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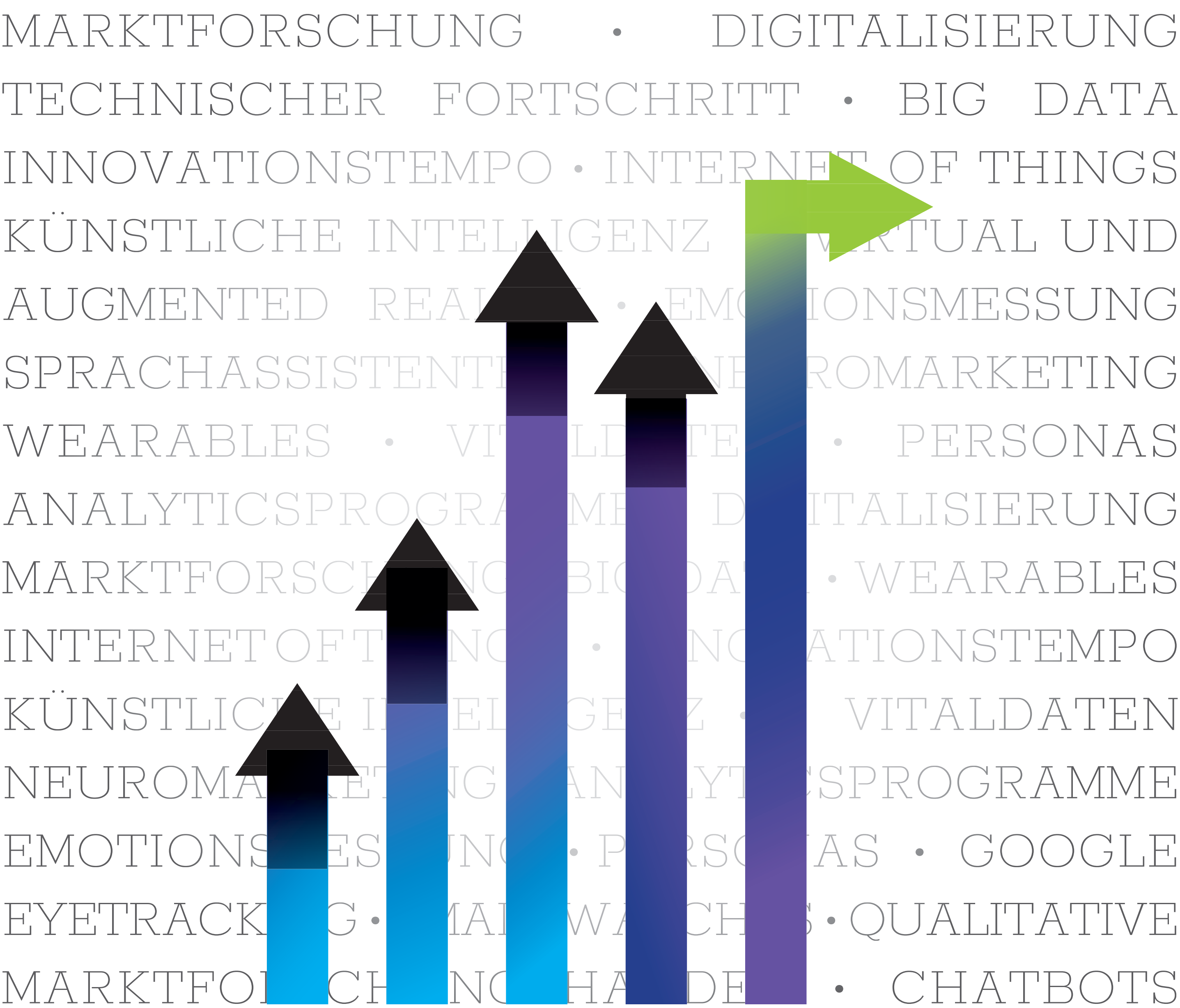

Innovation in der Marktforschung

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Vorwort

Die **Marktforschung** ist ein vergleichsweise **junges Fachgebiet**, das in seiner Entwicklung bereits eine **Vielzahl von Veränderungen** erfahren hat. Kaum eine Disziplin verändert den eigenen Methodenkanon aufgrund technischen Fortschritts so häufig wie das Handwerk der Marktforschung. Seit dem Aufkommen des Internets hat sich dort das **Innovationstempo**, wie in anderen Marketingdisziplinen auch, **deutlich erhöht**.

In den vergangenen Jahren waren die **Digitalisierung** sowie **Big Data** wichtige Themen. Technische Innovationen wie **Chatbots** werden zumindest testweise zunehmend eingesetzt. **Künstliche Intelligenz, Virtual** und **Augmented Reality** sind weitere Techniken, die das Potenzial haben, die Marktforschung nachhaltig zu wandeln. Die Vernetzung im **Internet of Things** kann der klassischen Marktforschung Konkurrenz machen, indem auch ohne klassische Marktforschung Nutzerdaten gesammelt werden. Auch **Sprachassistenten** können dazu eingesetzt werden.

