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Article

Testing Social Media Advertising Effectiveness with Multi-Method User Experience Research

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Marketing Review

St.Gallen

Data and
Creativity



Schwerpunkt

Die Magie der Daten
Gespräch mit Max Lederer,
Jung von Matt AG

The Data-Creativity Nexus –
Shaping the Future of Marketing
in the Age of Artificial Intelligence

Generative AI Tools in
Customer Service – Beyond the
Hype of 'Prompt Engineering'

Testing Social Media
Advertising Effectiveness
with Multi-Method User
Experience Research

Ein Stimulation Model für die
Marketingkommunikation

Spektrum

Gamification –
Anwendungen für Kundschaft und
Mitarbeitende der Baubranche

Drivers of Sustainable
Consumption –
Life Satisfaction and the
Concreteness of Sustainable
Product Attributes in Advertising

Testing Social Media Advertising Effectiveness

with Multi-Method User Experience Research

This study highlights the importance of pre-testing social media ads and explores the challenges of objectively assessing ad performance. It outlines how a multi-method approach combining facial coding and eye-tracking can help identify successful ads before launch. The findings emphasize the growing importance of user experience research (via digital empathy) for social media advertising and performance marketing.

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Prof. Dr. Katharina Klug, Prof. Dr. Dirk Totzek

93% of global working-age internet users spend about 2.5 hours a day on social media (DataReportal, 2023). Social media (SM) is the fastest-growing advertising channel, with an expected compound annual growth rate (CAGR) of 4.5% until 2027. In 2023, the social media advertising (SMA) market amounted to an estimated US\$207 billion (Statista, 2023). Accordingly, advertisers using SMA are increasingly competing for user attention (Davenport, 2001; Teixeira, 2014). Two of the major challenges in SMA are as follows (Liadeli et al., 2023; Oberlo, 2023): First, the **time lag in assessing performance**. Advertisers usually identify successful ads by measuring user behavior, such as engagement and conversions. This means that ad performance can only be judged *after* rather than *before* investing. Second, **subjective creativity**: Effective SMA includes creative content (e.g., pictures, stories, posts, videos) that should be evaluated *objectively* using implicit methods rather than *subjectively* using explicit methods. According to Nosek (2007), explicit methods are based on controllable, intended responses that require cognitive resources, such as survey questions about subjective experiences. In contrast, implicit methods aim to collect objective data on bodily expressions without any intended cognitive or conscious influence, providing subconscious user ratings. Advertisers are therefore faced with the question of how to cost-efficiently design and optimize creative and appealing SMA based on *objective* evaluation criteria *before* investing. This exploratory study examines why and how user experience (UX) research methods based on artificial intelligence (AI) can enhance a multi-method research approach for testing and optimizing SMA content. As UX research explicitly encompasses spontaneous hedonic user reactions in human-computer interactions, it is a promising way to measure the creative and business impact of SM activities. Using selected ads of a digitally oriented fashion brand, this

paper shows that implicit facial coding data matches actual ad performance. Facial coding uses measurements of subconscious physiological responses by tracking facial micro-expressions controlled by the autonomic nervous system (ANS) and provides objectivity in emotion analysis (Köster et al., 2015; Jiang et al., 2014). While survey data, which is the prevailing standard for pre-testing ads, has practical advantages and draws upon extensive experience to measure explicit responses, it may yield ambiguous results when it comes to capturing implicit reactions (Teixeira et al., 2012). To measure these implicit reactions, eye-tracking data is collected without cognitive processes of the participant by employing infrared sensors to capture precise local and temporal pupil fixation and movement (Blake, 2013), which subsequently helps to identify the elements in ad content that can lead to improved ad performance. These findings are meaningful for various target groups in a variety of ways to (better) understand the growing relevance of digital empathy for UX research methods and customer understanding (Klug & Hahn, 2021). Digital empathy focuses on emotionally adapted and optimized human-computer interactions based on users' moods and emotions (Hahn et al., 2020). In particular, the following groups involved in SMA can benefit from these findings of the multi-method approach:

- (1) *Advertisers* will be able to understand (sooner) which ad content has engaged and empathically captured their audience to design ad campaigns strategically.
- (2) *Advertising agencies* are empowered to provide a competitive advantage to both their corporate clients by creating objectively creative campaigns and advertisers by converting UX insights into effective campaigns. Therefore, agencies become 'translators', transforming digital insights into successful campaigns.



