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Persuasion-Induced Physiology Partly Predicts Persuasion Effectiveness

Hanne A. A. Spelt, Chao Zhang, Joyce H. D. M. Westerink, Jaap Ham and Wijnand A. IJsselsteijn

Abstract—Physiological responses to persuasion can help to increase our understanding of persuasive processes, and thereby the effectiveness of persuasive interventions. However, a clear relationship between psychophysiology and persuasion is not yet established. This study investigates if peripheral physiology predicts persuasion effectiveness, and whether peripheral physiology yields information that is not represented in other predictors of persuasion. We studied physiological reactions in the cardiovascular, electrodermal, facial muscle and respiratory systems of 75 participants while they read gain- or loss-framed persuasive messages advocating increased oral health care behavior. Persuasion effectiveness was measured as pre to post intervention changes in self-reported attitudes and intentions, as well as through changes in behavioral compliance over three weeks. Overall, participants showed stronger attitudes and intentions directly after the intervention (short-term persuasion), but did not show changes in behavior or attitudes two weeks later (no long-term persuasion). On an individual level, physiological reactivity parameters yielded additional information – next to self-report measures – to predict persuasion effectiveness on attitude, intention and behavioral compliance. To conclude, our findings suggested a positive relationship between physiological reactivity to persuasive messages and subsequent attitudes, intentions and behavior, and quantified the extra personalization that psychophysiological measures can bring to persuasive messaging.

Index Terms—Affective computing, Personalization, Psychology, Peripheral measures, Modeling human emotion

1 INTRODUCTION

PERSUASION is often used in technologies to promote health-related behaviors, such as physical activity or healthy eating. Traditionally, persuasive technologies use self-report and behavioral measures to predict susceptibility to persuasive messages and evaluate intervention effectiveness. Recently, researchers identified new ways of assessing persuasive processes that might enable new applications, namely using psychophysiology [1]–[5]. It has been established that conscious and unconscious psychological processes can reflect in physiology, e.g. [6], [7]. If persuasive processes indeed also show in physiology, physiological measures might function as an implicit measure of persuasion. In addition, knowledge of physiological responses to persuasive messages might help to increase our understanding of persuasive processes.

Wearable biosensors such as smartwatches enable unobtrusive, continuous and precise physiological measurement in daily life. This enables high temporal resolution and sensitivity to changes in the physiological patterns, as even small changes in arousal level (in response to particular persuasive content presented) can be insightful. Contrary to self-report measures, physiological measurement is not subject to introspection and enables real-time feedback.

If indeed related to persuasion effectiveness, inferences from physiological patterns might also be used to personalize and optimize persuasive messaging. Persuasive technologies can be in constant communication with biosensors. The resulting large amounts of data can be handled by machine-learning algorithms with the goal of improving interventions by physiology-dependent personalization of persuasive content. This would enable calibration to the optimal level of persuasion across individuals, context and time with great sensitivity and without disturbing the user. In this way, affective computing [8] can potentially be used to improve persuasive interventions and improve behavior.

Results from earlier research indeed hint at the presence of a psychophysiological relationship in persuasion [1], [3], [5], [9]–[11], but a firm link has not yet been established. This paper seeks to extend the body of knowledge, and begins by describing (differences in) the processing of persuasive information. Next, we argue why physiology can be a measure of persuasion and discuss earlier psychophysiological persuasion research. It will then go on to describe a study examining reactions of the peripheral nervous system to gain- or loss-framed persuasive messages and relating these reactions to persuasion-induced change in motivational state and behavior.

- *H.A.A. Spelt and J.H.M.D. Westerink are with the Brain, Behavior and Cognition Group, Group Innovation, Philips Research, High Tech Campus 34, 5656AE Eindhoven, The Netherlands. E-mail: {hanne.spelt, joyce.westerink}@philips.com.*
- *H.A.A. Spelt, J.H.M.D. Westerink, J. Ham and W.A. IJsselsteijn are with the Human-Technology Interaction Group, Faculty Industrial Engineering & Innovation Sciences, Eindhoven University of Technology, PO box 513, 5600MB Eindhoven, The Netherlands. E-mail: {j.r.c.ham, w.a.ijsselsteijn}@tue.nl.*
- *C. Zhang was with the Human-Technology Interaction Group at Eindhoven University of technology while doing the work, and is now with the Social Health, and Organizational Psychology Group, Faculty Social and Behavioral Sciences, Utrecht University, PO box 80125, 3584CS Utrecht, The Netherlands. E-mail: c.zhang@uu.nl*

1.1 Individual differences in processing of persuasive messages

Persuasion aims at changing attitudes and behaviors without coercion [12]. These attitudes and behaviors differ per individual because of underlying motivations of behavior, e.g., values, beliefs, and personality characteristics. Consequently, the processing of and susceptibility to a persuasive cue differs per person. Below, we will briefly explain the importance of perceived value of compliance and relevance of persuasive information and discuss two relevant mediators on the general process; *motivational orientation* and *message framing*.

The recipient of a message has greater motivation to elaborate on information that is perceived to be relevant [13], [14]. Persuasive messages aim to change the recipient's perceived value of an action and, thereby, motivate the recipient to perform message-consistent behavior [4], [15]–[17]. Thus, the perceived value of compliance and relevance of a persuasive message determines its effectiveness. Adapting messages in such a way that the recipient feels addressed by them makes elaboration, and thus persuasion, more likely to happen [11], [14], [18].

How valuable someone perceives a new piece of actionable information to be also depends on personality characteristics, and an important one is *motivational orientation* [17], [19]. Motivational orientation concerns how likely a person is to engage in risk-aversive or reward-focused behavior [20]. Two self-regulatory mechanisms control attitudes and behavior [20]: the behavioral approach system (BAS) responds to opportunities and initiates actions towards them (approach), whereas the behavioral inhibition system (BIS) seeks to avoid punishment or losses (avoidance)[20], [21]. Motivational orientation explains how the same message can be valued differently depending on more active BIS or BAS; people with active BIS will focus on the detrimental effects of inaction, whereas people with more active BAS will focus on the gains of action [19].

As a consequence, persuasion can be personalized [22] by adapting the *message framing* to the recipient's motivational orientation. The same factual information can be presented as a potential gain or as a potential loss [19], [21], [23]. In behavior change, gain-framed messages emphasize potential benefits of the behavior adjustment (compliance), whereas loss-framed messages focus on the costs of inaction (non-compliance). People tend to be more focused on persuasive messages in line with their own motivational orientation; aligned messages are likely to be closer to current goals, attitudes, and intentions, which promotes compliance and facilitates persuasion [19]. As such, loss framing is expected to be more effective for individuals with more active BIS, whereas gain framing for individuals with more active BAS, and matching persuasive messages to subjective valuation of potential consequences is key to successful influence.

