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Article

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Marketing Review St.Gallen

Marketingzeitschrift für Theorie & Praxis

5/2024

Marketing Review St.Gallen

The Role of Marketing in the Green Economy

Universität St.Gallen

Toward a Digital Empathy Framework

Evaluating User Experience Research Methods

New technologies require aesthetic and hedonic user experience (UX) design to remain competitive. For guidance, a conceptual digital empathy framework explains and recommends individual UX research methods. The digital empathy framework is supported by two case studies of triangulated UX research methods – facial coding, eye tracking, and surveys – that provide valuable complementary insights.

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The Covid pandemic has accelerated digital transformation and the adoption of new technologies (De' et al., 2020), requiring the expansion of current consumer research frameworks to understand how users interact with, perceive, and feel about these technologies (Hoffman et al., 2022). Over the last decade, holistic user experience (UX) has come into the focus of research. UX research findings provide functional, aesthetic, and emotional experiences as perceived by users (Pettersson et al., 2018). Due to increasingly digital customer journeys, UX is relevant in almost all business-to-consumer and business-to-business markets. Accordingly, the optimization of holistic UX is central to successful digitization (Märtin et al., 2021).

Functional UX has become a basic factor in technology design for users (Zomerdijk & Voss, 2010), while **hedonic UX** has become a critical success factor, enabling businesses to influence consumer behavior such as purchase intention, willingness to pay, and conversion rate. Accordingly, new technologies are increasingly geared towards aesthetic and hedonic UX design (Suh et al., 2017) to attract new users and retain existing ones (Harwood & Garry, 2015; Wolf, 2019). A very successful example is TikTok with its captivating UX design (Cosmann et al., 2022).

Users tend to respond to aesthetic and hedonic experiences emotionally and subjectively, both positively and negatively (Bhandari et al., 2019). However, explicit research methods such as surveys and interviews are limited in reliably collecting and analyzing emotional data, e.g., due to social desirability bias or instructor bias (Blair et al., 2020; Ekman, 2009). This leads to uncertainty for startups, small and medium-sized enterprises, and companies in the early stages (1–4) of Pernice et al.'s (2021) UX maturity model, about which methods (individual data collection approaches) to use for testing the aesthetic and hedonic aspects of their prototypes, products, services, and communications (Law et al., 2014; Tawfik et al., 2022). Digital and digitalized companies cannot rely on outsourcing, but should rather focus on implementing UX research as a core competency alongside UX design and UX strategy.

To address this need, this paper develops a framework for **digital empathy** (DE) that includes various individual methods for collecting and analyzing emotional and subjective UX data. Digital empathy involves empathizing with users' feelings and thoughts when interacting with digital technologies and designing user experiences of high functional, aesthetic, and hedonic quality (Klug & Hahn, 2021). This framework is necessary for marketing managers as UX research increasingly incorporates artificial empathy into marketing interactions, as users expect digital technologies to be tailored to their current cognitive and affective states (Liu-Thompkins et al., 2022). The DE framework recommends individual UX research methods in marketing that focus on product–solution fit and product–market fit to evaluate delightful, useful, and meaningful user interactions with new technologies.

This paper aims to showcase the DE framework's practical application and value through two case studies. The studies use both hedonic and functional visual content and rely on triangulated UX research methods. The framework will guide decision-makers in selecting methods, building a tool and technology stack, and developing internal UX skills.

DE Framework of UX Research Methods

Maia and Furtado (2016) found that the majority of UX studies implement one single form of UX measurement, which limits the holistic understanding of UX, which consists of functional, aesthetic, and hedonic dimensions. Aesthetic features include characteristics beyond utility, such as attractiveness, and the hedonic dimension includes user iden-

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tification, affect, and motivation (Hassenzahl & Tractinsky, 2006). Thus, no single research method can capture UX holistically. For companies in the early stages (1–4) of the UX maturity model, it is therefore challenging to choose methods for comprehensively exploring the three dimensions in various scenarios.

Management Summary

This paper presents a digital empathy (DE) framework that explains and recommends contemporary user experience (UX) research methods for evaluating users' delightful, useful, and meaningful interactions with new technologies. To substantiate the DE framework, the paper presents two case studies using triangulated UX research methods on both hedonic and functional visual content. Specifically, facial coding, eye tracking, survey questions, and log file analysis show the potential to complement work in UX contexts as diverse as price perception and social media advertisements.