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- (3) *Performance marketing professionals* strive to improve their understanding of customer behavior to rapidly adapt their marketing activities and gain insights into the critical drivers of ad performance. These findings enable them to refocus their efforts and optimize return on investment (ROI) by making informed decisions, tailoring their strategies, and allocating resources effectively.
- (4) *UX researchers* may (better) interpret and translate complex data on hedonic and aesthetic aspects of creative ad design.
- (5) *Campaign managers* can (better) identify the most promising ads during the initial campaign optimization process before spending on SMA fees.

The process of developing SMA (Barnhart, 2023) generally consists of three phases: strategy setting, content creation, and performance evaluation. In the **strategy setting phase**, *advertisers* and *ad agencies* define target audiences, desired steps, and actions in user journeys and business models to optimize the return on marketing investment (ROMI). In the content creation phase, ad agencies develop concepts and create brand-relevant and aesthetic ad content to attract and engage the target audience. This design phase involves creative and subjective tasks and can be very costly, especially when professional footage is used. In the final **performance evaluation phase**, *campaign managers* optimize the technical setup and integration of the ad campaign across platforms. After a campaign has been launched, *performance marketing professionals* analyze digital user behavior (e.g., impressions, likes, comments, and clicks) to drive insights based on KPIs (key performance indicators) and further optimize the campaign. This part involves highly analytical and objective tasks.

Clearly, the process of developing SMA combines strategic, creative, and ana-

lytical tasks. It involves developing a campaign strategy, creating compelling content, managing and evaluating campaigns. In this context, it is particularly challenging to bridge the two 'worlds' of the subjective creation phase and the objective performance evaluation by mirroring ad effects (at best, *before* investing in paid ads) (McDuff et al., 2017). Current UX research methods (e.g., facial coding) offer an option to bridge this gap by helping to implement practical and empathic SMA using artificial intelligence. These methods can complement both (1) the explicit evaluation of ad creation and (2) implicit measurements of behavioral ad performance (e.g., engagement rate and conversion rate).

UX Research Methods

User experience research methods integrate multiple comprehensive measurements to capture cognitive and emotional user reactions. This provides a valuable approach to combining the outputs of creative and analytical work.

Management Summary

Empathic user experience research offers innovative methods for the predictive evaluation of social media ad performance. This study presents an experiment that uses a multi-method approach combining facial coding and eye-tracking to identify successful ads before they are launched. The results suggest that facial coding helps to distinguish high-performing from low-performing ads by quantifying emotional reactions and translating them into user preferences. Eye-tracking subsequently identifies content that can capture users' attention.

Please note that facial coding, which is used in academic research on emotions and classical commercial testing, is not originally a UX method, but rather a method that is also used in UX research. UX research employs several research methods, such as facial coding, which recognizes human emotions and fosters empathy in human-machine interactions, to understand better which creative ad designs increase customer engagement (Klug & Hahn, 2021). This approach allows for a fast and resource-efficient analysis of user responses. Implicit measurement techniques can enable user-friendliness in UX research by collecting data subconsciously and implicitly (Hahn & Maier, 2018).

By incorporating implicit measurements into the research methodology, the multi-method approach enhances the objectivity of emotion and attention measurement using facial coding and eye-tracking data (see figure 1). User reactions are captured subconsciously and take into account the fluid nature of emotions, which cannot be reduced to a single data point as in a survey (Beer et al., 2015). After all, a user experiences multiple emotional reactions throughout a (digital) user journey.

By using eye-tracking for attention research, this study offers valuable insights into the exact visual triggers that capture users' attention while simultaneously recording participants' emotional responses (Wedel et al., 2016). Given the strong visual connection between attentional and cognitive perception processes, this methodology offers a unique opportunity to uncover the underlying mechanisms that drive user engagement to further optimize advertising strategies based on empirical evidence (Wedel et al., 2017).