Die **qualitative Marktforschung** profitiert ebenfalls von der Digitalisierung. So können **Smartphones** mit ihren integrierten Kameras dazu eingesetzt werden. Der technische Fortschritt beflügelt die Forschung unter dem Schlagwort **Neuromarketing**. **Eyetracking und Emotionsmessung** wird **via Webcam** möglich und bringt das Marktforschungslabor in nahezu jeden Haushalt. Einfache Hirnstrommessungen finden über Kopfhörer statt und mit Hilfe von **Smartwatches** und **Wearables** werden Vitaldaten von Menschen zum festen Bestandteil der Forschung. Last but not least sind **Google und Co.** zu nennen, die mit ihren **Analyticsprogrammen** der etablierten Marktforschung Konkurrenz machen.

Diese und weitere Veränderungen wollen wir in dieser Ausgabe von „PraxisWissen Marketing – German Journal of Marketing“ unter dem Titel **„Innovation in der Marktforschung“** analysieren. In acht Beiträgen werden der **Einsatz humanoider Roboter** in der Marktforschung, **qualitative Forschungsmethoden** wie etwa der Einsatz von **Gesichtserkennung** sowie des **Eye Trackings** näher untersucht. Es gibt ein Fallbeispiel aus dem **Handel**, in dem Erkenntnisse des **Neuromarketings** berücksichtigt werden sowie eines aus dem **Tourismus**, in dem **Personas für das nachhaltige Reisen** vorgestellt werden.

Wir bedanken uns ganz herzlich bei allen Autorinnen und Autoren, den Mitgliedern des Herausgeberbeirats und allen anderen Personen, die an der Entstehung dieses Werks beteiligt waren.

Berlin im Oktober 2020

Andrea Bookhagen Andrea Rumler

Inhalt

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Empathic market research: The added value of eye tracking data for affective computing UX research

Alexander Hahn, Katharina Klug, Florian Riedmüller

The use of innovative technology and artificial intelligence (AI) is fundamentally changing the way of gaining and analysing data. Regarding emotion, affective computing aims at automated, real-time-based measurement and recognition of emotions by sensors and learning algorithms. Regarding attention, eye tracking can identify the exact visual triggers which release emotional reactions. This article explains how researchers can use both methods to generate encompassing insights for UX research on user emotions and to identify the according visual trigger points. Therefore, experimental studies are conducted using affective computing and eye tracking methods on two digital use cases.

Der Einsatz apparativer Technologien und künstlicher Intelligenz verändert zunehmend die Beschaffung und Auswertung von Marktforschungsdaten. Immer häufiger erfasst geeignete Bildanalysesoftware emotionale User-Reaktionen mittels Affective Computing. Die visuelle Aufmerksamkeit von Personen lässt sich durch Eye-Tracking-Geräten präzise und unmittelbar nachvollziehen. Dieser Beitrag konzeptualisiert den kombinierten Einsatz der beiden apparativen Messansätze für Emotion und Aufmerksamkeit, um für die User-Experience-Forschung einen deutlichen Mehrwert zu schaffen. Hierfür werden anhand zweier empirischer Studien Vor- und Nachteile der spezifischen Methoden aufgezeigt und eine komplementäre Integration der Methoden vorgeschlagen.

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1. The need for empathic market research in a digital world

Over the last decades, digital expansion created a need for innovation in digital product and service development (Djambashi et. al. 2011, p. 121). This endeavor is challenging, as leading companies like *Google*, *Amazon* or *Facebook* set high standards in user experience [UX]. The competition is shifting towards extraordinary experiences for the consumers. Market research in this digital world accordingly focuses on user experience research and conversion rate optimization (Koch/Gebhardt/Riedmüller 2016, p. 210). This basically involves three questions: (1) "*What* do users do with the (digital) product?" (2) "*How* do users use the (digital) product or how do they buy it?" and (3) "*Why* do users evaluate the product positively, like it, love it... or not?". While, for instance, activity logging ana-lyses can answer the first two questions in a quick and valid manner, research into the *Why* is often associated with fluidly and individually and subjectively perceived **user attention** and **emotion**. This distinguishes pure usability (i.e. functional product evaluation) from user experience (i.e. holistic emotional product evaluation) (Pettersson et al. 2018, p. 1).

Within the Gartner Hype Cycle, market research focusing on **empathy** (e.g. affective computing) as a research branch of digital emotion research is currently in the early "innovation trigger" phase. Thus, technological development will advance strongly in a very short time frame (Fenn 2015). Analogous to similar technology innovations such as self-service surveys (e.g. Surveymonkey, Typeform), the market research industry currently faces both an immense opportunity (e.g. empathic digital user experience research as a new business field) and a potentially disruptive innovation (e.g. similar to Google Analytics as a scaled self-service technology).