In the next section we will argue that our understanding of these persuasive processes can be improved by considering physiological responses [24], and that physiology might therefore also be used to strengthen the described traditional personalization methods based on self-report and behavior measures [22].

1.2 Physiology as measure of persuasion

Research showed that emotions and cognitions have a neurophysiological basis [25], [26] and can influence nervous system activity [7], [27], [28]. The *autonomic nervous system* (ANS) helps the body to facilitate an optimal internal environment for cells, tissue and organs to execute their functions and cope with internal and external demands [27]. Processing a persuasive message could be such a demand. The ANS is divided in a *sympathetic* and *parasympathetic branch* that control organ activity by either increasing (sympathetic) or decreasing (parasympathetic) arousal [27], [29]. ANS activity can easily be measured in features of four subsystems; heart rate and heart rate variability in the cardiovascular system, skin conductance levels and the number of peaks in the electrodermal system, breathing rate in the respiratory system and facial activity in the facial muscle system [24], [29], [30].

Fluctuations in nervous system activity can reveal a psychological state or emotion (see [31] for a full review). Therefore, studying bodily activation during exposure to persuasive messages might help us understand their impact on human psychology. Physiology might also reflect parts of persuasion that are missed or misinterpreted in self-report or behavioral data. Combining physiological with self-report and behavioral measures renders an all-round picture of the active mechanisms during persuasion. It might be easier to pinpoint successful parts of a persuasive strategy in relation to individual differences based on physiological patterns.

Earlier research indeed suggests that this link between persuasion and physiology is present to some extent: Physiological patterns in the brain and peripheral nervous system during persuasion differ from rest states [10], [11]. Electrodermal and cardiovascular patterns can reveal effectiveness of narrative persuasion [1], [3], as well as resistance and reactance to persuasive messages [5], [9]. Brain activation during persuasion can predict behavioral compliance to the message [2], [32], [33] in studies about sunscreen use [34], smoking reduction [18], [33], and reduction of sedentary behavior [35].

In a non-persuasion context, research revealed that the cardiovascular system responds to gain- and loss-framing in task challenges; gain-framing led to lower peripheral resistance and higher cardiac output than loss framing [36]. Persuasion studies found more brain activity in gain- versus loss-framed messages and this activity predicted actual behavior [11]. Furthermore, as motivational orientation relies on two distinct neuro-chemical systems, it was found to reflect in electrodermal responding and vertical pupil dilation for BIS and in cardiovascular pre-ejection period, respiratory sinus arrhythmia and eye blink rate for BAS [37], [38]. Interaction effects between message framing and motivational orientation, i.e. personality-message congruency, on peripheral physiology have also been found: BAS sensitivity leads to with higher electrodermal response and lower cardiovascular arousal in response to positive stimuli, whereas BIS activity leads to with higher electrodermal response and lower heart rate during negative stimuli [39].

In sum, new measures of persuasion enable advanced applications. Physiology can expose psychological processes; among others (the interaction between) message framing and a person's motivational orientation. These latter characteristics are also known to influence persuasion effectiveness. Hence, physiology has the potential to be such a new persuasion measure.

1.3 Research goal

Early findings seem to suggest that to some extent peripheral physiology can reflect persuasion processes. However, the precise effect of persuasion on peripheral physiology has not been established, especially when also considering effects of motivational orientation and message framing on physiology and persuasion effectiveness. In addition, most studies do not analyze the long-term persuasion effects on behavior in relation to physiology. Moreover, to date the added value of psychophysiological measurement compared to traditional predictors of persuasion is unclear. Therefore, the first question this study tries to answer is; 1) does peripheral physiology reflect effectiveness of persuasive messages? Whilst answering this question, we will consider potential effects of motivational orientation and message framing on persuasion and physiology. In addition, we have a more generic question; 2) does the assessment of this psychophysiological relation yield information that is not represented in other predictors of persuasion?

To answer these questions, this study intents to link persuasion and peripheral physiological arousal. We build on earlier work on neural indices of persuasion by using a similar experimental set-up with persuasive content framed as either gains or losses [11], but now measuring peripheral physiology, tracking changes in behavior, and controlling for motivational orientation. The persuasive intervention will try to improve oral healthcare routines. As such, long-term persuasion effectiveness will be measured in terms of change in behavioral compliance to the goal, i.e. tooth brushing behavior, over several weeks. Short-term persuasion effectiveness of the intervention is defined as a change from directly before to directly after the invention. Since it is not feasible to measure that change in terms of behavioral compliance, it will be assessed using changes in motivational state, i.e. attitudes and intention. Based on earlier research, we expect that physiology reflects persuasion effectiveness, e.g. changes in motivational state or behavioral compliance will relate to increased physiological arousal. We also expect that these psychophysiological data hold extra information over other predictors of persuasion.

2 METHOD

2.1 Design

This study has a between-subjects repeated measures design in which participants received either loss- or gain-framed persuasive information promoting an optimal oral health routine[1]. The advocated goal focused on frequency, i.e. twice per day, and duration, i.e. two minutes per session, of brushing behavior. The study was reviewed and approved by the Internal Committee on Biomedical Experiments (ICBE) at Philips Research.

2.2 Participants

Seventy-eight healthy people who indicated to manually brush their teeth infrequently and/or less than two minutes per session were included in this study (41 women, 37 men; average age 40 years, SD = 11). At inclusion, the brushing length and frequency targets were not met by 58 and 4 participants respectively, while 16 participants did not meet both targets. Participants were recruited by a professional external recruitment agency with access to a database of active panelists. Panelists living nearby the study site received an email asking for their participation. The agency checked the extent to which willing participants qualified for the study via phone before inclusion. Exclusion criteria were (a history of) cardiovascular diseases, orthodontia, dentures or frequently using an electric toothbrush. Furthermore, participants had to have sufficient Dutch language skills, and be willing to provide informed consent and use a dedicated toothbrush with tracker for at least three weeks.

2.3 Materials

The oral care intervention had several persuasive elements. First, it took place in a professional oral healthcare laboratory at Philips Research to increase ecological validity. The room was equipped with dental-related ornaments such as a dentist chair, informational posters and hygiene accessories (Appendix A). Secondly, the participants were asked to perform a plaque-disclosing test and to verbally reflect on the results of the test. The disclosing solution reveals dental areas with persistent dental plaque with a blue color, whereas newer plaque colors are pink [40]. In front of a mirror, participants were asked if their teeth discolored as expected and how they judged these results. Confronting participants with their oral hygiene increased the relevance and value of the study. Thirdly, participants viewed an informational slideshow with motivational messages discussing why good oral care is beneficial (gain-framed) or why bad oral care is harmful (loss-framed). Both slide decks advocated to optimize oral care by brushing at least twice per day for two minutes per session. The two slideshows had exactly the same factual content, but differed in framing (Appendix C). For example, the gain-framed manipulation started with '*the positive consequences of healthy oral health behavior*', whereas the loss-framed manipulation started with ´*the harmful consequences of unhealthy oral health behavior*'. As a result, both slide decks had 14 slides with a similar number of words and lasted for six minutes, or longer depending on the participants' reading speed.