Unlike other implicit user data, such as engagement or conversion rates, measurements of emotions and attention provide valuable insights into user behavior

at an early stage, i.e., before making significant financial investments in SMA. This acknowledges the limitations of relying solely on explicit, self-reported surveys and highlights the importance of capturing implicit reactions and the multifaceted nature of emotions (Wedel et al., 2016).

For a more comprehensive understanding of user responses, a multi-method approach must include both behavioral performance measures (e.g., engagement and conversion rate) and implicit measures (e.g., emotions and attention) to shed light on the dynamic interplay between immediate user reactions, such as attention and emotions, and ad performance. Ultimately, this mix of methods aims to overcome biases, such as social desirability or the subjectivity bias (Blair et al., 2020; Ekman, 2009), which are currently an issue in standard methods of evaluating creative content such as ads, for example by using surveys only (see figure 1).

Empirical Study

Digital UX insights are essential, especially for digital brands and SM start-ups that mainly focus their marketing communication on SM and sell (exclusively) in online shops (Dwivedi et al., 2021). These businesses typically engage with their customers in a digital environment. Digital user experience insights, such as digital empathy, are essential for understanding customer needs and therefore a critical success factor.

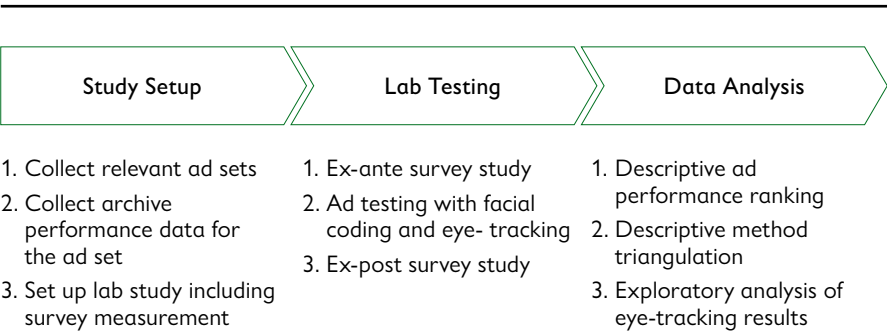
This study applies UX research methods to an exemplary SMA design process for an SM fashion brand focusing on sustainable women’s clothing. The brand is exclusively present on social networks and makes substantial investments in SM content creation and paid advertising, usually video content showcasing current fashion collections. Videos have a high potential for user engagement due

Figure 1: Overview of Multi-Method Research Approach

| | Before Ad Payment | After Ad Payment |
|-----------------|--|---|
| Subjective KPIs | Survey Data: Set of questions that are posed to a group of people | |
| Objective KPIs | Facial Coding: AI-based emotion detection based on facial expressions | Engagement Rate: Number of reactions, likes + comments + shares, divided by the number of impressions |
| | Eye Tracking: Identifies attention patterns based on eye movements and gaze patterns | Conversion Rate: Number of actual purchases in the online store divided by the number of impressions |

Source: Authors’ own illustration.

Figure 2: Overview of Research Process



Source: Authors’ own illustration.

to their ability to capture attention, facilitate information retention and comprehension, create emotional connections, and drive shareability and virality on SM platforms (Wertz, 2023).

In the study setup (see figure 2), four different current ads using brand videos were selected that varied in the number of text elements (text-intensive in ads 1 and 4 vs. less text-intensive in ads 2 and 3) and in the ad’s atmosphere (physically attractive models in ads 1 and 2 vs. funny/cuddly ones in ads 3 and 4). Moreover, the ads were chosen to have a wide range

of engagement and conversion rates (= behavioral data was higher for ads 1 and 2 vs. lower for ads 3 and 4), as measured by two KPIs from Facebook Analytics (Meta Business Suite, 2022).