To address this challenge, the DE framework evaluates the measurement quality, applicability, costs, and benefits of **six UX research methods:** (1) facial coding, (2) eye tracking, (3) qualitative interview, (4) think aloud protocol, (5) log file analysis, (6) survey/questionnaire, based on four main selection criteria. The order is based on their respective implicit measurement quality, as described in Table 1.

These methods are most commonly used in today's UX research and academic literature, and are suitable for existing products and services as well as new technologies and solutions, including prototyping and testing as early as the ideation phase. We also selected tools that are cost-efficient to implement and require only a reasonable level of expertise to use. Consequently, we excluded methods of clinical neuroscience that require specific medical training such as EEG (electroencephalography), MRI (magnetic resonance imaging), and fMRI (functional magnetic resonance imaging).

Ratings are based on the authors' literature review of methods and analysis of research projects from 2019 to 2022.

Table 1: Measurement Quality of Six Relevant UX Research Methods

	Organism		Response	Reliability
UX Research Method	Implicit Reactions (System 1)	Explicit Reactions (System 2)	Behavioral Reaction	Avoidance of Bias
Facial coding	+++	++	0	++
Eye tracking	++	++	++	+++
Qualitative interview	+	++	+	0
Think aloud protocol	+	+++	+	+
Log file analysis	+	0	+++	+++
Survey/questionnaire	0	++	+	0

[+++] high, [++] medium, [+] low, [0] very low

Source: Authors' illustration based on Barbour, 2018 ; Bharadwaj et al., 2021; Blair et al., 2020 ; Ekman, 2009; Hulland et al., 2018; Jaspers et al., 2004; Kumar & Ogunmola, 2020; McDuff et al., 2021; Wedel et al., 2019.

This analysis includes 25 triangulated research projects focusing on six highly relevant UX research methods (facial coding, eye tracking, qualitative interview, think aloud protocol, log file analysis, and survey).

We assessed each method's ability to measure the steps of the stimulus-organism-response model when studying user behavior (Table 1). For measuring functional, aesthetic, and hedonic user responses, decision-makers can focus on actual behavioral reactions (= responses) and cognitive and emotional reactions inside the user organism. The organism is represented by Kahneman's (2013) System 1 and System 2, where System 1 represents intuitive (= implicit) reactions, and System 2 characterizes analytical (= explicit) responses.

The methods were evaluated based on their measurement qualities, built-in objectivity, reliability, validity from a scientific perspective, and ability to avoid bias (Table 1). Implicit reactions are fast, while explicit responses are slower. Therefore, measuring the intuitive reactions of System 1 in UX research is more challenging than the analytical thinking of System 2. Finally, each method was evaluated based on its ability to measure user behavior (= responses).

In a second step, the methods were evaluated based on their investment and performance from a managerial perspective (Table 2). It is vital for managers to have tools that have an efficient ratio of low investment and high performance that can be easily scaled.

In the following, we summarize and briefly discuss the six selected UX research methods from an academic and managerial perspective:

(1) Facial coding, or affective computing, is "computing that relates to, arises from, or influences emotions" of users (Picard, 1997, p. 1). The Facial

Action Coding System (FACS) is currently used to measure user emotions through facial reactions in response to digital products (Cohn et al., 2007; Ekman & Friesen, 1978). The FACS measures participants` valence and arousal through an algorithm that detects specific facial muscle movements known as action units (Hahn & Maier, 2018). Available software programs include Affectiva, OpenFace, and Tawny. Facial coding enables the observation of implicit user reactions without questioning the users, thus minimizing conscious and unconscious bias (Bharadwaj et al., 2021; McDuff et al., 2021). However, there is a risk of bias from false positives, such as falsely detecting a positive reaction to a feature that actually elicited a negative response (e.g., a nervous smile).