[1] As the effects of message framing on physiology or persuasion effectiveness were not the main objective of the study, this study did not include a neutral-framed slideshow as control. Providing neutral-framed educational information can be persuasive in itself [63, Ch. 1]. A truly 'neutral activity' would therefore be a presentation on a topic entirely different from oral healthcare. In our study, this is a nature video preceding the intervention.

2.4 Measurements

2.4.1 Self-report measures

Demographic questions included age, gender, and education. Questions to assess participants' behavioral motivations were adapted from the theory of planned behavior [15]: The advocated goal considered clear target, action, context and time elements, and was defined as '*optimizing oral care by brushing at least twice per day for two minutes per session in the forthcoming week*'. Participants' view on this optimal oral health routine was assessed using questions about:

- *Instrumental attitude* towards this behavior using five items focusing on satisfaction in instrumental nature, e.g. useless – useful.
- *Experiential or affective attitude* towards this behavior using two items focusing on the experiential quality of the behavior, e.g. unpleasant-pleasant.
- *Intention* to perform this behavior using six items questioning whether the participant intended to perform the optimal health care routine, even in not optimal circumstances.

These items were presented as 7-point Likert scales ranging from '*strong disagreement*' to '*strong agreement*' with counterbalanced positive and negative endpoints.

In addition, participants' *motivational orientation*, i.e. tendencies to avoid punishment or approach reward, was measured using a validated Dutch version of the BIS/BAS scales [41]. The instrument consists of one inhibitory factor (BIS scale; 7 items) and three activation factors (BAS scales; 13 items). The BAS scales can be subdivided into drive (BAS_{drive}; 4 items), reward responsiveness (BAS_{reward}; 5 items) and fun seeking (BAS_{fun}; 4 items). The items were presented as 4-point Likert scales ranging from '*strong disagreement*' to '*strong agreement*' [20]. All questionnaires[2] in this study were presented in Dutch.

2.4.2 Behavior measures

An Axivity AX3 data logger attached to the lower-end of a manual toothbrush logged oral health behavior [42]. The Axivity AX3 contained a 3-axis accelerometer, could record for >21 days with a 50 Hz frequency and was waterproof [43], [44]. Sensitivity range for accelerations was set at 8g.

2.4.3 Physiological measures

A 10-channel NeXus with a sampling frequency of 1029.5 Hz measured physiology during the presentation of the persuasive messages and completion of the survey. Three sticky Kendal H124SG electrodes in Lead II placement were attached with wires to the NeXus for cardiovascular measurement (ECG), two dry electrodes on the thenar eminences of the non-dominant hand for electrodermal measurement (EDA) [45, p. 265], a piezoelectric belt transducer around the higher abdomen for measuring respiration, and four reusable Ag/Cl surface electrodes with disposable adhesives attached to the skin on the corrugator supercillii (EMG-CS) and the zygomaticus major (EMG-ZM) for facial electromyography [30].

2.5 Procedure

The experimental procedure included two visits to the experiment site, i.e. the intake and the laboratory session, and lasted three weeks, i.e. a control week and two monitor weeks (Fig. 1). During the *intake*, participants received general information about the experiment[3] and had the opportunity to ask questions before signing the consent forms. Participants were instructed to use a manual toothbrush with an AX3-tracker attached for at least three weeks. A survey captured demographic information, motivational state, and motivational orientation. Throughout the *control week,* participants were to perform their brushing behavior as usual to obtain a baseline measurement of brushing behavior.

Participants visited the oral health care laboratory for the *laboratory session*. Participants were instructed to refrain from caffeinated drinks in the two hours preceding the visit. The session had five segments; a pre survey, a tooth plaque-disclosing test, a baseline measurement of physiological state in rest, exposure to the slide deck with loss- or gain-framed persuasive information, and a post survey (Fig. 1). Both *pre* and *post surveys* assessed attitude and intentions towards tooth brushing. The *plaque-disclosing test* intended to increase participants' engagement to the intervention. The participants dripped 3-4 drops of solution in their mouth and swished it around for 30 seconds before spitting it out. The participants were given a mirror to review the discoloring of their teeth. After brushing their teeth, participants were attached to physiological recording sensors and seated in a dentist chair facing a TV-screen (Appendix A). Physiology was measured during the baseline video, motivational messages and post survey. Physiology in rest was measured during a 6-minute relaxing bird-wildlife video with classical music (*baseline video*). Next, the presentation with the *gain- or loss-framed motivational messages* appeared on screen. A python script assigned the participant to the gain- or loss framed condition

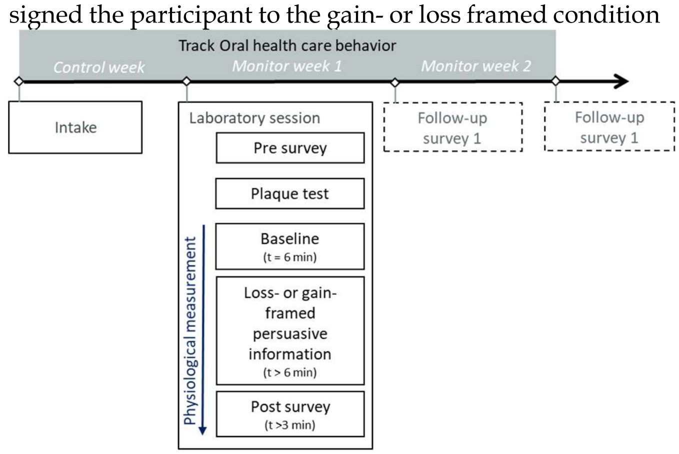

Fig. 1. Experimental procedure lasting three weeks with tracking of tooth brushing behavior, weekly surveys assessing motivational state and a persuasive intervention after one week.

[2] Other measures administered were trait self-control, behavioral automaticity, and self-reported past behaviors, but these are reported elsewhere [42].

[3] Participants were informed that the experiment was about oral health care, but not about the main goal of the intervention, i.e. persuasion towards an optimal oral health routine measured in physiology.

at random.

In the two consecutive *monitor weeks*, participants' brushing behaviors were again tracked continuously, while self-reported attitude and intention towards brushing was assessed weekly (*follow-up survey 1 and 2*). At the end of the three weeks, participants received a debriefing e-mail. They were thanked for their participation and reminded to send back the AX3-trackers using a prepaid envelope. Reimbursement was paid via the recruitment agency.