For laboratory testing, the software package *iMotions* 9.2 was used for eye-tracking (TOBII X2 Eye Tracker – 60Hz) and facial coding (Affectiva’s AFFDEX algorithm), and *Typeform* for survey measures. All empirical data was collected in the BeLab of the University of Applied Sciences in Nuremberg. Prior to the lab tests, an ex-ante survey was conducted

for screening and collecting demographic information. A total of 60 female users in the fashion brand's target group, aged between 18 and 54, participated in the study. Users were exposed to the four different ad stimuli in random order, with a neutral stimulus presented beforehand, and eye-tracking and facial coding data were recorded for each ad. Afterward, each ad was rated in an ex-post survey regarding ad perception, ad credibility, and ad mood. All constructs are based on established marketing research and were measured on a 7-point Likert scale ranging from (1) = strongly disagree to (7) = strongly agree (Bruner & James, 1992). For ad perception, the participants were asked to rate whether *'The ad was very relevant to me'*; ad credibility was determined by the participants' evaluation of *'This ad is believable'*, and ad mood was rated according to the participants' perception of *'I felt emotionally involved in the ad.'*

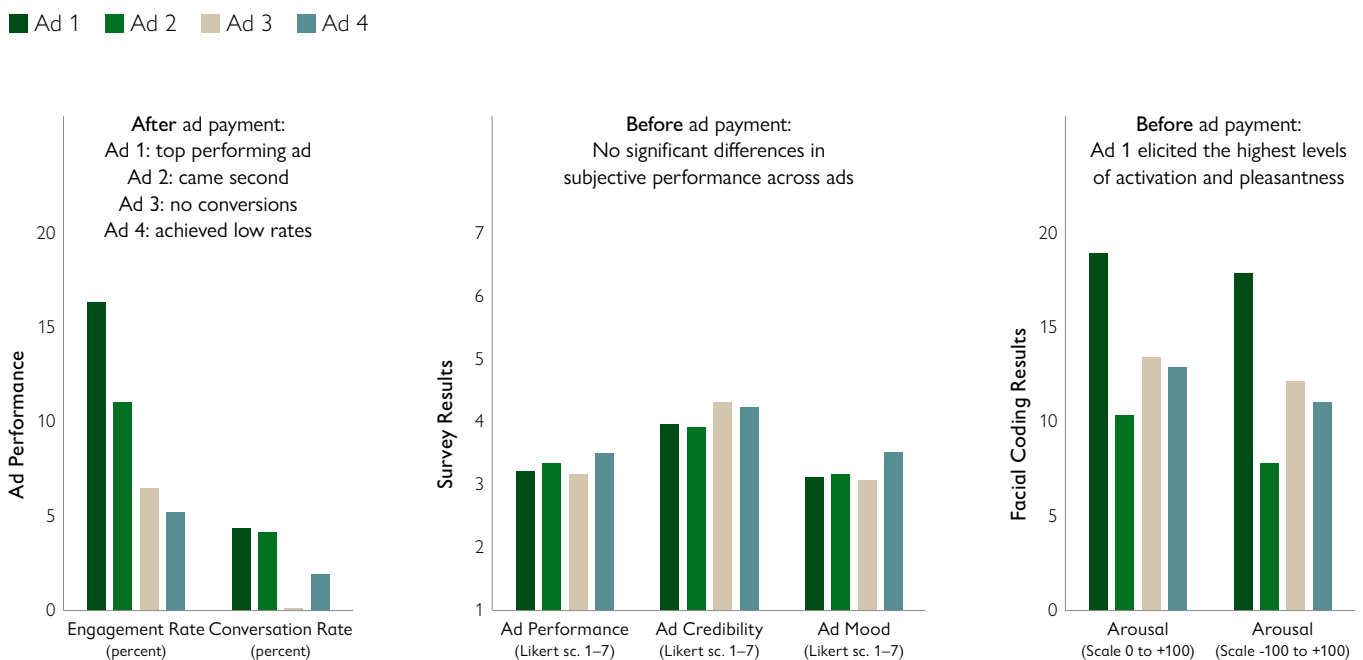
For data validation, a thorough cross-check was performed to ensure the presence of complete observations with sufficient data quality per participant. To assess the effectiveness of advertisements in the field, this research evaluated ad performance using two key performance indicators (KPIs): engagement rate and conversion rate, as derived from Meta Business Suite. The engagement rate is defined as the ratio of reactions (likes, shares, comments) to the total number of views (impressions). The conversion rate is measured as the percentage of website visitors who completed a purchase in the brand's online store relative to the total number of visitors who arrived via the ads in the online store. The data analysis includes (a) a descriptive ranking of the behavioral ad performance (engagement rate, conversion rate), (b) a triangulation of these rankings with survey data and facial coding data, and (c) an exploratory analysis of the eye-tracking results.

