displays, including happiness, exert significantly negative effects on sales.

What accounts for the U-shaped dynamics? The literature on advertising repetition (e.g., Berlyne 1970; Calder and Sternthal 1980; Naik, Mantrala, and Sawyer 1998; Pechmann and Stewart 1988) provides a plausible interpretation. As the sales pitch progresses, the repetitiveness of facial expressions exacerbates the negative sales impact (i.e., becomes more negative) and drives it to the lowest level. After that, often due to the tedium (Berlyne 1970) of a protracted sales pitch, viewers' attention drifts from the message-related thoughts to their own thoughts (Calder and Sternthal 1980) of purchase consideration, namely, balancing the benefits and costs of the presented item and deciding whether to buy. Consequently, the negative effect ameliorates during purchase consideration. Naik, Mantrala, and Sawyer (1998) find a similar U-shaped pattern for the effectiveness of television commercials (see their Figures 4 and 9 for chocolate and cereal brands, respectively).

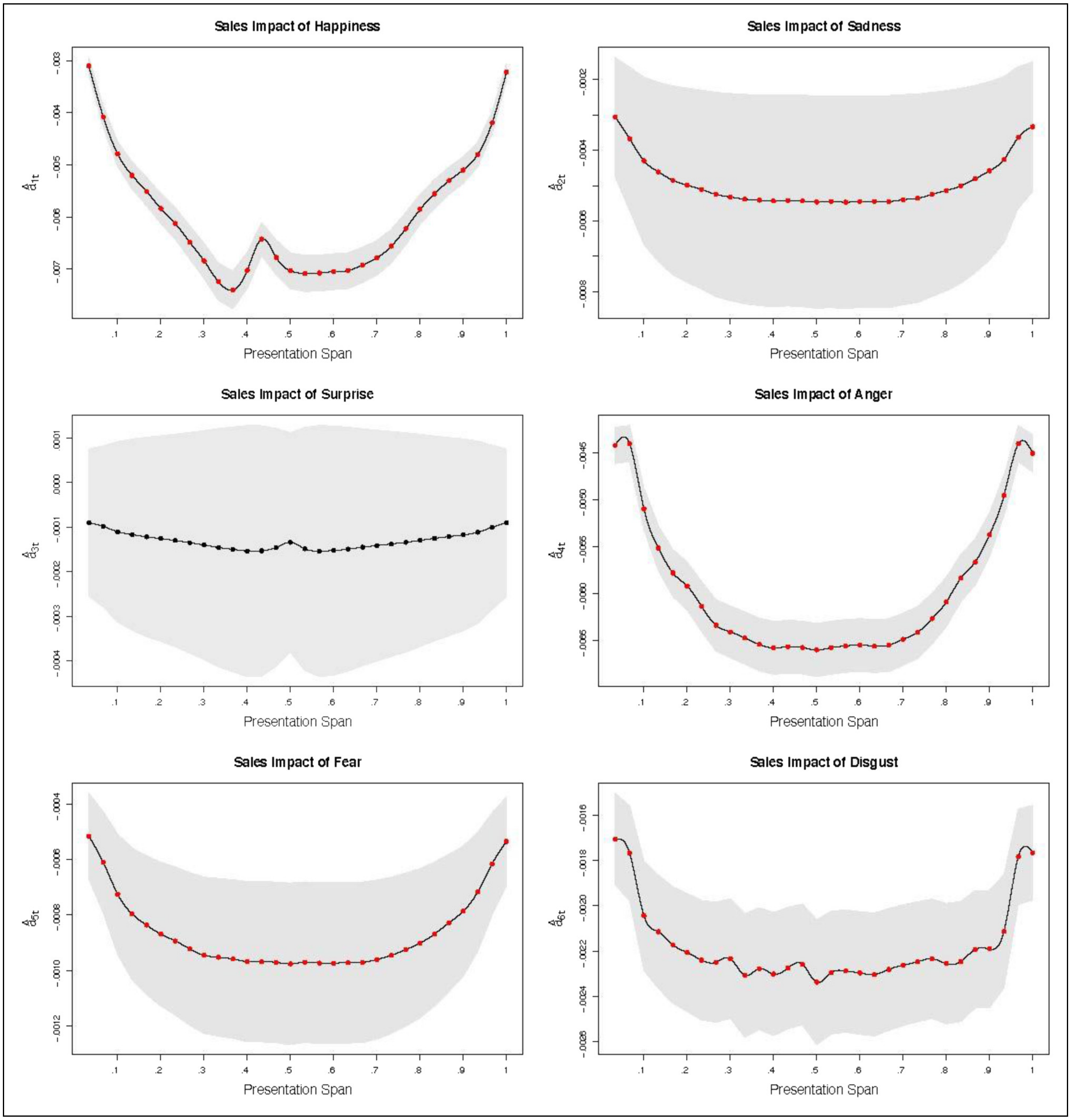

Figure 3. Time-varying sales impact of emotional displays with dynamic time warping.

Quadratic effects. Model 3 specifies the quadratic effects to explore whether emotional displays can be optimized. Table 4 shows that the conditions $\hat{\alpha}_k > 0$ and $\hat{\gamma}_k < 0$ are not satisfied by happiness, sadness, anger, fear, and disgust. Consequently, their resulting optimal level $E^*_{kt}=0$ according to Equation 4. Although surprise satisfies the conditions $\hat{\alpha}_3 > 0$ and $\hat{\gamma}_3 < 0$, the salesperson cannot express only surprise throughout the presentation in the absence of other emotions; thus, this corner solution does not seem practically useful. In contrast, the face presence satisfies the conditions $\hat{\alpha}_0 = 3.138 > >0$ and $\hat{\gamma}_0 = -4.641 < <0$, and the optimal $F^*=-\frac{3.138}{(-2\times 4.641)} = .34$. For comparison, the average face presence in Table 2 is .19. Thus, face presence should be increased from 19% to 34% to maximize sales.