2.6 Analysis

2.6.1 Preprocessing of the self-report and behavioral data

All questionnaires in this study were validated in previous research and analyzed as instructed [15], [41]. Outliers in the distribution of the parameters were detected using Mahalanobis distances [46] and removed if necessary. The items about attitudes and intention had acceptable psychometric qualities (see Cronbach's α in Table 1). Short-term persuasion, i.e. the change in intention and attitude caused by the persuasive messages, was calculated by subtracting the scores before the persuasive messages from the scores after.

Pre-processing methods of the raw 3-axis accelerometer data to behavior data are described elsewhere [42]. Brushing compliance rate was calculated at week and day-level by dividing total duration of brushing per day by the advocated duration per day, e.g. day duration in seconds / 240 seconds. Long-term persuasion was calculated by subtracting the average compliance rate in week one from the average compliance rate in week three.

2.6.2 Preprocessing of the physiological data

First, the signal quality was enhanced by eliminating artifacts or outliers; a 50 Hz notch filter was applied to all signals. After a manual check of the R-peaks in the ECG signal using EDFBrowser [47], the inter-beat intervals (IBIs) were derived. IBIs outside 0.2-2s were checked and interpolated if the values seemed an artifact [24]. Both EMG signals were band pass filtered within a 20-500 Hz frequency range, followed by a third order 20 Hz high-pass Butterworth filter and signal rectification [30]. The EDA signal was converted from a resistance to a conductance signal and down sampled to 5 Hz. A third order low-pass Butterworth filter was applied to the log-transformed conductance as well as to the respiratory signal [24], [48].

Parameter extraction was performed for three experiment segments – baseline, persuasive messages, and post survey – that differed in length depending on the participant. The physiological parameters of interest were calculated using the first 6 minutes of the baseline and persuasive messages, and the first 3 minutes of the post-survey. The extracted physiological parameters were mean heart rate (HR), standard-deviation from normal-to-normal peaks (SDNN) and root mean square of successive differences (RMSSD) from filtered IBI data [49], mean EMG-CS, mean EMG-ZM [30], mean skin conductance level (SCL), mean number of skin conductance responses (SCRs) [48], and mean respiration rate (RR). For SCRs and RR extraction, peaks were determined by a change of the first derivative of the physiological signal from a positive to negative sign. Outliers in the distribution of the parameters were detected using the Mahalanobis distances [46]. The difference in arousal between rest-state (baseline) and exposure to the persuasive information served as measure of reactivity.

2.6.3 Statistical analyses

The effect of the intervention on attitude, intention and behavior compliance was checked using multiple paired-sample left-tailed t-tests ($H_{pre} < H_{post}$). Short-term persuasion was investigated by comparing instrumental and affective attitudes as well as intention measured before and after the persuasive messages in the laboratory test. Long-term change was assessed by comparing the average behavior compliance in the first week with the compliance in the last week (week 1 vs. week 3). For each physiological reactivity parameter, a t-test ($H_{\text{reactivity to messages}} > 0$) showed if participants had more activity during either condition compared to baseline.

As main analysis, the best predictors of short- and long-term persuasion were established by evaluating several candidate models. We considered the change in behavioral compliance as the best measure of long-term persuasion. We investigated short-term persuasion by assessing the change in attitudes and intention from directly before to directly after the intervention.

We defined three clusters of variables that could possibly predict persuasion; 1) physiological reactivity during presentation of the persuasive messages (HR, SDNN, SCL, SCRs, EMG-CS, EMG-ZM, and RR), 2) personal characteristics including demographic information (age, gender, and education), motivational orientation (the BIS/BAS scores), and (interactions with) condition (gain- or loss-framing), and 3) motivational states (initial intention, initial affective and instrumental attitude). To rule out multicollinearity, we required that the predictors used had appropriate variance inflation factors (VIFs < 2.5, Appendix B), which led to the exclusion of RMSSD. For each cluster, the predictor model with the best fit was found by starting with a simple model and comparing it to increasingly more complex fits using AIC weights [50]. For each possible combination of clusters, e.g. physiological reactivity and states, this iterative model building process was also carried out. In combination models, all variables were considered, also the ones that did not appear to be significant in a single cluster model. Only significant models will be presented and only including those variables that improved predictive power of the model by explaining extra variance in the outcome measure based on AIC weights [50].

For each variable modelled, the best fit models were compared between clusters and cluster combinations looking for the largest AIC weights and lowest AIC [50]. This evaluation reveals not only the best fit, but also which cluster of variables predicts persuasion best and what the added value of each cluster in the prediction of persuasion is. Analyses were carried out in R Studio using *Psych* [46], *Tidyverse* [51], and *lme4* [52].

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3 Results

3.1 Descriptive results

The final dataset included self-report, behavioral and physiological data for 36 participants in the gain-framed condition and 39 participants in the loss-framed condition. Three datasets had to be excluded due to incompleteness. There were no significant differences between the two groups with respect to demographics (age, gender, and education), previous brushing behavior, motivational orientation (BIS, BAS) or starting attitudes and intentions (Table 1). Both groups started the procedure with relatively positive attitudes towards and strong intentions to perform an optimal oral health care routine. The participants scored relatively high on all subscales of the motivational orientation measures. Attitudes, intention, BIS and the BAS subscales could not achieve normal distribution using simple data transformations, e.g. Log, Tukey's ladder of Power, Square or Cube root. BAS_{fun} was excluded from the analyses due to insufficient reliability (a = 0.42). Other self-report scales had sufficient reliability (a > 0.7).

3.2 Overview of the dependent variables

For short-term persuasion, multiple paired sample left-tailed Wilcoxon signed-rank tests showed a significant increase in intention (Z = 124, p < 0.001), instrumental (Z = 97, p < 0.001), and affective attitude (Z = 184, p < 0.001) from before to after the persuasive intervention (Fig. 2). This increase persisted over time for instrumental attitude (Z = 371.5, p < 0.001), and intention (Z = 1001, p = 0.040). For long-term persuasion, behavior compliance rate did not significantly change during the course of this experiment. Multiple Wilcoxon signed-rank one-sample t-tests revealed that physiological reactivity during the persuasive messages was significantly different from zero (baseline) for HR (Z = 1932, p = 0.004), EMG-CS (Z = 2805, p < 0.001), SCRs (Z = 2234, p < 0.001), and RR (Z = 2458, p < 0.001). There was no difference between conditions (Fig. 3).

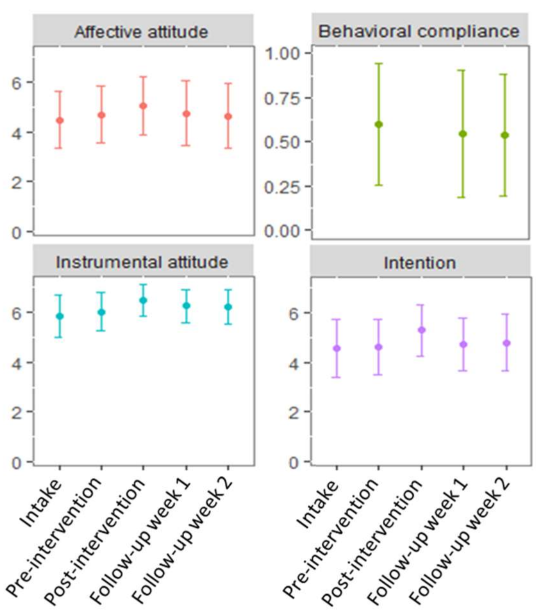

Fig. 2. Average self-reported motivational state and measured behavioral compliance over the course of the study with error bars representing standard errors of the mean.