Regarding digital **emotion** research, affective computing aims at automated, real-time-based measurement and recognition of users' emotions by sensors and learning algorithms in order to enable adapted reactions in human-computer interaction (Picard 2015, p.1) to inform user experience (UX) research (Hahn/Maier 2018, p. 32). Regarding **attention** research, eye tracking systems can identify the exact visual triggers which release users' emotional reactions. For digital UX research, visual measurement is the most relevant methodology, as 60-90 percent of all information is perceived visually (Steiner 2017, p.16) and, moreover, digital products lack haptic, scent or odor cues. So, the combination of affective computing and eye tracking measurement can bring empathic market research to a new level. This article explains how researchers can use both methods to generate encompassing insights for UX research on user emotions and to identify the according visual trigger points. Therefore, experimental studies are conducted using affective computing and eye tracking methods on two digital use cases: booking a hotel via chatbot communication and booking a gym membership via website. Based on these insights, the article outlines potential integrations of both research approaches.

2. Measuring emotions with affective computing

UX researchers currently collect data on attentions, emotions, attitudes and motives mainly via (UX-) user interviews and standardized or self-developed surveys (Pettersson et al. 2018, p. 6). The User Experience Questionnaire (UEQ), as one example for a UX survey, consists of 26 items, measuring six factors of user experience on the 7-stage Likert scale: Attractiveness, Perspicuity, Dependability, Efficiency, Novelty and Stimulation (Laugwitz/Held/Schrepp 2008, p. 68). Such methods are suitable for recording cognitive attitudes and motivations, but in the case of emotions they are likely to be biased, e.g. due to interviewer influence or socially desirable response behavior (Hahn/Bartl 2019, p. 2).

Up to now the measurement of emotional activation (e.g., in the context of reception tests in advertising effectiveness) has been associated with complex equipment for measuring **psychophysiological data**. However, rapid developments in the fields of machine learning, face recognition, sensor quality, data processing, etc. promise a radical change in attention and emotion research using affective computing technology to record and analyse user data on attention and emotions in a reliable, valid and scalable manner with reduced costs and at high speed. **Affective computing** (AC) hereby refers to the development of IT systems and equipment for capturing, interpreting, processing and simulating human emotions. This interdisciplinary research field integrates sensors, algorithms and the expertise of experts from computer science, medicine, marketing, psychology and cognitive sciences to capture, evaluate, classify and interpret psychophysiological signals and actions of human users (e.g., facial expressions, voice frequency, heart rate, gestures) (Picard 1997, p. 1).

Based on such psychophysiological input data, affective computing methods aim to recognize consumer moods and emotions (Hahn/Maier 2018, p. 59). For example, **wearables** (e.g., skin resistance meter, ECG) can record heart rate and skin resistance data to calculate moods. **Facial Coding** can record more discrete emotional states in a scalable manner and without any major influence on the subject (Picard 1997, p. 5). Facial coding enables recording emotional states without directly questioning users and thus minimizing conscious or unconscious biases. Video analysis can detect six basic emotions, namely joy, surprise, sadness, fear, disgust and anger, using the expression of the face.

Given the rapidly developing technological opportunities, central questions in the context of affective computing arise: *"How can user emotions, that are measured by objective data, improve empathic UX design?"* and *"Is it worthwhile to measure emotions using affective computing or are established methods sufficient?"*.

To explore such questions, a lab experiment with 30 participants and a field experiment with 127 participants was conducted from July to December 2018. Users were asked to make a pre-defined hotel booking via the brand hotel.com as a user task via a **text-based chatbot interface** (see Fig. 1). To test for potential differences between users' cognitive efforts, users were assigned to two experimental scenarios: version A (simple interaction design) and version B (more complex interaction design). In a similar manner to established experimental designs in emotion research, the users first saw a short excerpt of a humorous TV series ("Friends"), followed by an advertising commercial of the hotel.com brand to potentially trigger the "joy" emotion (Teixeira/Weder/Pieters 2012, p. 147).

Cognitive constructs, such as "ad liking" or "perceived usability", were measured via ex-ante and ex-post surveys based on established marketing research scales in order to additionally gather self-reported data. During the entire experimental period, user activities, such as mouse movements on the screen, were measured by video, user actions, such as clicks, by web log files and user emotions by facial coding of videos recording the user's face. An algorithm of the Munich Deep-Tech startup deeplyapp, based on the SHORE® library of Fraunhofer IIS (Fraunhofer IIS 2019), was used to evaluate the facial emotions. For validation purposes, a trained human coder rated each video interaction in terms of discrete emotions.