Moderation effects. Model 4 specifies the interactions of emotional displays with free shipping and price. Table 4 shows that the estimated $\hat{\omega}_k$ are not significant for all k. Hence, the main effects of emotional displays hold regardless of the shipping fee waiver. Similarly, the price interaction effects of fear

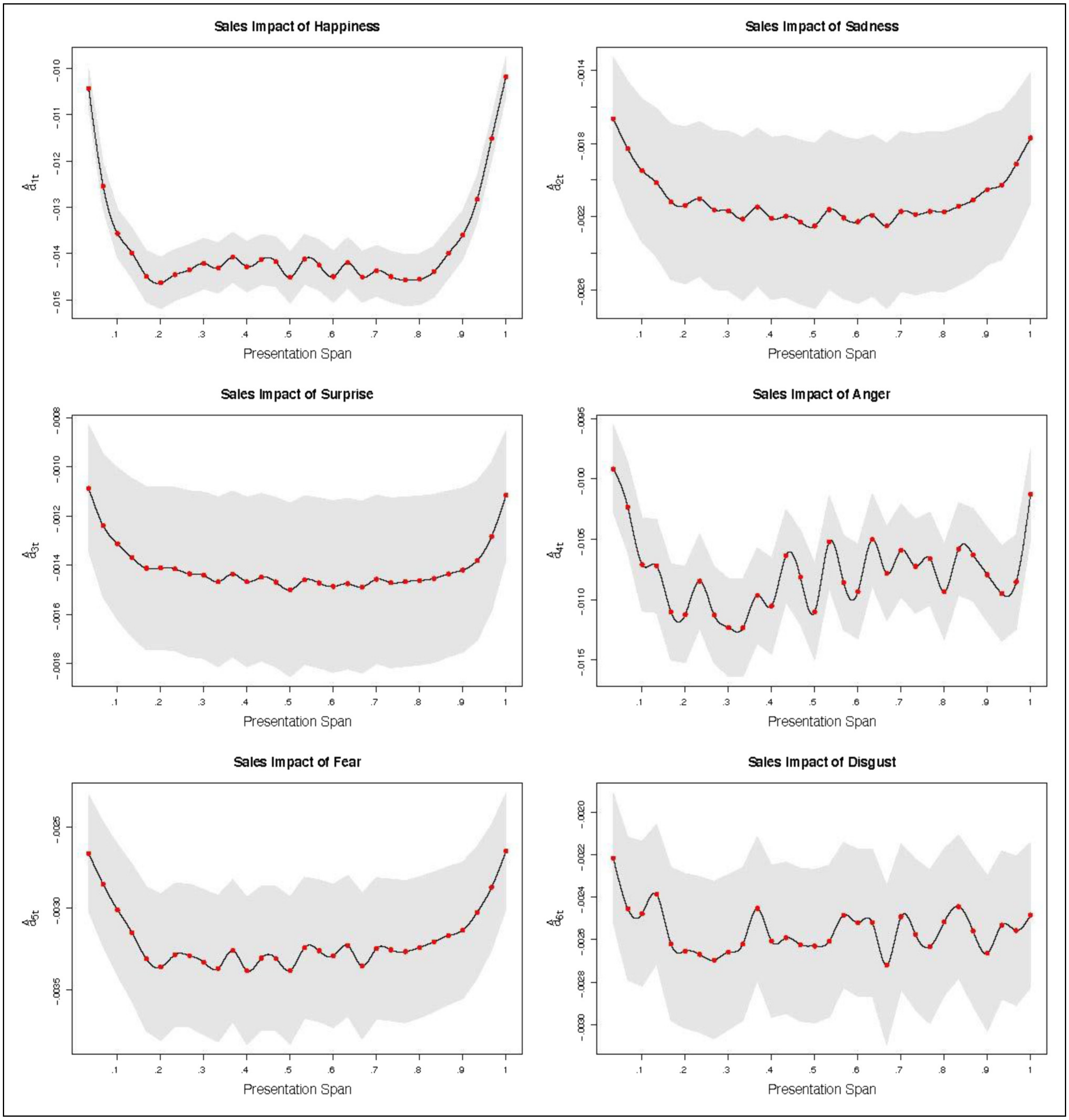

Figure 4. Time-varying sales impact of emotional displays without dynamic time warping.

($\hat{\delta}_4$), anger ($\hat{\delta}_5$), and disgust ($\hat{\delta}_6$) are not significant, thereby generalizing their main effects across various prices.

In contrast, the interaction effects of happiness ($\hat{\delta}_1$), sadness ($\hat{\delta}_2$), and surprise ($\hat{\delta}_6$) are significant and negative. They moderate price elasticity: $\eta_k = \frac{\partial \text{Ln(Q)}}{\partial \text{Ln(P)}} = \beta_1 + \delta_k z_k P$. Substituting $\hat{\delta}_1 = -.009$ for happiness from Table 4 and the average price of \$110.48 from Table 2, we get price elasticity $\eta_1 = -.77 - .99z_1$, which means viewers become more price sensitive as the intensity of sellers' happiness increases. Why? Because the buyers suspect that the seller is gaining at their expense (Van Kleef et al. 2010), and they exhibit "move against" tendencies (see Table 1). The qualitatively similar results hold for sadness and surprise. These interaction effects generalize our previous findings: emotional displays are bad for business.