TABLE 1
Descriptive statistics at intake

Persuasive messages	Gain condition	Loss condition		
N	36	39		
Gender (males)	17 (47.2%)	18 (46.2%)		
	Mean (SD)	*Mean (SD)*	*p-value*	*α*
Age	39.78 (11.01)	39.50 (11.04)	0.904	-
Instrumental attitude	5.80 (0.87)	5.93 (0.81)	0.526	0.93
Affective attitude	4.59 (1.10)	4.41 (1.20)	0.493	0.72
Intention	4.75 (1.14)	4.38 (1.17)	0.158	0.86
BIS	2.84 (0.59)	2.88 (0.54)	0.609	0.79
BAS_{drive}	2.73 (0.65)	2.89 (0.59)	0.348	0.80
BAS_{fun}	2.69 (0.48)	2.78 (0.50)	0.452	0.42
BAS_{reward}	3.47 (0.38)	3.49 (0.35)	0.634	0.71

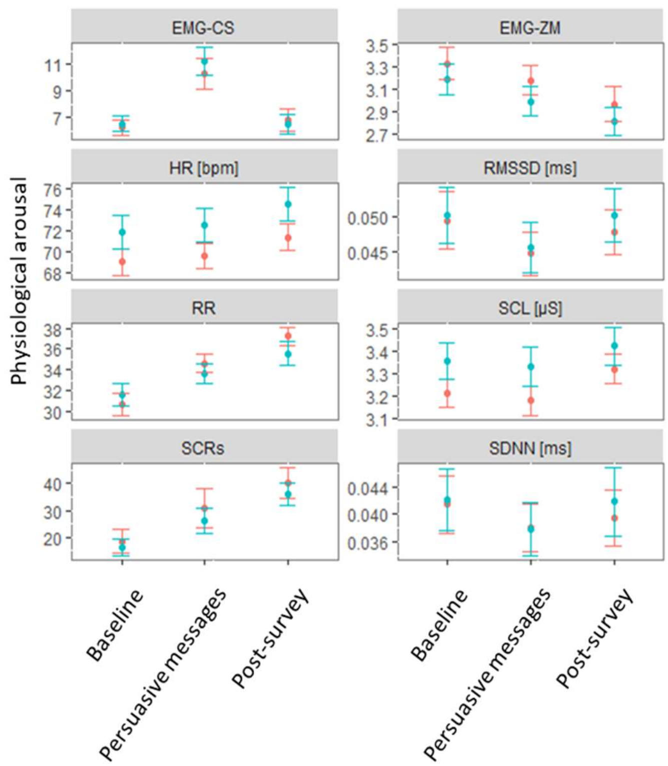

Fig. 3. Average physiological arousal during experiment segments in the gain-framed (red) and loss-framed (blue) condition with error bars representing standard errors of the mean. Baseline and persuasive messages lasted six minutes, whereas the survey lasted three minutes. Activity to persuasive messages was significantly different from baseline for HR, EMG-CS, SCRs and RR.

3.3 Model evaluation

First discussed are the short-term effects on motivational state (sections 3.3.1-3.3.3), then the long-term impact on behavior (section 3.3.4).

3.3.1 Instrumental attitude

Personal characteristics did not predict persuasion effects on instrumental attitude, and neither did the condition (manipulation). There were four potential models to predict the short-term change in instrumental attitude; a null

TABLE 2
RESULTS OF FOUR LINEAR MODELS PREDICTING SHORT-TERM CHANGE IN INSTRUMENTAL ATTITUDE DUE TO PERSUASIVE MESSAGES

	Null model		**Reactivity model**		**State model**		**Full model ***	
Predictors	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*
(Intercept)	0.46	**<0.001**	0.35	**<0.001**	1.34	**<0.001**	1.17	**<0.001**
HR reactivity			-0.07	0.051				
EMG-CS reactivity			0.04	**0.017**			0.03	**0.025**
Initial intention					-0.19	**0.003**	-0.18	**0.003**
Obs.	75		75		75		75	
R^2 / adj. R^2	0.000 / 0.000		0.115 / 0.091		0.118 / 0.106		0.177 / 0.154	
AIC	140.585		135.385		133.195		129.949	
AIC weights	0.005		0.051		0.171		0.773	

*Note: Est. = Estimated change in outcome variable, p = p-value (presented in bold if significant), R^2 = r-squared statistics, AIC = Akaike Information Criterion, * = indicating best fit*

model, a physiological reactivity model, a motivational state model and a full model, which was essentially a combination of the reactivity and state model (Table 2). All models had a significant positive intercept, indicating an increase in instrumental attitude. The predictors in the full model provided the best fit, followed by the state and reactivity models, respectively. The reactivity model revealed that an increase in instrumental attitude relates to increased EMG-CS reactivity and lowered HR-reactivity during persuasive messages. The state model revealed that stronger initial intention leads to less change in instrumental attitude. The full model had an adjusted R^2 of 0.154 and contained EMG-CS reactivity and initial intention as predictors. More EMG-CS reactivity during the persuasive messages predicted an increase in instrumental attitude change. Participants with a stronger initial intention demonstrated a smaller change in instrumental attitude.

3.3.2 Affective attitude

None of the predictor clusters significantly explained the short-term change in affective attitude caused by the experiment (Table 3). The null model reveals an increase in affective attitude due to the persuasive messages. The full model with an adjusted R^2 of 0.055 had the best fit and reveals an effect of manipulation; loss-framed messages lead to a 0.38 smaller change in affective attitude than gain-framed messages.