(2) **Eye tracking** is a validated research method in marketing (Wedel et al., 2019) that measures user attention in terms of perception and provides insights into the cognitive and evaluative processes during user tasks (Wedel et al., 2022). Although an all-round performer (good implicit, explicit, and behavioral measurement), eye tracking is not a stand-alone solution in UX research as it cannot explain the reasons for positive or negative emotional reactions to content. However, it can measure arousal states and be used as a supporting method to validate findings (Skaramagkas et al., 2021). Today, high-quality and affordable eye trackers can be easily connected to laptops via USB cables. The use of advanced algorithms for webcam eye tracking is a cost-effective alternative, although it may compromise data accuracy in favor of speed and lower research costs. This facilitates field experiments with participants from the comfort of their computers. Examples of these budget-friendly alternatives include iMotions, Tawny.ai, and RealEye. Moreover, researchers can now take advantage of predictive eye tracking tools that use AI to anticipate users' eye movements and generate predictive heatmaps (3M, 2023; Attention Insight, 2023; Neurons, 2023). These tools are trained on extensive datasets from numerous eye tracking studies to improve their predictive capabilities.

(3) **Qualitative interviews** are a well-known research method in the field of qualitative research (Barbour, 2018). Interviews are conducted in a one-on-one setting, but can be enhanced with semi-automated evaluation methods such as MAXQDA (Kuckartz & Rädiker, 2019). However, interviews are subject to instructor bias and social desirability bias and require very careful preparation and execution (Blair et al., 2020; Ekman, 2009). Additionally, interviews have limitations in measuring implicit thinking and behavioral reactions. UserBit is a great example of a tool that can efficiently analyze qualitative data at low costs (UserBit, 2023).

(4) **Think aloud protocol** is a widely used method in usability testing for measuring explicit thoughts in real-time. Users are asked to verbalize their thoughts while their voiced responses are recorded and later transcribed for later analysis. However, there is a potential risk to affect the tests themselves because talking may distract users (Jaspers et al., 2004). Additionally, this method is cost-intensive and difficult to scale. Exemplary tools like Lookback can record online sessions and transcribe voice recordings for further analysis in tools like UserBit (Lookback, 2023).

(5) **Log file analysis** is used to analyze stored data on online servers like websites. In UX research it accurately measures online user behavior in metrics such as page views or button clicks, making it a scalable and cost-efficient method. However, it has limitations in measuring implicit and explicit (Kumar & Ogunmola, 2020). Microsoft Clarity is an exemplary free tool to effectively analyze website log file data.

(6) **Surveys/questionnaires,** which can be conducted either offline or online, **are** a very popular research approach in marketing research. However, researchers must be aware of both a priori and post hoc methods to deal with

Main Propositions

1. New technologies prioritize aesthetic and hedonic UX design, shaping user preferences.
2. Users respond more emotionally and subjectively to aesthetic and hedonic experiences.
3. Aesthetic and hedonic UX is harder to measure than functional UX as users are often unaware of their implicit thinking.
4. The DE framework assists managers in choosing appropriate UX research methods to research implicit and explicit user behavior.
5. The triangulation of UX research methods is key to generating valid and valuable insights.

Table 2: Cost-Benefit Ratio/Value Added of Six Relevant UX Research Methods

	Investment[1]		Performance
UX Research Method	Cost	Required Expertise	Scalability
Facial coding	+	++	++
Eye tracking	++	+++	+
Qualitative interview	+++	++	0
Think aloud protocol	+++	++	0
Log file analysis	+	++	+++
Survey/questionnaire	+	++	++

[+++] high, [++] medium, [+] low, [0] very low

1 please note that lower levels are desirable due to the scale for these criteria

Source: Authors' illustration based on Barbour, 2018 ; Bharadwaj et al., 2021; Blair et al., 2020 ; Ekman, 2009; Hulland et al., 2018; Jaspers et al., 2004; Kumar & Ogunmola, 2020; McDuff et al., 2021; Wedel et al., 2019.

common method variance (Hulland et al., 2018). Additionally, this method has a high risk of social desirability bias (Ekman, 2009), which could lead to biased measurements regarding implicit thinking. It is also important to note that this method focuses on attitudes and intentions for future behavior or memories of past behavior, rather than current behavior. Typeform is an intuitive survey creation tool for easy online integration and effective analysis and reporting.