Marketing mix effectiveness in the presence of emotions. According to the log-linear specification, the estimated coefficient of .386 (see Model 2 in Table 3) means that, ceteris paribus, a product from category 1 sells 1.47 (= Exp(.386)) times more than a product from category 2. The estimated price elasticity equals –.765 (see Model 2 in Table 3), which means a 10% increase in price corresponds to a 7.65% decrease in sales. Similarly, the estimated display duration elasticity equals .626 (see Model 2 in Table 3), which means a 10% increase in display duration corresponds to a 6.26% increase in sales, which is about 2 to 6 times larger than advertising elasticity (see Sethuraman, Tellis, and Briesch 2011). The free shipping increases the quantity sold by .198% (see Model 2 in Table 3). Using the average price of \$110.48 and the average quantity of 69.64 (see Table 2), the shipping waiver increases revenues by \$15.23 $\left(= \$110.48 \times \frac{.198}{100} \times 69.64\right)$ and is profitable when the shipping costs are below \$16.

Ranking salespeople. Human biases affect the performance appraisal process (e.g., pay, bonus, advancement rate, prestige). We propose that to mitigate these biases, salespeople should be ranked on their individual effectiveness (objective attribution) rather than average sales (naïve attribution). Model 1 facilitates the estimation of the effectiveness of an individual salesperson by controlling for prices, duration, free shipping, time of day, and week. Table 3 reports the estimates of percentage sales increase for an individual salesperson relative to the group average based on effects coding of the dummy variables (see Hardy 1993). Consider the estimate of –.488 for salesperson 1 from Model 1 in Table 3. That estimate means salesperson 1's performance is .488% below the group average. Similarly, salesperson 6's performance is .083% above the group average. These estimated effects are not affected by human cognitive biases.

We compare the salesperson's performance rank based on the naïve versus objective attributions. Panel A in Figure 5 shows the ranking of 23 salespeople based on the average sales, which ignores the effects of prices, duration, free shipping, and time of day and week. In contrast, Panel B shows the ranking of the same 23 salespeople based on their individual effectiveness. The top and the bottom three salespeople remain the same under both metrics, thereby showing that the ranking attains convergent validity by identifying the same set of best and worst performers. However, the majority of salespeople (~75%) reside in the middle, where the rank ordering differs across metrics. Thus, the objective attribution based on salesperson's effectiveness after controlling for prices, duration, free shipping, and time of day and week should guide supervisors in more objectively selecting salespeople for rewards, recognition, and retraining.

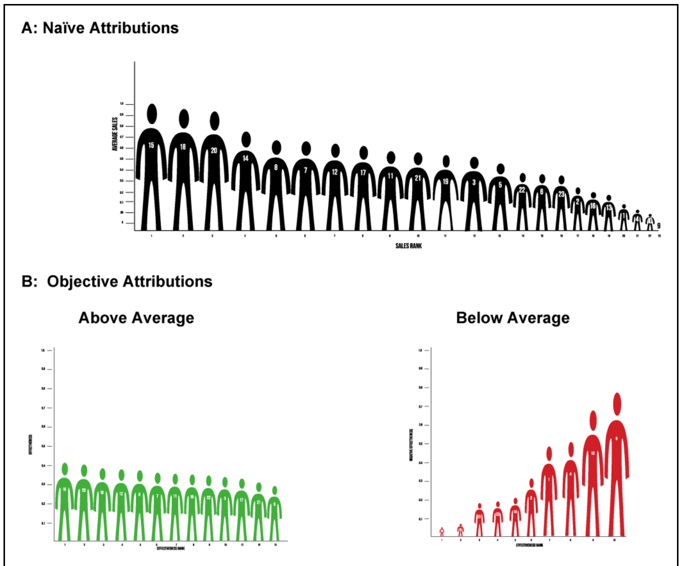

Figure 5. Salesperson performance appraisal.

Understanding moderation effects. Figures 6 and 7 depict the sales impact of emotional displays based on the full model (Model 4). In these figures, a low (high) price refers to the 25th (75th) percentile of the price distribution. First, emotional displays decrease sales. This finding holds uniformly for negative and positive emotions. Because Ln(Q) serves as the dependent variable, the marginal change in it equals $\Delta Q / Q$, which represents "percentage change in sales." Thus, a marginal increase in emotional display corresponds to a sales decline that ranges from .004% to .18%. Across the six emotions, the magnitude of the total sales decline (.47%) is more than double the free-shipping effect (.20%). Second, because the tangent to the curves in Figures 6 and 7 becomes steeper as the intensity of emotional display increases, the sales decline *accelerates*. In other words, the sales decline increases at an increasing rate. Thus, not displaying emotions emerges as the optimal course of action. So, salespeople should sell with a neutral face, although how consumers interpret "neutral" depends on the sellers' gender, facial morphology, and contextual factors (e.g., Hareli, Shomrat, and Hess 2009). Finally, the parallel curves in Figures 6 and 7 reveal the modest magnitude of moderation effects: sales decrease as price increases or promotion decreases (see the dashed curves).

Time effects. In the week effect, sine and cosine variables jointly identify the sales variations across days of the week. The cosine variable differentiates the first half of the week (Monday to noon Thursday) from the second half of the week (noon Thursday to Sunday). The sine variable differentiates the middle of the week (9 p.m. Tuesday to 9 p.m. Friday) from the end of the week (9 p.m. Friday to 9 a.m. Tuesday). Similarly, in the day effect, the sine and cosine variables identify the sales variations across hours of the day. Specifically, the cosine variable differentiates post meridiem (p.m.) from ante meridiem (a.m.), while the sine variable captures the rhythms across the late evening (6 p.m. to midnight) through the night hours (midnight to 6 a.m.) to the morning hours (6 a.m. to noon) and the afternoon (noon to 6 p.m.). Because the empirical results indicate that the cosine variable is less important than the sine variable, the a.m./p.m. distinction is not critical. As expected, sales occur 24 hours a day, including the nights; peak during the day; and are larger during the weekends.