Analysis and Results

The descriptive analysis of behavioral and performance data measured over a 4-week period with more than 12,000 impressions for each ad revealed specific and consistent orders of engagement and conversion rates for each ad. The top-performing ad 1 achieved an engagement rate of 16.3% and a conversion rate of 4.3%. Ad 2 came second with an engagement rate of 11.0% and a conversion rate of 4.1%. Ads 3 and 4, in the third and fourth positions, respectively, had lower engagement rates of 6.4% and 5.2% and conversion rates of 0.0% and 2.0% (see figure 3).

The survey data showed no significant differences in means based on t-tests of the explicit perception of ad items across ads. Thus, explicit survey data did not accurately predict ad performance.

Figure 3: Descriptive Results



Source: Authors' own illustration.

Facial coding analysis provided data on arousal and valence levels (30 frames per second). While arousal ('activation') measures the level of excitement, valence ('pleasantness') indicates the direction or value of emotions (Barrett et al., 1999). Compared to the performance analysis, the analysis of emotional data suggests conclusions that are in line with the performance analysis but contrary to the survey results (see figure 3). The ad with the highest engagement rate (ad 1) also had the highest mean scores for arousal and valence. Accordingly, ad 1 elicited the highest levels of activation and pleasantness in the participants, with significant differences in the means according to the t-test conducted.

Triangulation of the data revealed a positive, strong correlation (Spearman correlation coefficient) between arousal and engagement rate ($r = 0.54$) and between valence and engagement rate ($r = 0.54$). Weaker correlations were found between arousal and conversion rate ($r = 0.08$) and between valence and conversion rate ($r = 0.08$). However, the correlations are not significant due to the small sample size of ads ($n = 4$).

A follow-up exploratory **eye-tracking analysis** was conducted to identify content-related differences that might explain variations in ad perception and performance. Relevant eye-tracking KPIs included areas of interest, respondent count, time to first fixation, fixation duration, dwell time, and first and last fixations. These measurements provide insights into users' visual attention and ad engagement (Mustikawan et al., 2021).

From an eye-tracking perspective, the 'winning ads' based on the conversion and engagement performance data (1 and 2) have two key characteristics: (1) The ads feature more content with exposed skin, which appears to be more appealing and attractive. (2) The ads predominantly showcase darker-colored fashion compared to the brighter-colored, lower-perfor-

Main Propositions

- 1 Understanding the importance of digital empathy helps to create engaging advertising content.
- 2 Multi-methods of digital empathy research can be used to create a competitive advantage.
- 3 Emotion and attention research can help evaluate the performance of social media advertising.

ming ads. This is in line with the darker colors of the brand's signature items. An implicit finding may be that a higher degree of congruence with the brand image achieves higher engagement and conversion rates. Further research could explore the nuances of this relationship and provide more detailed insights.

As might be expected, the higher-performing ads attracted more attention to the products, resulting in higher respondent counts, more fixations, and longer fixation durations for the claim at the end of

formance, which only became apparent in behavioral data (see figure 3). By incorporating facial coding and eye-tracking into SMA testing, the study was able to predict the winning ad's performance based on implicit reactions (subconscious emotion and visual attention). Eye-tracking data provides further insights into ad content characteristics that may influence ad performance. The results clearly demonstrate the value of integrating facial coding and eye-tracking techniques to understand ad performance better and predict ad effectiveness *before* investing in SMA. As such, the findings challenge the reliance on explicit, self-reported survey data and highlight the need to consider implicit measures for more accurate assessments of ad performance.