Screen design of the chatbot interface

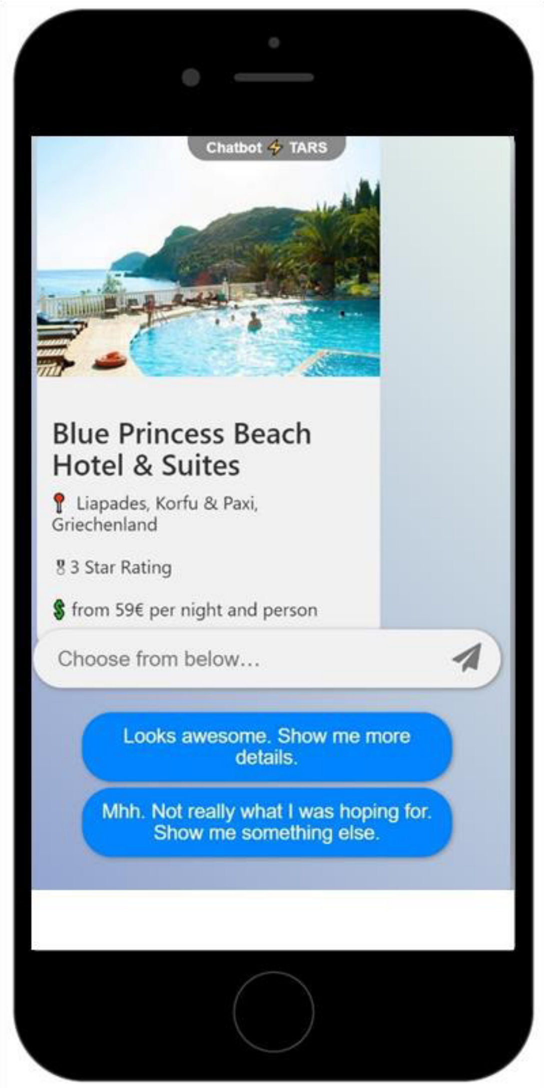

Fig. 1 Booking chatbot used in the experiment

The results of the laboratory experiment indicate that the objective measurement of discrete emotions, such as "joy during the advertising commercial", tends to be more valid than the subjective, self-reported emotion measurement based on the survey. In detail, the correlation of the objectively measured, facial coding-based joy correlates significantly and strongly with an ex-post coding of perceived user pleasure by external human coders ($r = 0.69$, $p < 0.01$). The correlation between the survey-based self-assessment of joy and the objectively measured joy is substantially lower ($r = 0.29$, $p > 0.10$). Thus, these results seem to indicate that users are not able or not willing to report their own emotions in a valid manner, while the **objective measurement** generates more **valid data**. This implies that using affective computing methods in empathic market research enables higher validity in measuring user emotions in real time and without any additional time burden for the user.

The objective data of the experiments also tends to follow classical theoretically established patterns of the influence of the emotion "joy / excitement" on the probability of successful completion of a user task. According to the **Yerkes-Dodson law**, the probability that the user solves a user task correctly (= booking the "ideal" hotel according to the briefing) is highest at a medium activation level (see Fig. 2). With both lower and higher activation, the probability decreases (Parsons 2017, p. 287). The objective emotion and behavior data of the experiments follows this pattern. There is a significant, inverse u-shaped relationship between objectively shown "joy", e.g. the user's arousal, and "objective user success", e.g. user performance.

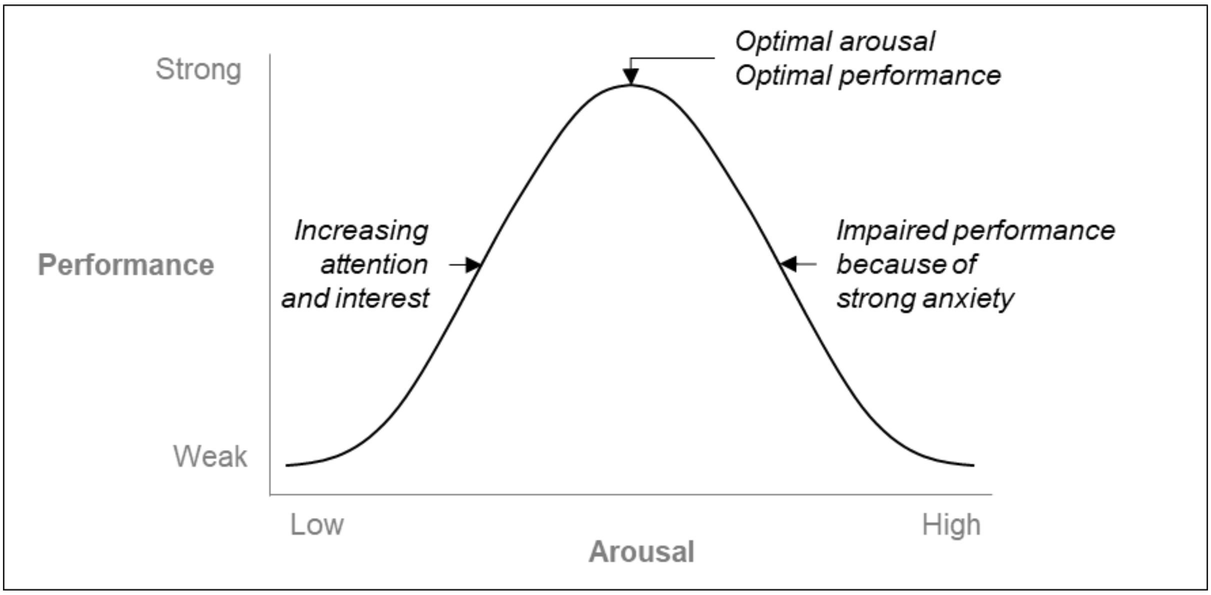

Fig. 2 Relation of arousal and performance (based on Yerkes/Dodson cited from Parsons 2017, p. 287)

This connection is also moderated by the **complexity** of the chatbot: It is invertedly u-shaped in the complex chatbot and linearly increasing in the simple chatbot variant (see FigFig. **3**).