Relative variable importance. Figure 8 presents the relative contribution of marketing mix and nonmarketing variables: the

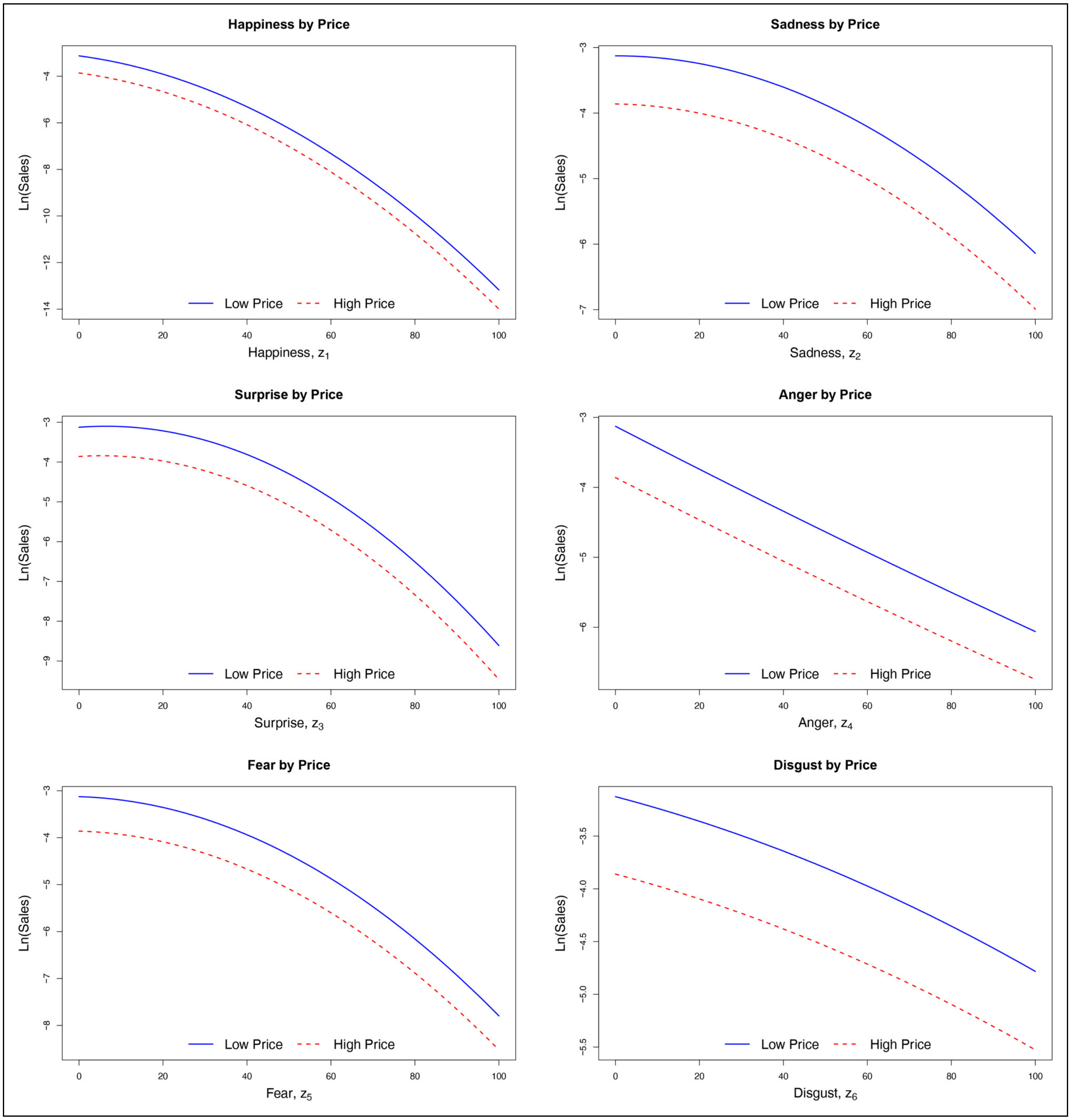

Figure 6. Emotional displays by price interactions.

former contributes 71%, whereas the latter accounts for 29% of the total $R^2 = 80\%$. The time of day, the day of the week, and the week of the year explain 20%. Emotional displays and face presence further explain 9% of the explained variance. Thus, nonmarketing variables boost explanatory power.

Robustness checks

Parameter stability. A glance across the columns in Table 3 indicates a remarkable robustness. The columns reveal the estimated marketing mix effects in the presence of various operationalizations of emotional displays. For example, across Models 1–4 the price elasticity varies from –.76 to –.77, and the duration elasticity ranges from .55 to .67. Likewise, shipping and product estimates are (.22, .41), (.20, .39), (.19, .36), and (.19, .36) across Models 1–4, respectively. Salesforce effectiveness across the four models is also stable; for example, the percentage sales increase due to salesperson 15 hovers around .42. Even the rhythms of daily and weekly sales deviate only marginally. These results hold even when we replaced the static face variable F_{is} in Equation 3 with the dynamic component $z_{0,is} = \sum_{t=1}^{30} \hat{e}_{0t} F_{is,t}$