Discussion, Limitations, and Further Research

This study makes notable contributions to the field of multi-method UX research and the effectiveness of SMA, as outlined above. However, it is important to emphasize that while the results demonstrate a degree of generalizability in improving the understanding of user responses, further research is needed to establish the reliability and validity of these findings.

Integrating facial coding and eye-tracking can enhance our understanding of social media ad performance.

the ad. Surprisingly, the 'call-to-action button' received the least attention across all ads. The fashion models drew attention away from the intended action (to buy) but not from the ad's overall message conveyed by the tagline, which had an inspiring and positive attitude.

Interestingly, explicit, self-reported survey data could not predict actual ad per-

formance. It is worth noting that while the top-performing ad could be reliably predicted, the results for the second-best performing ad remained ambiguous. In line with some existing studies that address the prevailing challenges associated with facial coding, such as the accurate detection of conscious expressions like simulated or forced smiles (Höfling et al., 2021), this research seeks to contribute

to this ongoing discourse. Additionally, some studies claim that micro-expressions can only be detected using facial electromyography (EMG) (Dong, 2022).

It is important to note that this experiment only focuses on the products of a single brand within the fashion industry, with four social media ads ($n = 4$). Expanding the industry and product scope could potentially improve the predictive capabilities across a wider range of product performance levels. Furthermore, 44% of the users were familiar with the brand and 11% had already purchased at least one item. The relationship of such prior brand knowledge to user reactions and advertising effectiveness could also be explored. Broadening the research in terms of product scope and industry and using a wider set of survey constructs might also be topics for future research.

While this study informs agencies and UX researchers that testing the effectiveness of social media advertising is feasible, it does not outline the investments

and skills required. Thus, future research should evaluate concrete cost-benefit ratios by comparing multi-method UX research costs with actual monetary SM marketing efficiency/effectiveness gains. Future research might explore the fastest and most cost-efficient technologies on the market across providers and explore the value of 'automated' eye-tracking

UX Researchers,
brand managers,
advertisers, and
agencies can use UX
methods for creating
and pre-testing
engaging ad content.

and facial coding methods. Falling prices and technological advances in sensors, software, and interfaces to downstream systems will lead to decreasing prices for these UX research methods.

Implications

This study extends SMA research by adding implicit UX-based measurements to well-established explicit (e.g., surveys) and behavior-based (e.g., conversion rate) evaluation tools. The findings suggest that ad effectiveness can be implicitly predicted by considering facial coding and eye-tracking data before releasing the ad on SM, thus avoiding misguided investments. Accordingly, the integration of modern UX research methods into the SMA process helps reduce misdirected SM investments. Therefore, marketers should integrate implicit data in the early stages of ad development (Hahn et al., 2018). Facial coding can discriminate between high- and low-performing ads by quantifying emotional reactions and translating them into user preferences; eye-tracking identifies content that can capture users' attention.

Using survey data alone is not a valid approach to predicting ad performance. This may be due to users' lack of self-awareness or inability to articulate the cognitive and emotional processes that lead to their actions (Klug & Hahn, 2021). Moreover, users are often unable to identify subconscious influences in their actual behavior.

The box **Lessons Learned** summarizes these findings for advertisers, ad agencies, performance marketers, UX researchers, and digital campaign managers. They need to understand the growing importance of adding UX research (digital empathy methods) to their current toolkit to understand better what ad content will engage their target audience.

Ad agencies and campaign managers may use these methods to pre-test future ad campaigns before investing in SMA. Ad agencies can employ these methods to create a competitive advantage for their corporate clients and differentiate themselves from competitors.