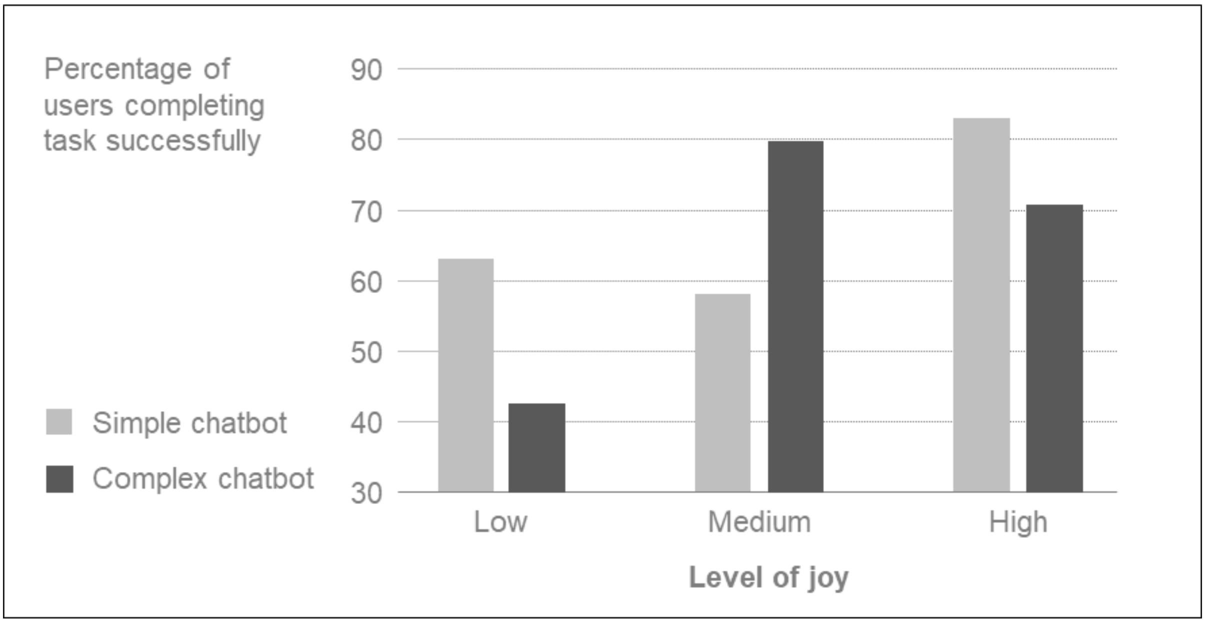

Fig. 3 Relation of joy and performance considering task complexity

When the objective emotion data is substituted by the subjective emotion data based on user surveys, the relationship between joy and user success becomes linear. While violating established theoretical findings, this – likely biased – result would also yield questionable implications. Based on such a relationship, the managerial implication would be: "The more emotion, the better" – a common approach in creating advertisements. However, in this experiment setting, this would lead to a misleading assessment of the optimal UX design in order to increase user task success. Thus, the results indicate that users are biased in assessing their emotions during UX testing and that misinterpretation based on biased data could lead to non-optimal implications and results.

Interestingly, the results are different when the dependent variable "user success", based on objective data, is replaced by subjective, self-reported data. Specifically, the users were asked to report the "perceived usability" based on the System Usability Scale (SUS) (Brooke 1996, p. 193). While the theoretically established, inversely U-shaped relationship between joy and user success remains, it is no longer significant. This implies that users can make valid statements about cognitive constructs such as "perceived usability", but that the objective measurement based on actual user behavior yields still more valid results. This corresponds to the digital industry practice using log file analyses instead of user self-reports.

Therefore, measuring user emotions by **affective computing** technologies – here exemplified by lab and field experiments considering chatbot communication – reveals three central insights:

- The **interplay** between **user emotions** and **user experience** influences the **objective user task success** and, thus, the business success of digital interactions.
- **Measuring emotions** based on **objective** facial coding **data** provides more reliable and valid data than measuring emotions based on subjective data (e.g., user surveys).

- The **inclusion of emotions** in **UX design and testing** based on **objective data** delivers valid results.

Overall, the study demonstrates the additional value of measuring the theoretically well-founded connection between "joy" and "user success" by objective, unbiased data. Moreover, this measurement approach allows real-time analytics and also avoids disruptions in the user experience, as caused by user surveys.