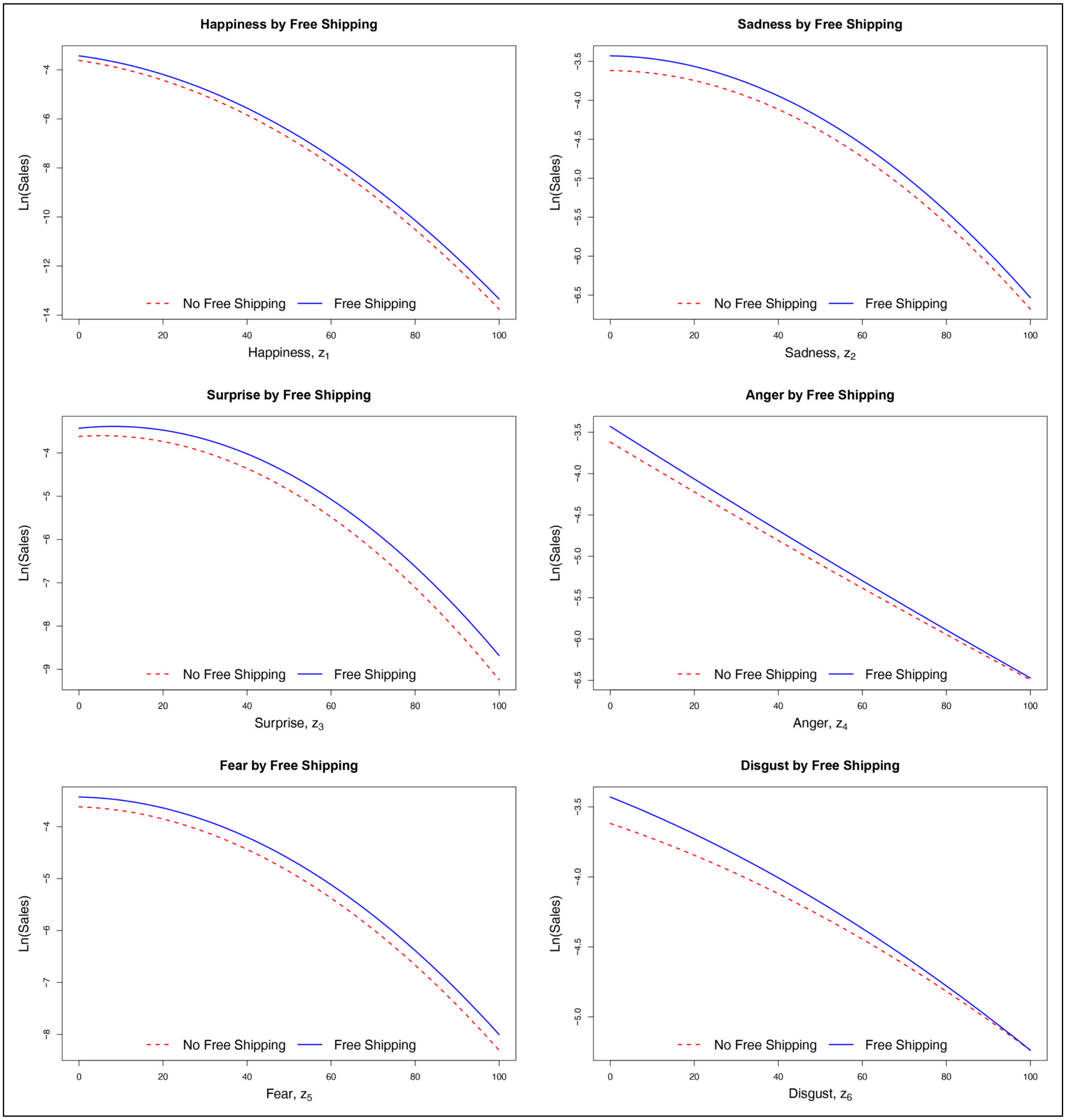

Figure 7. Emotional display by free shipping interactions.

across the epochs $t = 1, \cdots, 30$. Furthermore, we tested for heterogeneous effects of emotional displays and found that the effects were homogeneous across the two product categories (see Figures 6 and 7). Thus, the broad robustness —for all the variables and across all the models— enhances confidence in these results.

Tercile analysis. We also analyzed data by splitting the presentation span of an item i displayed in a show s into three time segments. We discovered V-shaped effects across the beginning, middle, and end of the presentation span for all the six emotions, including happiness. We then extended this analysis tenfold to 30 epochs and found that not only does the parameter stability hold in both analyses, but also qualitatively similar results persist: negative U-shaped effects of emotions over the presentation span. Furthermore, the average variance inflation factor across all independent variables was 1.66, ranging from 1.01 to 5.17, which is far below 10 and thus rules out multicollinearity concerns.

Dynamic time warping. To our knowledge, this study marks the first time dynamic time warping appears in marketing. To

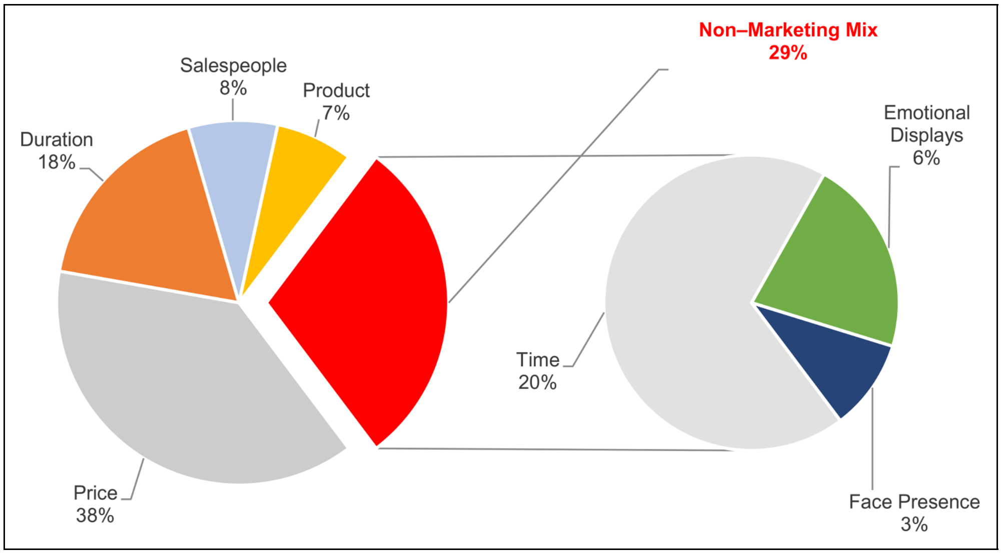

Figure 8. Variable importance.