Lessons Learned

- 1 Performance marketers, ad agencies, ad designers, and UX researchers should use digital empathy research to learn what ad content engages their audiences and to design future campaigns.
- 2 Ad agencies can employ multi-methods of digital empathy research to create a competitive advantage for their corporate clients and differentiate themselves from their competitors.
- 3 Ad agencies and ad designers can use the findings on the role of implicit measurements to create and test future ad campaigns before spending their SMA budget.
- 4 UX researchers may utilize their multi-method research to evaluate SMA performance and bridge the gap between designers and performance marketing experts.
- 5 Using existing data from past campaigns they can explore on a large scale what content drives engagement and conversion.

Moreover, they may use them to quickly prototype effective ads for performance testing as a unique service for corporate clients.

UX researchers can use existing data from past ad campaigns for lab studies to determine which content drives engagement and conversion rates on a large scale. They can employ a set of SMA performance measurement methods to bridge the gap between designers and performance marketing managers.

Digital campaign managers can use these methods to (better) focus on the most promising ads rather than spending impression-based ad fees on SM platforms during the initial campaign optimization process.

In the long run, such tests will guide brand managers, advertisers, and agencies in creating brand-relevant creative content assets while ensuring user engagement with their ads. Thus, combining creative work and AI-based marketing

analytics will become an essential skill in the future (Ameen et al., 2022), as the efficient prediction of human behavior through real-time, AI-based evaluations and the correct application of UX research methods will become increasingly important.

Overall, this study contributes to a greater awareness of the factors that influence customer behavior and provides insights for improving marketing strategies. ■