3. Measuring attention with eye tracking systems

While affective computing focuses on the measurement of emotional reactions, eye tracking brings insights into consumers' visual attention. **Attention** is an essential part in users' perception processes describing the persons' readiness to receive and interpret stimuli from the environment. Attention can be triggered in two different manners (Geise 2011, p. 164). Endogenous attention is a human-initiated conscious focus towards relevant information (e.g., shoppers looking for price information). Exogenous attention is activated by involuntary external stimuli (e.g., billboards using signal colors). Our attention capacities are limited and selectively steered to avoid an overload of information. The rising number of brand communication channels compete for consumer attention, making it one of the key performance indicators in marketing.

Common market research instruments measuring attention are ex-post surveys using questions like the aided or unaided recall and challenging spill-over- and carry-over-effects. Based on this insufficient explanation of attention genesis, market research has further developed a set of machinery-based systems, measuring the psychophysiological perception of individual human senses through skin resistance (tactile), decibel perception (acoustical) and eye movements (visual) (Koch/Gebhard/Riedmüller 2016, p. 121f.). Last-mentioned becoming an increasing factor in modern marketing analytics over the last decades.

Eye tracking systems measure attention through visual perception using unequally distributed viewing areas and differentiate between peripheral and foveal vision. Peripheral vision captures the broad spatial landscape scene in a 160 degrees angle. Foveal vision focuses on a small central area of ones field of view (Blake 2013, p. 368). According to the eye-mind-hypothesis, information within the foveal vision is closely related to what people really process (Bojko 2013, p. 13). In the past, eye tracking technology was initially restricted to expensive laboratory environments with complex hard- and software settings. Today, leading vendors like *SMI* and *Tobii* have established high quality solutions for stationary and mobile use, offering a broad collection of features and supported tools for data analysis. Eye-tracking devices at the entry price point level offer limited features, but even these solutions can track fixations, offer point-of-regard-analyses and pupillometry (Burger/Guna/Pogacnik 2018, p. 3).

Classical eye-tracking studies have been qualitatively oriented, focusing on retracing scan-paths to explain how users visually perceive external stimuli. So-called **Gaze Plots** represent individuals' fixations as dots and saccades. The dots' size represents the duration of fixation (e.g., larger dots illustrate longer fixations). The dots are numbered capturing the chronological fixation order. Gaze plots from several persons are merged to so-called **Heat Maps,** where red areas represent plenty accumulated dots, yellow and green indicate a lower number of dots, respectively fixations, and areas with no color show no fixation (Djambashi et. al. 2011, p. 136). This visualization provides an easy and understandable overview of the general attention (e.g., towards a landing page; see Fig. 4a).

To enhance the visual description of heat maps, quantitative performance indicators are used. **Time-to-first-fixation** (TTFF) indicates the duration from the first appearance of the stimulus in the users' visual field to its first perception. **Fixation duration** measures the length of visual perception. **Fixation count** tracks the number of visual visits towards a stimulus within a session (Geise 2011, p. 204). Additionally for digital products, **Time-to-click** (TTC) measures the time until a user enters the area of interest (AOI; e.g., presses a button; see Fig. 4b).

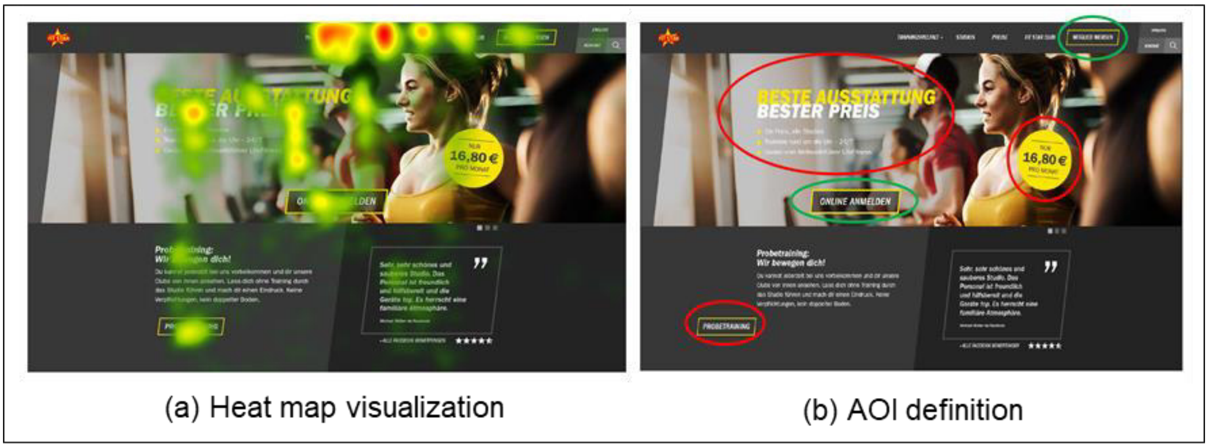

Fig. 4 Gym website including heat map and AOI definition

For an empirical study on attention performance conducted from July to December 2017, we compared the visual perception of design award-winning **landing pages** (category "excellent communications design web") with competing web pages within the fitness sector. In a lab setting with 100 students, the participants had to find predefined **special offer** information on the web pages. As expected, the award-winning pages achieved better target findability (TTFF) and recognisability values (TTC) than their competitors.