Table 5. Models Comparison.

R^2	Model 1 79.10%	Model 2 79.7%	Model 3 80.0%	Model 4 80.0%
Log Likelihood	−110,560	−108,447	−107,472	−107,456
AIC	221,184	216,972	215,036	215,027
BIC	221,488	217,343	215,473	215,579
Fixed Parameters	32	39	46	58
Observations	99,451	99,451	99,451	99,451

further assess robustness, we reestimated Model 2 without dynamic time warping. As mentioned previously, dynamic time warping aligns landmarks such as the peaks, valleys, and inflections of the raw emotional curves $E_{is}^k(t)$. Such landmark alignment homogenizes the timing of peaks, valleys, and inflections in $E_{is}^k(t)$. Consequently, the estimated trajectories, $\hat{a}_{kt}$, in Figure 3 are smoother than those in Figure 4 without landmark alignments. More importantly, the overall pattern remains the same: the sales impact $\hat{a}_{kt}$ is negative, U-shaped, and similar across the six emotions. In summary, the U-shaped patterns as well as other results are robust. We close this section by comparing the performance of models on multiple metrics.

Model comparison. Which one of the four models is the best? Although the adjusted R^2 of about 80% is remarkable, especially given 99,451 sales pitches, it does not discriminate among the four models as the log-likelihood, Akaike information criterion, and Bayesian information criterion do. Therefore, we compared the models using these metrics and present the results in Table 5. Specifically, Models 3 and 4 dominate Models 1 and 2 on all the metrics. The Bayesian information criterion selects Model 3, whereas both the other metrics (log-likelihood and Akaike information criterion) indicate that Model 4 outperforms the rest. We used Model 4 to plot Figures 6 and 7. We next discuss the implications of these findings.

Discussion

This research offers important insights into livestream retailing by addressing two foundational questions identified in this special issue dedicated to understanding the interface of technology and marketing: (1) How can managers use new types of data to improve marketing decision making? and (2) What new methods can deliver the best consumer insights to improve marketing strategy? To address the first question, the second pennant in Figure 1 captures the new type of data available from streaming videos of sales presentations, which can identify a large-scale, unobtrusive, and comprehensive set of emotions. To address the second question, the fourth pennant in Figure 1 contributes the new methods to create six emotional trajectories via functional principal components analysis and dynamic time warping to align them. Incorporating them as quadratic and moderating variables, we then assess the value of emotional displays. Building on Models 1–4, we discuss the following theoretical and managerial contributions.

Theoretical Contributions

Livestreaming technology opportunities in marketing. Livestream e-commerce, which features hosts promoting and selling goods and services in real time via screen-mediated sales presentations, represents an emerging opportunity for marketers to create, deliver, and communicate content so as to monetize in ways not possible previously. Specifically, marketers can, first, reach customers via new channels such as social messaging apps (Facebook, WeChat), livestreaming services (e.g., Twitch), and internet platforms (e.g., Taobao Live) that integrate shopping and entertainment. Second, these technology platforms facilitate purchases from wherever and whenever customers are seeking to buy. Third, they shorten the purchase funnel by demonstrating a product and describing why it is a must-have item; conveying that only limited quantities are available; counting down the time remaining on the item before the next item is to be introduced; and injecting such calls to action as "grab it before its gone." Finally, technology allows value capture in formats not possible previously: noncash payments (e.g., PayPal, Venmo), installment payments (e.g., Klarna unsecured loans), and barter payments (e.g., BarterOnly.com, which provides exchanges of used products). Marketers need to imagine how they can integrate such value creation and value capture opportunities made possible by technological advances.

Large-scale unobtrusive emotions data. Earlier studies used human intervention to collect data on emotional displays at a small scale (e.g., Brown and Sulzer-Azaroff 1994; Lee and Lim 2010; Pugh 2001). In contrast, applying artificial intelligence (see, e.g., Luo et al. 2021; McDuff and Berger 2020), we extract face presence and facial expressions from 62.32 million frames of streaming video sales presentations automatically and unobtrusively, thereby responding to calls to harness machine learning to generate meaning from big data (e.g., Balducci and Marinova 2018; Lam et al. 2017; Oblander et al. 2020; Wedel and Kannan 2016).

Multiple emotions. Earlier studies consider either a single (e.g., Liu et al. 2018; Wang et al. 2017; Wang et al. 2018) or a select few emotions (e.g., Cheshin, Amin, and Van Kleef 2018; Teixeira, Wedel, and Pieters 2012; Van Kleef et al. 2009; Van Kleef, Van den Berg, and Heerdink 2015), potentially resulting in biased estimates due to omitted variables. Hence, Model 2 specifies a comprehensive set of six emotional displays simultaneously. Our focus on salespeople's emotional displays is also responsive to an earlier call to devote greater attention to emotions on the seller side of the exchange dyad (see Bagozzi, Gopinath, and Nyer 1999).

Dynamic effects. Earlier studies focus on static episodic expressions (e.g., Cheshin, Amin, and Van Kleef 2018; Van Kleef, Van den Berg, and Heerdink 2015). Our Model 2 permits capturing the dynamic trajectories of emotions at a more granular level, thereby revealing time-varying patterns of sales impact (see Figure 3). More importantly, the Web Appendix makes original contributions to the theory of inference on the effects of functional principal components.