References

- Ameen, N., Sharma, G. D., Tarba, S., Rao, A., & Chopra, R. (2022). Toward advancing theory on creativity in marketing and artificial intelligence. *Psychology & Marketing*, 39(9), 1802–1825. <https://doi.org/10.1002/mar.21699>
- Barnhart, B. (2021, March 29). Paid social 101: The basics of running effective ads. Sproutsocial. <https://sproutsocial.com/insights/paid-social-101/>
- Barrett, L. F., & Russell, J. A. (1999). The structure of current affect: Controversies and emerging consensus. *Current Directions in Psychological Science*, 8(1), 10–14. <https://psycnet.apa.org/doi/10.1111/1467-8721.00003>
- Beer, J. M., Smarr, C. A., Fisk, A. D., & Rogers, W. A. (2015). Younger and older users' recognition of virtual agent facial expressions. *International Journal of Human-Computer Studies*, 75, 1–20. <https://doi.org/10.1016/j.ijhcs.2014.11.005>
- Bruner, G. C., Hensel, P. J. & James, K. E. (1992). *Marketing scales handbook: A compilation of multi-item measures*. American Marketing Association.
- Blair, G., Coppock, A., & Moor, M. (2020). When to worry about sensitivity bias: A social reference theory and evidence from 30 years of list experiments. *American Political Science Review*, 114(4), 1297–1315. <http://dx.doi.org/10.1017/S0003055420000374>
- Blake, C. (2013). Eye-tracking: Grundlagen und Anwendungsfelder. In W. Möhring & D. Schlütz (Eds.), *Handbuch Standardisierte Erhebungsverfahren in der Kommunikationswissenschaft* (pp. 367–387). Springer Fachmedien Wiesbaden.
- Datareportal. (2023). *Global social media statistics*. <https://datareportal.com/social-media-users/>
- Davenport, T., & Beck, J. (2001). *The attention economy: Understanding the new currency of business*. Harvard Business School Press.
- Diefenbach, S., Kolb, N., & Hassenzähl, M. (2014). The 'hedonic' in human-computer interaction: History, contributions, and future research directions. *Proceedings of the 2014 Conference on Designing Interactive Systems*, 305–314. <http://dx.doi.org/10.1145/2598510.2598549>
- Dong, Z., Wang, G., Lu, S., Dai, L., Huang, S., & Liu, Y. (2022). Intentional-deception detection based on facial muscle movements in an interactive social context. *Pattern Recognition Letters*, 164, 30–39. <https://doi.org/10.1016/j.patrec.2022.10.008>
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59. <https://doi.org/10.1016/j.ijinfomgt.2020.102168>
- Ekman, P. (2009). *Telling lies: Clues to deceit in the marketplace, politics, and marriage* (revised edition). WW Norton & Company.
- Hahn, A., Klug, K., & Riedmüller, F. (2020). Digital empathy: Kombinierte Erfassung über Affective Computing und Eye-Tracking. *Digitale Welt*, 4, 24–27. <https://doi.org/10.1007/s42354-020-0278-4>
- Hahn, A., & Maier, M. (2018). Affective computing: Potenziale für empathisches digitales Marketing. *Marketing Review*, 35(4), 52–65.
- Höfling, T. T. A., Alpers, G. W., Gerdes, A. B., & Föhl, U. (2021). Automatic facial coding versus electromyography of mimicked, passive, and inhibited facial response to emotional faces. *Cognition and Emotion*, 35(5), 874–889. <http://dx.doi.org/10.1080/02699931.2021.1902786>
- Jiang, Y., King, J. M., & Prinyawiwatkul, W. (2014). A review of measurement and relationships between food, eating behavior and emotion. *Trends in Food Science & Technology*, 36(1), 15–28. <https://doi.org/10.1016/j.tifs.2013.12.005>
- Klug, K., & Hahn, A. (2021). Digitale Empathie von Conversational Interfaces: Wie sich automatisierte Interaktionen mit Chatbots empathisch gestalten lassen. *Marketing Review St. Gallen*, 38(4), 18–25.
- Köster, E. P., & Mojet, J. (2015). from mood to food and from food to mood: A psychological perspective on the measurement of food-related emotions in consumer research. *Food Research International*, 76, 180–191. <http://dx.doi.org/10.1016/j.foodres.2015.04.006>
- Liadeli, G., Sotgiu, F., & Verlegh, P. W. (2023). A meta-analysis of the effects of brands' owned social media on social media engagement and sales. *Journal of Marketing*, 87(3), 406–427. <https://doi.org/10.1177/00222429221123250>
- McDuff, D., & El Kaliouby, R. (2017). Applications of automated facial coding in media measurement. *IEEE Transactions on Affective Computing*, 8(2), 148–160. <https://doi.org/10.1109/TAFFC.2016.2571284>
- Mustikawan, A., Swasty, W., & Naufalina, F.E. (2021). Utilization of eye-tracking technology in design and marketing decision making. *ASEAN Marketing Journal*, 13(2), 158–170. <https://doi.org/10.21002/amj.v13i2.13542>
- Nosek, B. A. (2007). Implicit-explicit relations. *Current Directions in Psychological Science*, 16(2), 65–69. <https://doi.org/10.1111/j.1467-8721.2007.00477.x>
- Picard, R. W. (2003). Affective computing: Challenges. *International Journal of Human-Computer Studies*, 59(1–2), 55–64. [https://doi.org/10.1016/S1071-5819\(03\)00052-1](https://doi.org/10.1016/S1071-5819(03)00052-1)
- Statista. (2023). *Social media advertising: Worldwide*. <https://www.statista.com/outlook/dmo/digital-advertising/social-media-advertising/worldwide>
- Teixeira, T. (2014). The rising cost of consumer attention: Why you should care, and what you can do about it. (Harvard Business School Working Paper, 14–055). https://www.hbs.edu/ris/Publication%20Files/14-055_2ef21e7e-7529-4864-b0f0-c64e4169e17f.pdf
- Teixeira, T., Wedel, M., & Pieters, R. (2012). Emotion-induced engagement in internet video advertisements. *Journal of Marketing Research*, 49(2), 144–159. <https://psycnet.apa.org/doi/10.1509/jmr.10.0207>
- Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97–121. <https://doi.org/10.1509/jm.15.0413>
- Wedel, M., & Pieters, R. (2017). A review of eye-tracking research in marketing. *Review of Marketing Research*, 4, 123–147. [http://dx.doi.org/10.1108/S1548-6435\(2008\)0000004009](http://dx.doi.org/10.1108/S1548-6435(2008)0000004009)
- Wertz, J. (2022, October 30). How to increase engagement through video marketing. *Forbes*. <https://www.forbes.com/sites/jiawertz/2022/10/30/how-to-increase-engagement-through-video-marketing/>