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The Role of Emotions in Personalization: Detecting Emotions in Real-Time as Context Information

Master's thesis in Interaction Design
Supervisor: Frode Volden
June 2019

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Preface

The following thesis is my final examination for the master's program in Interaction Design at the Norwegian University of Science and Technology in Gjøvik. The project planning and literature review were conducted during the fall semester of 2018, and the research conducted during spring 2019. The project's methods were approved by the Norwegian Centre for Research Data (NSD), and the workload corresponds to 30 ECTS.

I want to thank my supervisor, Frode Volden for his guidance, input, and discussions through the work with this thesis. It would have been an impossible task to finish my dissertation and degree as an off-campus student without you taking the time to reply to my e-mails, text messages, and phone calls.

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Thanks to everyone that participated in the user research and experiments, for taking the time to help me with my thesis work.

Thanks to my friends and colleagues for sharing their experiences, expertise, and encouraging words throughout my degree. A special thanks to everyone that spent hours reading through my drafts and providing feedback.

Thanks to my family for your never-ending love and support.

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01-06-2019
M.T.N.

Abstract

Emotion as contextual information is increasingly recognized to be essential variables to web personalization but is still an underresearched topic. Poor assumptions are made about user preferences as current personalization technology only gather historical data, without considering real-time information besides factors like time, location, and device. As a consequence, consumers have a bad user experience because the content is deemed to be irrelevant. The researcher introduces contextual personalization as a system-initiated process that considers the user's current emotional state as contextual information to address the individual user with relevant content.

This master's thesis investigates how providers can offer a better user experience by utilizing emotions as part of contextual information in the personalization process. By employing a mixed-method design, combining both qualitative and quantitative methods from user-centered design and affective computing, user needs and user behavior during specific emotional states were identified. The following investigation is twofold; the first part involves identifying emotional states with current emotion detection technology on the market, as well as empirically validate the effectiveness and reliability of the software. The second part of the project investigates whether the user's emotional state affects the user experience and the user's perception of content relevance. By using methods adapted mainly from previous studies, participants were induced with a specific emotion before interacting with a website. The results in the first experiment suggest that current face analysis technology can detect the intended emotion from even microexpressions. The results in the second experiment did not show significant differences between the two groups on perceived content relevance or the user experience. The data still yields indications that there is an emotional affect in interaction.

Keywords: contextual personalization, contextual information, facial analysis, emotion detection, emotional affect, online consumer behavior, user experience, content relevance

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Acronyms

HCI	Human-Computer Interaction
SDK	Software Development Kit
FACS	Facial Action Coding System
GDPR	General Data Protection Regulation
UI	User Interface
AEMT	Autobiographical Emotional Memory Task
IxD	Interaction Design
AI	Artificial Intelligence
GSR	Galvanic Skin Response
PQ	Pragmatic Quality
HQ	Hedonic Quality
HQ-I	Hedonic Quality - Identity
HQ-S	Hedonic Quality - Stimulation
ATT	Attractiveness
EV	Evidence Value

1 Introduction

The widespread use of information technology available has made the race to provide personal relevance more extensive than ever. Research has shown that personalized products and services are more appealing to use than non-personalized, creating and enforcing interactive relationships with the users (Sunikka and Bragge, 2012), but at what cost? Before digital media, all content was featured the same for all users. Now, everything online is targeted to the individual user, based on things you have done, things you seem to like, and things your friends like (Praiser, 2012; Haim et al., 2017). This altering of information creates a filter bubble that one cannot escape nor change. The results one gets from performing a search is entirely dependent on what the algorithm thinks is best for you – and someone else might get a completely different result (Praiser, 2012). Critics argue that offering personalized content fragments the population (Praiser, 2012), and while some agree that filter bubbles can lead to partial information blindness, it also helps people find what they are looking for, as well as can widen and create a commonality of interests (Hosanagar et al., 2014; Haim et al., 2017).