TABLE 3
RESULTS OF TWO LINEAR MODELS PREDICTING SHORT-TERM CHANGE IN AFFECTIVE ATTITUDE DUE TO PERSUASIVE MESSAGES

	Null model		**Full model***	
Predictors	*Est.*	*p*	*Est.*	*p*
(Intercept)	0.39	**<0.001**	0.58	**<0.001**
Loss condition			-0.38	**0.025**
Observations	75		75	
R^2 / adjusted R^2	0.000 / 0.000		0.067 / 0.055	
AIC	169.294		166.069	
AIC weights	0.180		0.820	

*Note: Est. = Estimated change in outcome variable, p = p-value (presented in bold if significant), R^2 = r-squared statistics, AIC = Akaike Information Criterion, * = indicating best fit*

3.3.3 Intention

There were no state variables that proved to explain (extra) variance in short-term intention change. Four models were qualified to predict the short-term change in intention; a null model, a physiological reactivity model, a personal characteristics model and a full model (Table 4). In all models, the intercept revealed an increase in intention caused by the persuasive messages. Adding HR-reactivity improved model fit; participants had a 0.10 smaller change in intention for each bpm rise in HR. The characteristics model revealed a main effect of manipulation, e.g. loss-

TABLE 4
RESULTS OF FOUR LINEAR MODELS PREDICTING SHORT-TERM CHANGE IN INTENTION DUE TO PERSUASIVE MESSAGES

	Null model		**Reactivity model**		**Characteristics model**		**Full model ***	
Predictors	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*
(Intercept)	0.69	**<0.001**	0.75	**<0.001**	0.51	**<0.001**	0.56	**<0.001**
HR reactivity			-0.10	**0.030**			-0.10	**0.024**
Loss condition					0.40	**0.021**	0.41	**0.015**
BAS_{drive} (centered)					0.28	0.142	0.27	0.149
Interaction loss condition and BAS_{drive}					-0.65	**0.019**	-0.62	**0.021**
Observations	75		75		75		75	
R^2 / adjusted R^2	0.000 / 0.000		0.063 / 0.050		0.137 / 0.101		0.198 / 0.152	
AIC	173.951		171.108		168.871		165.391	
AIC weights	0.018		0.068		0.159		0.755	

*Note: Est. = Estimated change in outcome variable, p = p-value (presented in bold if significant), R^2 = r-squared statistics, AIC = Akaike Information Criterion, * = indicating best fit*

TABLE 5
RESULTS OF FIVE LINEAR MODELS PREDICTING CHANGE IN BEHAVIORAL COMPLIANCE DUE TO PERSUASIVE MESSAGES

	Null model		**Reactivity model**		**Characteristics model**		**Reactivity & Characteristics model**		**Full model ***	
Predictors	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*	*Est.*	*p*
(Intercept)	-0.07	**0.005**	-0.06	**0.017**	-0.22	**0.024**	-0.06	**0.014**	-0.24	**0.006**
SCL reactivity			0.52	**0.006**			0.56	**0.003**	0.61	**0.001**
EMG-ZM reactivity			-0.10	**0.003**			-0.10	**0.003**	-0.10	**0.003**
HR reactivity			-0.02	0.100			-0.02	0.082	-0.02	0.069
BAS_{reward} (centered)					0.15	**0.036**	0.13	**0.038**		
Age					0.00	0.119				
Education									0.05	**0.031**
Observations.	68		68		68		68		68	
R^2 / adjusted R^2	0.000 / 0.000		0.221 / 0.184		0.080 / 0.052		0.273 / 0.227		0.277 / 0.231	
AIC	-22.013		-32.988		-23.686		-35.678		-36.040	
AIC weights	<0.001		0.127		0.001		0.396		0.474	

*Note: Est. = Estimated change in outcome variable, p = p-value (presented in bold if significant), R^2 = r-squared statistics, AIC = Akaike Information Criterion, * = indicating best fit, BAS_{reward} = BAS reward responsiveness*

framed persuasive messages lead to 0.40 more change in intention, and an interaction between the manipulation and BAS_{drive}. The full model with an adjusted R^2 of 0.152 had the best fit and combines the physiological reactivity and the characteristics model.

3.3.4 Behavioral compliance

Five models qualified to predict long-term change in behavioral compliance, i.e. week 3 minus week 1. From least until best fit, these models were; a null model, a personal characteristics model, a physiological reactivity model, a physiological reactivity plus personal characteristics model, and a full model (Table 5). The significant negative intercepts revealed that on average behavioral compliance decreased over time. Reactivity parameters revealed an increase in compliance of 0.52 for each unit rise in SCL, while each unit rise in EMG-ZM reactivity decreased compliance by 0.10. According to the characteristics model, more active BAS_{reward} increased compliance (*Est.* = 0.12, *p* = 0.083). The full model had the best fit with an adjusted R^2 of 0.231 and combines physiological reactivity and demographic variables; there was a positive relation of compliance with SCL or education and a negative link with EMG-ZM and HR. The full model is the best of these models based on AIC weights (0.474).

4 DISCUSSION

Assessing persuasion with physiology might entail important insights of the psychology behind persuasion and, thereby, help to optimize persuasive interventions. Physiology might enable new methods to personalize persuasive technologies as current wearables can measure physiology all day, every day, with little effort. As such, people who intend to behave more healthily or sustainably can be helped to act on their intention. We investigated whether physiology reflects persuasion effectiveness, while considering potential (interaction) effects of motivational orientation and message framing. We also analyzed the added value of this assessment over traditional predictors of persuasion.

Physiology was measured while people read gain- or loss-framed persuasive messages advocating healthy oral care behaviors. Over the course of three weeks changes in attitudes and intentions towards tooth brushing, as well as actual brushing behavior were monitored. We indeed found more physiological arousal when processing persuasive messages compared to rest state. On average, the persuasive messages did change people's motivational state, but not their behavior. Part of the variability in the change in motivational state and behavior caused by the persuasive messages could be explained by physiological reactivity to them. Particularly for behavior change, physiological reactivity was more insightful than self-report data. Thus, in this study physiological measures complemented traditional persuasion predictors like personality characteristics, demographics and subjective states.

4.1 Variance in persuasion is partially explained by physiological reactivity

Our first research question concerned whether peripheral physiology reflects effectiveness of persuasive messages. Our findings indeed indicate a different physiological pattern during processing the persuasive messages compared to rest state; as indicated by an average increased heart rate (HR), respiration rate (RR), frowning muscle activity (EMG-CS) and more skin conductance peaks per minute (SCRs) (Fig. 3). This change in physiology likely results from exposure to the persuasive messages; frowning can indicate the presence of negative cognitions or emotions, e.g. frustration or guilt, or relate to increased concentration. Elicitation of SCRs is associated with orienting responses and brain areas evaluating the significance of stimuli or affective associations [24, p. 161]. This could mean that the participants elaborated more on the persuasive information than during the baseline video, which fosters persuasion.

Results indeed indicate that our manipulation was successful; the messages helped to persuade people to change their thoughts about brushing their teeth two times per day for two minutes on the short-term. Even though participants had strong attitudes and intentions to perform

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healthy oral care behaviors already at the beginning of the experiment, these feelings increased by both gain- and loss-framed persuasive messages. The increase in instrumental attitudes and intentions lasted as long as three weeks. However, overall oral health care behaviors did not increase over time. Presumably, the intervention was not persuasive enough to have long-lasting effects on behavior. Surprisingly, the messages were not more persuasive in personalized settings, e.g. loss-framing for people with higher BIS activation, possibly because the motivational states were already high to start with, which reduces the range for improvements and with it the possibility to find differences according to message congruency.