In summary, our analysis shows that there is no one best method to capture the full spectrum of DE. Emotional reactions within the user's organism are crucial for understanding hedonic UX, and these implicit (cognitive and emotional) reactions can be measured objectively and accurately through methods such as facial coding and eye tracking. Various methods can measure explicit reactions, while log file analysis and eye tracking are ideal for capturing behavioral responses. Facial coding is a low-cost, low-bias option for measuring implicit reactions. In contrast, widely used methods such as surveys and interviews carry a high risk of bias, and the latter can be costly.

Facial coding, eye tracking, and think aloud protocols are promising methods for capturing DE in an integrated manner. Also, widely used methods such as log file analysis can be seamlessly combined with other methods for DE assessment. However, there is still a lack of systematic cross-method evaluation in UX research (Pettersson et al., 2018). To avoid bias, UX studies should use a multi-method approach and not rely on a single measurement method. Moreover, not all methods can measure implicit user reactions, especially surveys. These challenges call for a multi-method approach. A successful triangulation approach that can be used in UX research is usability testing, which applies a multi-method approach to broaden the spectrum of insights collected (e.g., combining log file analysis, think aloud protocol, and qualitative interview).

Pettersson et al. (2018) substantiate the rationale for triangulating multiple methods in UX research, i.e., combining individual data collection methods from the DE framework that together can capture implicit (e.g., via facial coding), explicit (e.g., via eye tracking), and behavioral (e.g., via log file analysis) reactions to holistically capture all three UX dimensions.

The following case studies illustrate our recent integration of methods from the DE framework applied to both hedonic and utilitarian use cases, highlighting such triangulated mixed-methods research.

Case Studies

Table 3 summarizes the two use cases that implement both a quantitative and a qualitative approach. Case 1 focused on functional UX and Case 2 focused on aesthetic and hedonic UX.

Case Study 1: True Pricing

This study (n = 67, 50.7% female, mean age 24 years) analyzed users' perceptions of sustainable pricing using facial coding, eye tracking, and survey data. The study used iMotions and Typeform to collect data. Price labels included the "true" price of a good as determined by the true cost accounting (TCA) approach, which includes all external costs across the value chain, such as energy, greenhouse gas and reactive nitrogen emissions, and biodiversity loss (Michalke et al., 2022).

An A/B test was conducted for three different products (bananas, milk, and minced meat). Version A presented a simple true price by showing the difference from the standard price. Version B presented the complex true price, explaining the cost per factor in a utilitarian manner (see Figure 1).

Multiple methods were triangulated as we expected different modes of thinking to be activated by the different price labels: simple price information vs. more complex price information, as sustainability pricing may influence the perception of price fairness (Habel et al., 2016). **Facial coding** showed that Version B activated System 2 (explicit thinking). Furthermore, **eye tracking** showed that in Version B, users were significantly drawn to the utilitarian information (green area) rather than the standard price (red area). **Survey**

Figure 1: True Pricing of a Banana (A/B Testing)

Source: Authors' illustration.

items confirmed that Version B activated a higher intention to pay the true price.

Case Study 2: Social Media Ads

This study (n = 60, 100% female, mean age 23 years) used facial coding, eye tracking, and surveys via iMotions and Typeform to analyze how users reacted to social media ads. Field data from log file analysis (all ads ran for four weeks) was also included for comparison with performance data (e.g., engagement rate) and shop data (e.g., purchase value) of the ads in Meta Business Suite. The stimuli varied from A/B versions of image posts to storytelling and campaign videos. Triangulation of the methods provided insights into users' implicit thinking when viewing different ads, while log file analysis determined the "winner" (ads with higher post engagement and shop turnover in an A/B setting). Facial coding identified four of the five winners. Eye tracking supplemented the facial coding analysis by explaining user attention (e.g.,

Table 3: Case Studies with Methods and Findings

UX Research Method		Case 1: Price perception			Case 2: Social media ads		
UX research focus		Qualitative Problem-Solution-Fit Testing			Quantitative Product-Market-Fit Testing		
Context		Respondents viewed A/B price tag versions for multiple conventional products, differentiating between a simple true price and a true price that includes complex sustainability explanations.			Respondents viewed social media ads (image and video stimuli) in an A/B setup. Objective log-file data from the social media platform and online store performance data from the ads serve as performance benchmarks.		
Visual content: utilitarian vs. hedonic		Utilitarian			Aesthetic & hedonic		
No. of respondents tested		67			60		
Research method implemented		Facial Coding	Eye Tracking	Survey	Facial Coding	Eye Tracking	Survey
Main findings	Method insight	Explaining emotional state	Explaining attention focus	Explaining purchase intent	Explaining A/B winner with 80%	Explaining attention focus	Cannot explain A/B winner (20% hit rate)
	Cross-Method findings	Methods provide consistent findings on outcomes of A/B testing			Methods provide consistent findings on outcomes of A/B testing		Method does not explain the outcomes of A/B testing