According to a survey conducted by Infosys (2013), 86% of consumers say personalization has some impact on what they purchase, and 25% say personalization significantly influences their buying decisions. A study conducted by Adobe found that 67% of respondents think it is vital that content is automatically adjusted based on their current context, and when it is not, 42% find the personalized content annoying because it does not fit their interests (Abramovich, 2018). 66% of consumers said encountering a situation where the content is not optimized or poorly designed would stop them from making a purchase (Abramovich, 2018). The success of personalization strategies relies on data collection and processing, but current algorithms are not complex enough to account for fluctuating user preferences (Salonen and Karjaluoto, 2016). Traditional recommender systems only deal with two types of entities, users, and items, without considering the context (Adomavicius and Tuzhilin, 2011). Context is defined as “the location of the users, the identity of people near the user, the objects around, and the changes in these elements” by Gorgoglione et al. (2006). Other researchers, like Dey et al. (2001), include more variables as contextual information, such as the user’s emotional status. Several studies in affective neuroscience and psychology have reported that human affect and emotional experience play a significant role in decision making (Loewenstein and Lerner, 2013; Naqvi et al., 2006; Lekkas et al., 2009; Brosch et al., 2013). As a transaction takes place, a user’s preference and purchase process are contingent upon the context of the transaction (Gorgoglione et al., 2006). The one-size-fits-all strategy is no longer effective, in which marketers and providers will benefit from the realization of the need to account for contextual information in real time (Aguirre et al., 2015; Garcia-Garcia et al., 2017). Gorgoglione et al. (2006) argues that companies that know what their customers are feeling have an advantage in the market.

Although several researchers in different disciplines have recognized contextual information as essential variables to web personalization, it is still an underresearched topic to this day (Adomavicius and Tuzhilin, 2011; Salonen and Karjaluoto, 2016; Huang and Zhou, 2018). Prior research has significantly focused on various aspects of implementing personalization, such as recommender systems or recommender agents (Salonen and Karjaluoto, 2016). Emotion detection is one of the most considered aspects of Affective Computing. The field is relatively new and focused on developing technologies that can detect human emotions from a specific input, such as the face, body movements, or tone of voice. Human emotions play an important role in decision making, as well as product experience (Spinelli et al., 2014; Cambria et al., 2012). An emotion is aroused in the user based on a response to design elements in web design (Cyr, 2013). Accordingly, it can be assumed that emotion is aroused in the user based on a response to the content. If the content is considered to be relevant, the interface design appealing, and the interaction user-friendly, then it would arouse a positive feeling toward the brand, foster loyalty, and returning in the future. As such, if companies conceptualize emotions as contextual information, emotion detection technology could be utilized to provide personalized applications that dynamically adapt the digital environment to the user's benefit.

This thesis project aims to explore how companies, marketers, and users can benefit from contextual personalization in web environments. In this thesis, contextual personalization is defined as a system-initiated process to address the individual user with relevant content in the situational context. The situational context considers real-time information, such as the current emotional state of the user. The researcher intends to answer whether more complex factors such as human emotions can be utilized as contextual information, as well as the emotional effects on perceived content relevance and the user experience, to make more accurate predictions on user preferences in real-time, ultimately to build better customer profiles and foster user satisfaction.

1.1 Motivation, Justification, and Benefits

Personalization has drawn increasing attention from both academia and industry, but the field has reached no consensus regarding the question of personalization effectiveness. While the question remains debatable, effectiveness appears to be related to how and where personalization is implemented (Fan and Poole, 2006; Salonen and Karjaluoto, 2016). The field continues to expand and advance rapidly as new possibilities appear due to technological advances. Given the diversity of contextual information, employing entities besides time, location, and devices such as the user's emotional status could increase the potential to design and build more personalized experiences. User preferences are fluctuating in nature, in which utilizing technologies to identify the situational context would be advantageous as the system would dynamically adapt and provide relevant content to the user.

Many fields are central to the discussion on web personalization, but it is more prominent in the field of information systems. The literature mainly focuses on recommender systems and data collection, and the effectiveness of personalization is yet concluded significantly. Salonen and Karjaluoto (2016) suggest contextualization as an area suitable to advance personalization, but more complex factors such as consumer emotions need to be conceptualized as contextual information first. Companies that employ technology to detect human emotions can adapt their services and applications to build better user models, to provide content that is perceived as interesting and relevant to the individual user.

The master's thesis aims to benefit companies and marketers that wish to understand and meet customer expectations and emotions, as well as consumers to be more aware of how user data is being collected and used. Companies that recognize user emotions as contextual information could significantly ensure that the content meets user's needs, ultimately creating for better user experiences.