We investigated how much of the persuasive messages' effectiveness can be predicted by physiological reactivity to them. The results in section 3.3 indicate that various physiological reactivity parameters explained variance (from 5 to 18.4%) in instrumental attitude, intention and behavioral compliance, but not in affective attitude. The following part describes the results in more detail per outcome measure. Since message framing [36], motivational orientation [37], or an interaction between the two [39] can affect persuasion as well as physiology, results from these parameters are also discussed.

For instrumental attitude, frowning and heart rate (HR) reactivity explained 9.1% variance. Participants were more persuaded if they frowned. As frowning can indicate increased concentration and active processing, the participant might be assessing the relevance and value of the message. More HR reactivity in exposure to persuasive messages related to less persuasion, both for intention and instrumental attitude change. As HR accelerations are associated with emotions that are high in arousal and negativity, such as fear, anger or sadness [31], [53], this finding might indicate the presence of psychological reactance [5], [54].

Since autonomic nervous system activity is closely related to affect [31], we anticipated to find this link in our study. While affective attitude did change over time, its change was not related to physiological reactivity according to our results. A reason for this unexpected finding could be that our measurement of affective attitude was lacking construct validity; only two items addressed this variable instead of five for instrumental attitude. Yet, the measurement had sufficient reliability ($\alpha > 0.7$). The loss-framed messages appeared to be more effective in influencing affective attitude.

For intention, HR reactivity explained 5.0% variance in the physiological reactivity model; acceleration of HR related to less persuasion. The loss-framed messages were more effective in general, except for BAS_{drive} sensitive people. Contra-tailoring can indeed decrease the persuasiveness of a message [55]. Compared with information from physiological reactivity, message framing and motivational orientation contributed more to the prediction of persuasion effectiveness.

The psychophysiological relationship with persuasion was most convincing when considering long-term effects on behavioral compliance; although on average compliance rate decreased over time, reactivity in SCL, HR and EMG-ZM explained 18.4% of its variance. This is in line with earlier results [11], [34], where neural activity predicted behavior change even when controlling for not correlated attitudes and intentions. Assumingly this neural activation was related to elaborating on the information and integrating it in one's self-image [34].

This psychophysiological relation could also hint at the involvement of affect in persuasion. SCL was the strongest predictor of behavioral compliance; each unit rise in SCL while reading the persuasive information resulted in an increase in compliance rate by 0.52 on a 0-1 scale. Skin conductance level is known to reflect affective responses [31], [53], [56] over attentional efforts [57]. Additionally, people became less compliant when they exhibited increased HR and EMG-ZM activity during the messages. The zygomaticus major is the main smiling muscle [30]. The messages might have made these participants feel skeptical or cynical - which reflects in laughing or grinning – and consequently did not change their behavior. Again, a possible explanation for lower compliance with higher HR could be feelings of reactance [5]. Potentially, participants that did change their behaviors were emotionally affected by the persuasive stimuli. While reading the messages, participants might have experienced emotions that influenced physiological arousal, for example guilt, frustration [31], or more complex ones such as cognitive dissonance [58], [59].

4.2 Persuasion is best predicted by a combination of measures

In our second research question, we examined the added value of physiological reactivity over traditional self-report predictors of persuasion. In this study, we used demographic information, initial motivational state based on the Theory of Planned Behavior (TPB) [60], and motivational orientation [20] to explain the persuasiveness of our messages. Currently, self-report measures are the golden standard for prediction persuasion effectiveness. Indeed these measures predicted intention and attitude change better than only physiological measures (as indicated by the adjusted R squared in Tables 2 and 4). However, results in section 3.3 reveal that physiological measures complement traditional predictors of persuasion for all outcome measures except affective attitude. Especially for behavior change, physiological reactivity was more insightful than self-report data. This means that considering physiology yields information that would otherwise be missed.

The added value of physiological assessment was most obvious considering behavioral compliance. For change in behavioral compliance, the addition of physiological reactivity, i.e. SCL, HR and EMG-ZM, explained 17.9% extra variance over self-report measures, i.e. 23.1% versus 5.2%. In addition to physiological reactivity, personal characteristics, i.e., motivational orientation and demographics, explained variance in brushing behavior; more active BAS_{reward}, higher age or education related to more behavior change. The results indicate that behavioral compliance is best understood using multiple predictors; physiological reactivity, motivational orientation, and characteristics.

Importantly, while physiology correlates with changed behavioral compliance, attitudes and intentions did not

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(Table 5). This is not in line with behavior models viewing attitudes and intentions as determinants of behavior [60], [61]. A reason could be that, independent of the (change in) valence of the attitudes, their strengths were not enough to (persistently) affect behavior [62], as attitude strength refers to the extent that attitudes are durable and depend on, amongst others, importance, accessibility and certainty [62]. Although our participants felt more positive about healthy oral care, they might not have valued this attitude as important.

4.3 Limitations

This study is not without limitations. Firstly, we would like to emphasize that this study was not designed to investigate the effects of message framing per se. Because of the lack of a neutral-framed control condition, we therefore cannot be sure that the persuasive effects of our gain-framed and loss-framed slide shows were due to the framing, rather than to the educational material itself, especially since it is known that also neutral-framed educational material can be persuasive [63, Ch. 1]. And indeed, we found little evidence for differences between gain- and loss-framing, or that gain-framed messages were more persuasive for more BAS activated participants. The results of a neutral-framed control condition might have given more context to the absence of significant differences in this respect. Nevertheless, the current design does permit to draw conclusions at a higher level that is regarding the link between physiology and persuasion-induced change in motivational state and behavior.

Secondly, we could not control the results for the effects of the tooth plaque test (section 2.3). Upfront, we did not expect the plaque test to be a considerable persuasive element. Therefore, we did not record nor rate the participant's reactions to the test. In retrospect, pointing out oral hygiene to people could have had an impact on their subsequent responses in this study. Even though these tests are a regular part of dentist procedures, the amount of plaque, and its exposure to the experimenter, indeed appeared to be uncomfortable for some participants. It is quite possible that for these high responders the slideshow was more persuasive. Whether reactions during such reflective moments are indicative for (individual differences in) the persuasiveness of an intervention, is an interesting avenue for future research.

Thirdly, relating short-term persuasion interventions to longer-term behavior change will require further work. It is more than likely that any lasting behavior change will require repeated interventions over a longer period of time in order to affect habitual behaviors alongside reported attitude changes [42]. However, the long-term results still hold merit, as the participants who did change their behavior had particular physiological responses (section 3.3.4). The psychophysiology of behavior change could be an interesting avenue for future research.