Source: Authors' illustration.

to text, models, call-to-action buttons, and products). However, survey results contradicted facial coding and performance data, suggesting a social desirability bias.

Discussion

Digital empathy is a phenomenon that will accompany companies that intend to conduct UX research as a core competence alongside UX strategy and UX design. This **DE framework**, consisting of six UX research methods, assists decision-makers when considering which methods to use for evaluating UX. Though the case studies differ in research question and communication style, the triangulated multi-method approach provided valuable insights. **Case 1** demonstrates that although the survey provided results on the A/B "winner" (i.e., the successful attempt to alter purchase intent), facial coding and eye tracking better explained the underlying cognitive and emotional processes. **Case 2** provides high-value insights from each method in the multi-method approach, with log file analysis defining the winning ads in terms of engagement and turnover, and facial coding (supported by eye tracking data) accurately predicting the winning ad. Survey data, however, shows more bias. Finally, triangulation of the methods indicates that facial coding could also be used to predict future ad winners.

Modern IT solutions, particularly SaaS-based platforms such as UserBit, have significantly reduced the cost and time associated with triangulating multiple research methods (UserBit, 2023). While cost may not always be a top priority, a more comprehensive approach to method triangulation is crucial in certain scenarios, such as broken user journeys or new product development. In contexts that involve highly hedonic or implicit tasks with low failure tolerance, such as B2C fashion or B2B urgent implicit tasks, prioritizing a more nuanced approach to method triangulation becomes critical. This ensures that the selected methods are aligned with the specific demands of the research context, providing valuable insights while optimizing costs.

Summary and Future Research

The convergence of new technologies into new customer touchpoints is driving adoption research (Hoffman et al., 2022). To meet user expectations for functional UX and influence customer behavior through hedonic UX, triangulation of UX research methods (focusing on hedonic aspects and implicit reactions) will be key for future UX research. The use cases demonstrate the implementation of triangulated UX research methods in practice, producing valuable insights that are objective, reliable, and cost-effective. Case 2 shows how triangulation can potentially be used to predict ad performance. Further research should test other channel settings (e.g., TikTok or Instagram vs. offline touchpoints). Furthermore, future research could extend the DE framework with methods that focus on existing secondary data, e.g., user-generated content on social media (via methods such as netnography and sentiment analysis). However, these methods are not entirely feasible for new product innovations or prototype testing in UX research because they require users to have had substantial time to interact with the new technologies.

As for **managerial implications**, the DE framework with its six UX research methods can guide startups, small and medium-sized enterprises, and companies in the early stages (1-4) of the UX maturity model in deciding on an appropriate method mix. Each method was rated in terms of the quality of measuring the user's internal organism, namely implicit thinking and explicit thinking, as well as the quality of measuring the behavioral response. The methods were also rated on their respective avoidance of the biases involved, their costs of implementation, the expertise required to conduct the research, and their scalability potential. Furthermore, the framework helps decision-makers set up a tool and technology stack that can be used for various research projects. Finally, the DE framework can be used to nurture future UX talents and further develop current UX skills.

Lessons Learned

1 Managers need to understand the increasing relevance of aesthetic and hedonic UX for their respective industries.

2 Managers should use the DE framework to assess which tools are best suited for their research project.

3 Managers can build a UX hardware and software stack that can measure the three UX dimensions (functional, aesthetic, and hedonic) using digital tools for optimal efficiency and return on investment.

4 In contexts that involve highly hedonic or implicit tasks with low error tolerance, such as B2C fashion or B2B fast implicit tasks, prioritizing a more nuanced approach to method triangulation becomes critical.

5 In particular, facial coding triangulated with eye tracking and survey yields valid and valuable results for aesthetic and hedonic UX.

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