Tobii TX60 stationary devices were used to track users' fixations. First, users were engaged in a 10-second calibration procedure. Then the users viewed all landing pages successively and randomized. Finally, the users answered a questionnaire evaluating the websites using a 5-point-Likert scale. To analyse the TTFF-values of the pre-defined AOIs, *Tobii Studio* software was used. TTC-values were manually integrated into the recordings, counting clicks within the AOI. For multidimensional data analysis *Tobii* datasets were merged with the questionnaire data using *SPSS*.

Comparing award winning landing pages and regular competitors, t-tests show that participants focus on special offers on award winning sites only slightly faster ($\bar{x}_{TTFFA}$ = 1.9 sec. vs. $\bar{x}_{TTFFB}$ = 2.1 sec.; $p > 0.5$). This can be explained with the

common knowledge about visual attraction effects of specific colors, contrasts and forms, which are almost equally used for special offer communication across industries (Djambashi et. al. 2011, p. 124). In contrast, TTC values differentiated significantly ($p < 0.01$) for award winning landing pages (requiring 6.9 seconds to call-to-action click) compared to regular websites (requiring 9.9 seconds). Accordingly, excellent website design seems to be based on the recognisability regarding call-to-action-features. Fig. 5 shows the eye-tracking results for the web pages from the fitness sector (e.g., a fitness gym announcing a special membership offer).

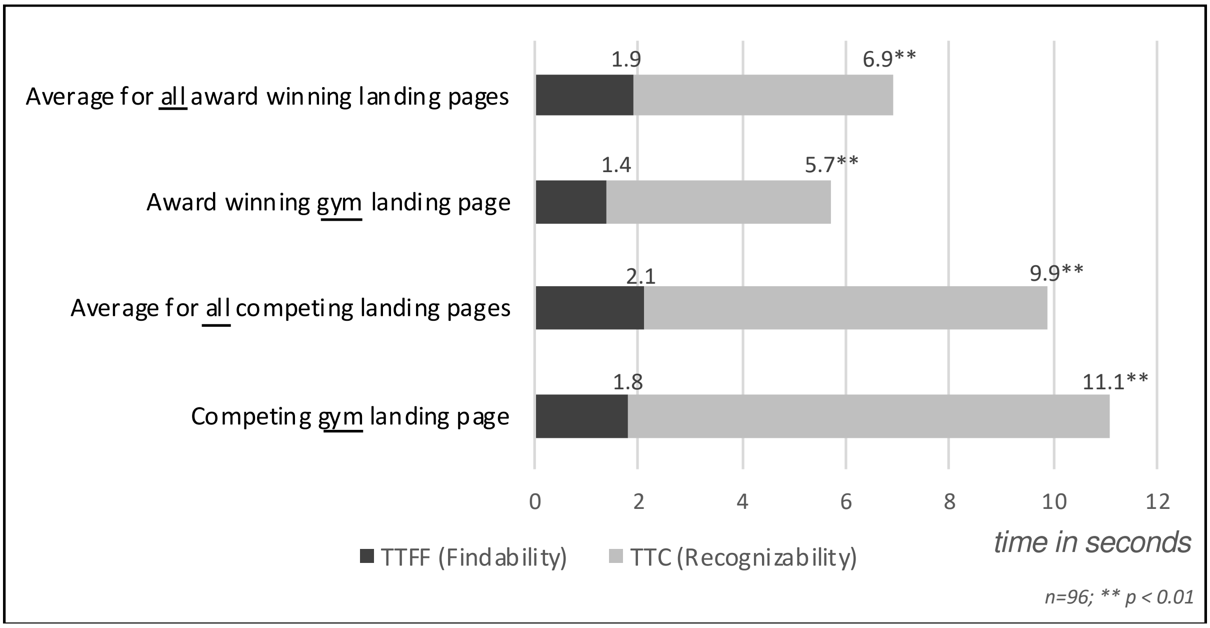

Fig. 5 T-tested eye tracking KPIs for all and specifically gym landing pages

Interestingly, the participants of this study did not articulate their faster success rate when completing the task with award winning pages in the final questionnaire. When asked about which web page provided better information, award winner and non-award-winner websites achieved similar results ($\bar{x}_{Q1A} = 4.7$ vs. $\bar{x}_{Q1B} = 4.6$; $p > 0.1$), indicating that objective eye tracking data provides more valid data for measuring attention than classical ex-post surveys.

4. Requirements for the combination of affective computing and eye tracking measurement

More and more digital products and advertisements rely on the emotional part of user interactions. However, digital market and usability research focuses largely on measuring *what* users do and *how* they do it. Thus, this article focuses on less biased and more valid methods for measuring *why* users behave in a certain manner: Affective computing and eye tracking research. This yields the question how to improve and combine these measurement methods. The two studies above show that emotion and eye-tracking analytics can contribute more valid results in comparison to established and wide-spread methods, such as surveys. While both methods are well established on their own, they offer different but complementary insights on emotion and attention.