Lastly, our sample consisted of volunteer participants, which may limit generalizability in that they may have been interested in the topic or sensitized to behavior change in relation to their oral hygiene prior to the experiment. This may be difficult to avoid, but points to the necessity of sampling strategies that help draw a representative sample from a larger, perhaps more diverse population through, for example, oversampling underrepresented groups.

4.4 Implications of the findings and further research

In this study, physiological responses to persuasive messages yielded additional insights in the underlying processes of persuasion. The most powerful predictor of behavior appeared to be skin conductance level, which mainly reflects affective responses. This seems to indicate that in this study the processing of persuasive information was not purely a cognitive process. It is also important to note that physiology appeared to be effective especially when attitudes and intentions failed to predict behavior. This shows that studying physiology adds value to persuasion research.

The considerable amount of extra variance that was explained by physiological reactivity over self-report measures encourages further research on this topic. Although we only considered averaged physiological reactivity in a one-time intervention, we still found that physiological reactivity explained between 5.1-17.9% extra variance in persuasion in addition to that explained by self-report measures. To put this in perspective; a meta-analyses of 185 independent studies on the TPB revealed that multiple self-report measures of motivational state explain respectively 39% and 31% of the variance in intention and observed behavior [61], and these explained variances in the TPB-model result from years of research. The prediction rate of physiology might be even more promising in longitudinal field studies where, in addition to summative self-report measures, physiological arousal is measured continuously and analyzed in relation to the target behavior.

The consistency between findings of various psychophysiological persuasion studies highlights the potential of this research domain. Our study design was based on earlier research from Vezich et al. [11]. Both studies analyzed framing-effects of persuasive messages concerning preventive health behavior on physiology, but we studied a different target behavior, i.e. oral health care instead of sunscreen use, measured other physiological features, considered other covariates and used different methods of analysis. Despite these differences, we did find similar results, i.e., physiological reactivity predicts behavioral compliance.

Psychophysiological insights can have implications for future design of persuasive technologies. If persuasion has clear and identifiable psychophysiological underpinnings, this information can be used to optimize behavior change interventions by personalization of the persuasive technology. The added benefit of physiology for persuasive design is the high temporal resolution and sensitivity to change as well the ability to process reactions in real-time. Physiological measurements yield large amounts of data that might bring new insights through e.g. data mining or machine learning. Potentially, persuasive technologies could learn to interpret the user's physiological responses overtime and tailor their persuasive content as part of a biocybernetic loop [64]. However, more research is needed before it is clear if such a system can be realized.

5 Conclusion

This study investigated if peripheral physiology can reflect persuasion effectiveness, and what the advantage of this psychophysiological assessment is over traditional predictors of persuasion. Results suggested that peripheral physiology indeed reflects 5 to 18.4% of persuasion effectiveness. Additionally, the analysis of physiological responses generated insights that would have been missed in traditional self-report measures, especially in the prediction of long-term behavioral compliance.

The current research is a step towards understanding the psychophysiological relationship in persuasion. This psychophysiological approach improved our understanding of the underlying psychological processes of persuasion. The important role of physiological features as skin conductance and facial muscle activity hint at the involvement of affect in persuasion. However, further research is needed. Potentially, insight from physiology can be used to advance persuasive technologies by physiology-contingent personalization.

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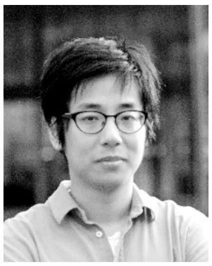
Hanne A.A. Spelt holds a B.Sc. in Bèta-gamma with the majors Business Studies and Brain & Cognitive Psychology obtained in 2014 (University of Amsterdam) and a M.Sc. in Applied Cognitive Psychology obtained in 2016 (University of Utrecht). Currently, she pursues a Ph.D. in Psychophysiology and Persuasion at Philips Research (NL) and Industrial Engineering and Innovation Sciences at Eindhoven University of Technology (TU/e). Her research in this field resulted in several peer-reviewed papers in several international journals and conference proceedings. In this role, she was part of INHERIT, a European Union Horizon 2020 research and innovation program.



Chao Zhang has a background in psychology, industrial design, and human-technology interactions (MSc. Eindhoven University of Technology, TU/e). He obtained his Ph.D. in 2019 at TU/e on the topic of applying theory-based computational models of human behavior in digital health interventions. Currently, he is working as a post-doctoral researcher in the Department of Social and Behavioral Sciences at Utrecht University. Chao has published several peer-reviewed papers in international journals and conferences. His research interests include habit formation, behavior change, computational modeling, and human aspects of artificial intelligence.

Joyce H.D.M. Westerink was originally trained as a physicist at Utrecht University and graduated in 1985. Afterwards, she expanded her horizon towards human-technology. She is affiliated with Philips Research (NL), where her research focused on psychological topics in a technological context, such as visual perception & image quality, human factors & user interfaces, and more recently psychophysiology in the context of emotions, wellbeing and affective computing. In 1991, she received her Ph.D. from TU/e. She currently holds a chair on Wellbeing and Psychophysiology in Human-Technology Interaction at Eindhoven University of Technology. Written output of her work can be found in some 40 articles in books and international journals, and some15 US patents and patent applications.

Jaap Ham obtained his Ph.D. in Social Psychology and Social Cognition from Radboud University Nijmegen in 1994. At Utrecht University, he investigated the social cognition of social justice as a post-doc. He joined the Industrial Engineering and Innovation Sciences at Eindhoven University of Technology (TU/e) in 2007 as an Assistant Professor and became Associate Professor in 2012. In his research, Jaap focuses on ambient forms of technology (such as lighting and behavior change in Virtual Reality) and social forms of technology (such as social robots) to influence people with, and on influencing two kinds of behavior: health behavior (for example exercise behavior, medication adherence) and sustainability (e.g., energy conservation, littering). He has won several Best Paper and Best Teacher awards, has published more than 100 journal papers and conference proceedings papers. He has organized several scientific conferences (e.g. ICSR2011, Symbiotic 2017), and has served on many program committees, and was program chair of Persuasive2017.

Wijnand A. IJsselsteijn has a background in artificial intelligence and cognitive neuropsychology (MSc, Utrecht University). He obtained his Ph.D. in 2004 on the topic of telepresence. He is a member of the Jheronimus Academy of Data Science (JADS) in 's-Hertogenbosch, the Netherlands, and is scientific director of the interdisciplinary Center for Humans and Technology at TU/e. Currently, Wijnand is a full professor of Cognition and Affect in Human-Technology Interaction at Eindhoven University of Technology (TU/e). He has an active research program on the impact of media technology on human psychology, and the use of psychology to improve technology design. Wijnand has published over 200 peer-reviewed academic papers in journals and conferences and has (co-)edited 10 volumes. His most recent co-edited book 'Immersed in Media: Telepresence Theory, Measurement, and Technology' appeared in 2015. His work has been supported through several industrial, national (NWO), and EU (FP6, FP7, H2020) grants.