1.2 Research Questions

To investigate how services and applications can offer a better user experience by utilizing user emotions as part of contextual information used for personalization, following research question and sub-questions will be addressed in the thesis:

1. Is emotions as contextual information a variable that should be taken into account in web personalization?
   a. Can variables such as the user's emotional state be detected in real time and used as contextual information?
   b. Does emotions affect how users perceive content relevance?
   c. Does emotions affect the total user experience of the product?

1.3 Planned Contributions

Through this thesis, the researcher hopes to contribute to the personalization literature by combining several approaches to advance web personalization. Personalization is a controlled system-initiated activity that identifies and assumes user-preferences based on previous behavior. The researcher investigates if human emotions can be detected with current technologies and whether contextual information such as user emotions impacts the perception of content relevance, the usability and the design of a website.

1.4 Thesis Outline

The structure of the thesis is as follows:

Chapter 1 introduces the problem that is addressed in this thesis project, as well as the motivation, justification, and benefits of addressing this problem. Planned contributions to the research community as well as to users are also stated in this chapter.

Chapter 2 introduces the background, theory, and existing literature regarding personalization, emotion detection technology, and consumer behavior.

Chapter 3 explains the methodology of the thesis. A mixed-method design was used to investigate user needs and user behavior during specific emotional states. The following parts are twofold: the first part explains the methodology to conduct a validity test of a current emotion detection technology. The second part describes the experiment used to investigate the effects emotions have on perceived content relevance and the user experience.

Chapter 4 presents the results from the data analysis of the interviews, questionnaire, workshop, and the statistical analysis of the validity test and the experiment.

Chapter 5 includes the discussion and interpretation of the results, as well as a discussion of contextual personalization.

Chapter 6 gives a summary of the thesis and the final conclusions of the study. The research questions and hypothesis are answered in this chapter. Suggestions for future work to extend the topic is also proposed.

2 Background

Through a literature review, previous research findings and theoretical perspectives related to the research topic were identified and evaluated. Searches were done in the Web of Science database with the following keywords: web personalization, web customization, effectiveness of personalization, timing of personalization, message tailoring, recommender systems, consumer behavior online, contextual information, emotion detection, persuasive technology, and affective modeling. A systematic review process followed to segregate relevant articles from non-relevant, using a checklist. Articles categorized as having significant relevance had been peer-reviewed, published in conference proceedings or journals, or cited several times. Additionally, the search was focused on information systems and business-related topics in web environments, leaving topics such as healthcare and learning out of the scope. By reviewing the current state of research literature in the field, contextual information was found to be relatively new in personalization and adds to a new dimension for assessing the effects of personalization (Salonen and Karjaluoto, 2016). The following sections summarize and define concepts intertwined with personalization, to investigate and identify contextual elements to emphasize in personalization.

2.1 Personalization

Personalization varies in how it is defined, characterized, and implemented in the literature, but it is considered to be an umbrella term for individualized preference matching (Salonen and Karjaluoto, 2016). Personalization is commonly found to be related to personalization in web services and systems. Personalization is hence often referred to as web personalization. The term is not differentiated in the thesis and used interchangeably.

Current approaches to personalization have adopted relatively narrow views on the subject. Information systems and marketing dominate the literature and have focused on the execution and effectiveness of personalization strategies, recommender systems, and data collection. Nonetheless, the fundamental idea of web personalization is to identify and use the customer's information to automatically deliver an individualized interface with relevant content based on previous behavior. It is the system-initiated tailoring and modification of functionality, interface, content, and features to increase the personal relevance to an individual user (Fan and Poole, 2006; Kwon and Kim, 2012; Schade, 2016).

The personalization process relies on data that extrapolate based on things you seem to like, the actual stuff you have done, or the things people like you like (Praiser, 2012; Haim et al., 2017). The result of the personalization process is often called the filter bubble (Praiser, 2012). The filter bubble fundamentally alters the way people encounter ideas and information, creating a unique universe of information for each person, which can be successful, but more than often is not (Salonen and Karjaluoto, 2016; Adomavicius and Tuzhilin, 2011; Zuiderveen Borgesius et al., 2016). Given the extensive information available online, personalization can help people to find things they want, providing suggestions that pique their interest and curiosity. But a customer has different preferences and decision making strategies depending on the context, and different phases in the purchase process keep preferences in flux (Gorgoglione et al., 2006; Salonen and Karjaluoto, 2016). For instance, purchasing a birthday present to a friend can result in implicit assumptions about the user's interest and lifestyle, which can lead to improper suggestions, consequently annoying the user. Further unfit suggestions can quickly lead to dissatisfaction and lost customers. The user's context has been considered to play an essential role in the success of personalization strategies, but obtaining basic information such as time of day or location is no longer sufficient (Gorgoglione et al., 2006). More complex factors, such as human emotions could be the key to making personalization valuable for the user.