A combination of these methods therefore might lead to even more valid and complementary insights: Eye tracking enriches emotion analysis, because it enables to clearly identify which exact visual stimulus triggered a certain emotion or mood reaction. If users show similar emotional reactions in a study, certain emotion peaks can be easily deduced to the sequential flow of the stimuli. In case of user groups showing different emotional reactions, eye tracking allows insight into whether these groups focus their attention on different stimuli.

Emotion analysis enriches the attention information giving insights on a deeper processing layer of attention-inducing stimuli. Fixation on a visual element does not necessarily mean that the observer is happy about the displayed visual element. In fact, the content might be confusing or associated with memory about previous negative experiences (Jokinen/Silvennoinen/Kujala 2018, p. 383). Using affective computing and eye tracking in combination allows to triangulate the sources to explain and validate results (see Fig. 6).

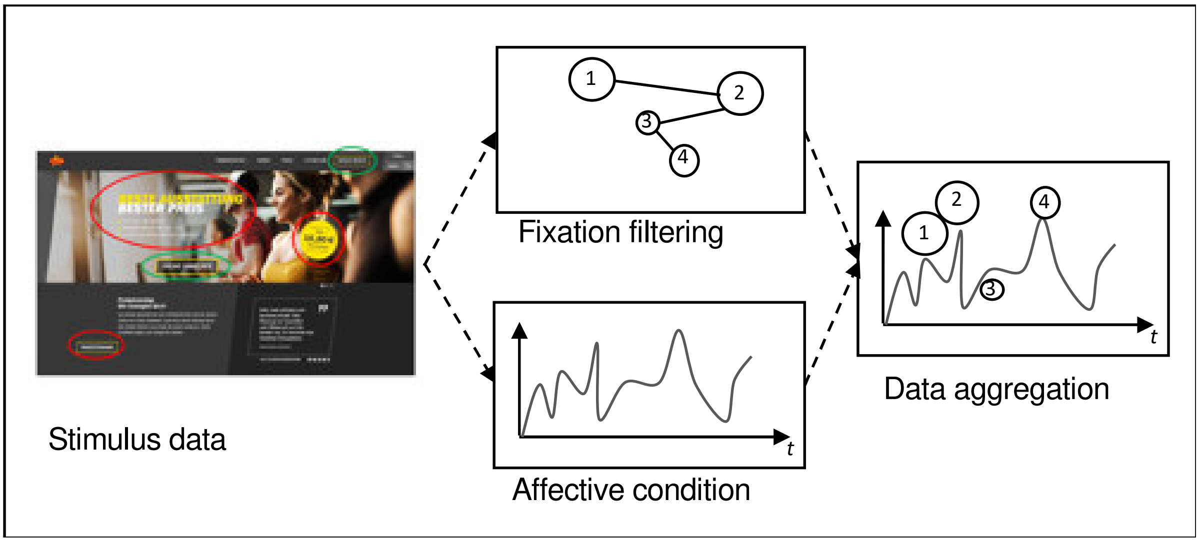

Fig. 6 Triangulation of affective computing and eye tracking measurement

Based on the preliminary findings of the two studies, this article proposes two directions for the analysis and interpretation of aggregated datasets. First, connecting visual elements with **user experience:** A screen-based design approach can be utilized for the detection of specific bottom-up design factors influencing users' aesthetic experiences. This approach is an attempt to identify visual features that consistently seem to contribute to perceived beauty and aesthetics measurable via users' affective response. Emotions are analysed first and enriched by timestamps of eye tracking data to measure the users´ exact emotional root cause (Tulius/Albert 2013, p. 276). Second, considering users' **perception of aesthetics:** This approach might focus on user experience from a top-down perspective. Such a perspective traditionally postulates a "beauty is in the eye of the beholder" paradigm and is measured by reporting methods like thinking aloud. Eye tracking AOI-Hypotheses could be enriched by additional emotional data to generate more valid data. As users are compensating usability flaws with appealing aesthetics (e.g., beautiful websites), a method triangulation might help to reveal the true user value of aesthetics (Djambashi et al. 2011, p. 124).

Accordingly, this article calls for combining affective computing and eye tracking technology in order to enrich empathic market research by quickly, validly and scalably measuring user emotions and attentions. Especially the field of digital market research needs easy to handle and cost-effective solutions. Regarding the implementation we see three main **challenges** for future research: Automatic synchronization of data inputs to enable (near) real-time analytics (Bielikova et al. 2018, p. 10), (semi-)automatic analysis of qualitative and quantitative data to reduce costs and privacy by design for users (e.g., as guaranteed by SHORE®).

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Schlüsselwörter

Digital Empathy, Affective Computing, Eye Tracking, Emotion Research, Chatbot Communication, UX Design

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