Optimal emotions. Virtually all studies on emotions have used customer mindset metrics as the dependent variables (e.g., Van Kleef et al. 2009; Wang et al. 2017; Wang et al. 2018). While Liu et al. (2018) use box-office revenues, they specify happiness to monotonically affect sales, ruling out the possibility of that an optimal level of emotions exists. Given the nonmonotonic effects in Models 3 and 4, the theoretical existence of the optimal mix arises. Equation 4 presents the optimal emotions to display so as to maximize sales. These results not only make original contributions to the extant literature but also offer guidance to design technology-inspired service agents (e.g., avatars, virtual news anchors) to be more humanlike (Crivelli and Fridlund 2018; Miao et al. 2022). They also inform the discussion about technology and marketing in that artificial intelligence can be used to monitor the seller's facial activity, provide real-time coaching, and thus assist in training salespeople to improve business outcomes (Grewal et al. 2020; Luo et al. 2021).

Salesperson's impact in screen-mediated exchanges. A marketplace increasingly characterized by greater technological connectivity and interactivity has prompted calls to investigate the business impact of a seller's facial expressions in screen-mediated commercial interactions (Bharadwaj and Shipley 2020). Kidwell et al. (2021), for instance, underscore the need to evaluate whether their results from in-person, face-to-face customer encounters involving "emotionally calibrated" salespeople will hold in digital exchanges. The authors contend that this type of salesperson exhibits calmness and that exuding calmness builds rapport, which in turn drives favorable sales performance outcomes. Our theorizing, which is steeped in EASI's predictions about the inferences that buyers draw about a seller's facial expressions in a competitive exchange (see Table 1), and findings from a one-to-many livestream broadcast setting reaffirm the importance of reducing emotional displays in driving sales effectiveness. We thereby contribute to understanding the communicative role of facial expressions in screen-mediated exchanges and elaborate further in the following section on "selling with a straight face."

Managerial Contributions

Optimal face allocation. How should face presence be allocated over an item's presentation span? Should frames containing a face be displayed uniformly or in chunks? If the latter, should they be concentrated in the middle, when sales resistance is highest? To this end, we evaluate Equation 4 and present the optimal percentage allocation of the total number of frames with a face over an item's presentation span in Figure 9. We observe that the optimal allocation is neither uniformly

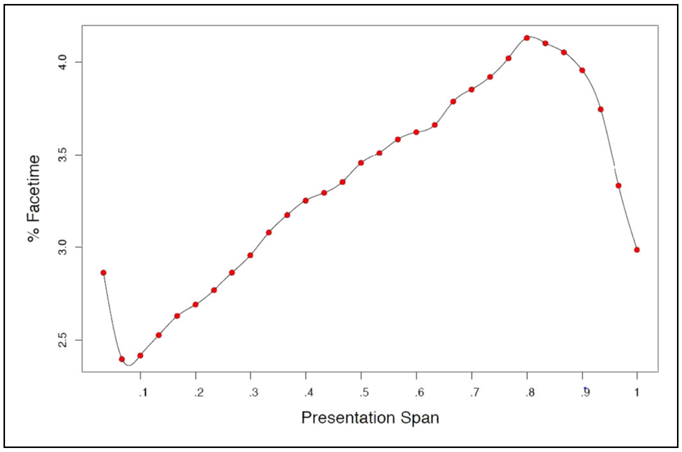

Figure 9. Optimal face allocation.

displayed nor chunked in the middle. Rather, the optimal number of face frames wanes at the start, gradually builds to a crescendo, and eventually ebbs. Specifically, the optimal allocation decreases on the initial 10% span, then gradually increases as the presentation progresses, and finally decreases in the last 15% span. Remarkably, this optimal allocation conforms to the three-part structure of stories: the beginning, the middle, and the end (see McKee 1997).

Sell with a straight face? Figures 6 and 7 uncover the novel and provocative findings that, first, positive emotional displays reduce sales. Second, the greater the intensity, the larger the decline. To mitigate the negative effect, salespeople should consider toning down their facial expressions. To mitigate the quadratic effects of intensity, they can abate their exaggerated expressions. Together, these findings indicate a new maxim: sell with a straight face. Consistent with this maxim, Eicoff (1995, p. 82) advocates that direct marketers should use a "journalist approach" to answer the "who, what, why, when, where of a product. Whom is the product for? What does it do? Why is it beneficial? When can it be used? Where can it be bought?" In other words, livestream salespeople should broadcast their pitch with a stoic expression akin to that of news anchors, though we acknowledge that this implication may not generalize to face-to-face communications in business markets.

Sales resistance curve. Figures 3 and 4 can be interpreted as the sales resistance curve. The maximum sales resistance is near the middle of an item's presentation; the least sales resistance is at the beginning and end of presentations. This U-shaped sales resistance curve provides actionable guidelines to practitioners. Emotional displays at the beginning and end of presentations help engage consumers and build rapport. However, during the livestream show, hosts should monitor the frequency and intensity of their emotional expressions. Because genuine interactions involve less emotional and more neutral expressions, salespeople can make emotional connections with the audience with neutral expressions and lessen the insidious effects of sales resistance. Although hosts cannot completely avoid emotions, they should take advantage of livestreaming platforms to emotionally connect the brands with customers.

People analytics in sales performance appraisal. A naïve assessment of a salesperson's performance is based on the actual quantity sold. However, this quantity depends on factors such as prices, duration, free shipping, and time of day and week. In other words, a salesperson can validly object that another salesperson's larger actual sales are not reflective of his/her performance alone because price, duration, free shipping, and time of day and week also impacted sales. Cognitive biases further compound such performance appraisals. Prominent factors driving cognitive biases include the fundamental attribution error, halo effects, the leniency bias, the recency bias, selective perception, the self-serving bias, and the similarity bias (e.g., Siders, George, and Dharwadkar 2001). Fundamental attribution error refers to supervisors underestimating the influence of external factors and overestimating the influence of internal factors when judging a salesperson's performance; halo effects arise when a general impression of a salesperson overshadows the relevant metrics; leniency bias refers to a supervisor's tendency to rate all salespeople positively (or negatively), reducing the difference between top and bottom performers; recency bias creeps in when recent events (e.g., bumper sales, sharp declines) influence supervisors' judgments; selective perception refers to the supervisor's tendency to notice certain metrics and filter out others; self-serving bias emerges when a salesperson attributes own successes to internal factors and failures to external factors; and similarity bias (i.e., homophily) shapes the evaluation when supervisors reward a salesperson similar to themselves.

Using Table 3, managers can objectively rank salespeople (see Panel C in Figure 5) to circumvent the effects of the aforementioned biases. Indeed, the CEO and senior leadership team of the livestream retailer we examined found our proposed framework valuable to recognize excellence and identify candidates for retraining. Both recognition and training, in turn, help improve future sales performance (Zoltners, Sinha, and Lorimer 2008). Thus, the framework in Figure 1 unlocks the power of data and contributes to sales performance analytics.

Future Research

Content effects. Hu et al.'s (2021) recent study suggests that information content can matter. Specifically, they analyze 275 sales pitches from the Home Shopping Network, manually code the minute-by-minute content on the cumulative sales thus far during an item's presentation span, and show that the intermittent availability of this information increases item sales by .084 units at the onset and decreases linearly to .015 units at the end for a unit increase in the displayed cumulative sales. We encourage future researchers to automate such content analysis to extract and incorporate facial expressions.

Two-way communications. Our empirical study pertains to one-to-many screen-mediated competitive exchanges, and it shows that the salesperson's emotional expressions evoke negative inferences by viewers about the salesperson's intentions. One explanation may be the absence of social interaction. When the salesperson smiles, the viewers may not reciprocate because the salesperson's emotions are not targeted to a specific viewer. Such differences provide the impetus to study screen-mediated face-to-face interactions in the presence of social others. For example, Hamilton et al. (2020) contend that the customer purchase journey involves traveling with *social others*, which necessitates investigations into the various influences that members of the social network can have on buyers' appraisals, intentions, and actions. In a livestream e-commerce setting, the host becomes an important social other. Viewers can readily communicate with the influencer via live chat texts, emojis, voice, and/or video and further enhance their sense of connection with that celebrity (i.e., parasocial relationship).

Does the host's verbal and nonverbal communications influence viewers' behavior in such communal, two-way screen-mediated exchanges? Do purchases by social others induce "fear of missing out"? Rockwater (2020) suggests conversion rates of 30% in livestream shopping versus 3% in traditional marketing. To incorporate such two-way communications in the models, researchers should augment the regressors with the characteristics of not only the items and sellers (as in this study), but also the network of social others and the hosts. We encourage further research to shed light on two-way communications in livestream shopping.

Authentic emotions. Hennig-Thurau et al. (2006) manipulate authenticity (i.e., surface or deep acting) and emotional intensity in simulated service encounters (i.e., actors played the role of employees) with 223 consumers to understand the effects on customer satisfaction, customer–employee rapport, and loyalty intentions. They show that authenticity rather than intensity influences customers' reactions (for similar results, see Wang et al. 2017). We encourage future researchers to design emotion recognition algorithms that can classify facial expressions on the basis of emotional authenticity in addition to intensity.

Conclusion

Previous studies predominantly focus on marketing mix effects on sales because when they were conducted, machine learning technology was not available to detect faces and extract emotions at scale. This study combines machine learning technology and marketing. Specifically, we develop the retail analytics engine (see Figure 1) to unobtrusively collect data on face presence and emotional displays. Applying this technology to livestream retail data, we found that facial expressions, including happiness, adversely impact sales. This counterintuitive and provocative finding suggests that salespeople should sell with a straight face. These negative effects exhibit U-shaped dynamics over an item's presentation span, uniformly across six emotions, revealing that the largest sales resistance occurs during the middle of the presentation. Furthermore, the presence of a face matters because it impacts sales positively; therefore, it should be present more than is currently the case. Yet, its optimal allocation over time should be reduced over the initial 10% span, then gradually increased as the presentation progresses, and subsequently tapered down in the last 15% span. Finally, the retail analytics engine empowers managers to more objectively assess the effectiveness of each individual salesperson (see Figure 5), thereby circumventing cognitive biases in performance appraisals.

This study highlights the importance of monitoring and managing facial expressions. One implication is to train new salespeople. The firm can analyze the video footage, much like sports teams watch films of critical moments in previous games to learn what individual players did well and not so well, and sales coaches can help discern the extent to which they displayed emotions and the proportion of each emotion expressed. The feedback from such debriefing sessions could be used to modify sales pitches. Another implication is to retrain experienced sales professionals. The firm can compare each salesperson with the top performer (see Figure 5) and identify which emotions the salesperson ought to tackle. Happiness is the first one that should be addressed. While previous research advocates "service with a smile," we suggest selling with a straight face. Smiling may be off-putting because it lacks authenticity (Hennig-Thurau et al. 2006), reducing trust in the seller (Cheshin, Amit, and van Kleef 2018). Subsequently, salespeople should address displays of anger, then fear, and other negative emotions. Last, this study has implications for bot marketing. As technology advances, bots will more closely mimic human facial expressions and supersede humans in monitoring and managing facial expressions. Chat bots, like humans, provide voice assistance to customers. Similarly, three-dimensional audiovisual bots, like salespeople, can engage with customers. For example, HSBC Bank in Northern California employs Pepper, a social humanoid robot (Eng 2019). Further technological advances will bestow bots with the ability to express and reciprocate emotions, thereby assisting livestream retailers to nudge prospective customers through the purchase funnel by explaining features and benefits, instilling urgency to buy, and entertaining them along the way.

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