2.2 Related Terms

Customization is a term closely related to personalization. Researchers have yet achieved consensus in conceptualizing the terms across domains. Some scholars distinguish personalization and customization as two different concepts, whereas others use the terms interchangeably (Treiblmaier et al., 2004; Sunikka and Bragge, 2012). The distinction between the terms lies in the control of the adaption process and is of importance as they can have different impacts on users. Personalization is system-initiated, identifying and using customer's information to fit their needs automatically. In contrast, customization is under direct user-control in which users directly can adapt and tailor system-components to their specific needs (Nielsen, 1998; Treiblmaier et al., 2004; Schade, 2016). Customization reflects users' priorities, whereas personalization reflects users' behavior that the system has identified and adapted automatically.

2.3 Context

Schilit et al. (1994) defined context when they first introduced another concept, context-awareness. They claim that the most important aspects of context are where you are, who you are with, and what resources are nearby. Since then, multiple fields have proposed alternative definitions of context, including more types of contextual information (Dey et al., 2001; Gorgoglione et al., 2006). Dey et al. (2001) defines context as "any information that can be used to characterize the situation of entities (i.e., whether a person, place, or object) that are considered to be relevant to the interaction between a user and an application, including the user and the application themselves. Context is typically the location, identity, and state of people, groups, and computational and physical objects." The provided definition is considered to be relevant because it can include the user's emotional status as contextual information. However, the definition is quite general, in which any information that is considered an entity is context.

2.4 Contextual Personalization

Implementation of personalization to web environments is strategic, especially in the currently highly competitive market. The widespread use of technologies and interdisciplinary characteristics have resulted in several personalization strategies to enforce interactive relationships with customers. Consequently, scholars have reached no consensus on the most effective personalization strategy. Till now, personalization strategies have focused on gathering consumer data and historical data without considering real-time information. In information systems and marketing, one-to-one personalization is the most utilized strategy. However, the division between information systems and marketing have been criticized in several studies as complex algorithms could benefit from the input of marketers (Kwon and Kim, 2012; Salonen and Karjaluoto, 2016). To make accurate predictions of user preferences, a more in-depth analysis of the user's emotional status with web personalization would benefit companies to deliver relevant and interesting experiences. Derived from existing definitions of context and personalization (Dey et al., 2001; Fan and Poole, 2006; Kwon and Kim, 2012; Schade, 2016), the researcher defines contextual personalization as:

> A system-initiated process to address the individual user with relevant content in the situational context. The situational context considers real-time information, such as the current emotional state of the user.

2.5 Emotion

There is never nothing going on in the human mind, as motions can have significant effects on how we think, behave, decide, and solve problems (Jung et al., 2014). Emotions also play a significant role in product experience (Spinelli et al., 2014; Cambria et al., 2012). Researchers in several fields have studied and tried to understand the motivations that drive our behaviors and choices. Consequently, several theories of how emotions occur, and definitions of the term exists and is used interchangeably.

James (1884) proposed that emotions occur as a result of the experience of bodily changes. The theory is named James-Lange theory of emotion as a similar concept was developed by Carl Lange around the same time. Cannon (1927) proposed several numbers of criticisim to the James-Lange theory: (1) removing or separating viscera from the central nervous system does not alter emotional behavior, (2) identical physiological responses could be associated with several different emotions, (3) arousal does not necessarily evoke an emotional response, (4) the physiological response system is too slow to generate emotions, and (5) bodily responses of strong emotions that have been artificially induced (such as adrenaline) does not produce emotions. The Cannon-Bard theory argued instead that the physiological responses and the experience of emotion are triggered simultaneously and independent of each other. Contrary to this theory, Schachter and Singer (1962) suggested that cognitive factors could be major determinants of emotional states. Experience of emotion happens when physiological arousal occurs, and the individual interprets cues from the immediate environment by past experiences to label the physiological arousal. The label is determined upon the cognition whether the felt emotion is, e.g., "fear" or "anger."

Today, most researchers in different fields agree that emotions are tangled up with cognition (Norman, 2004; Cambria et al., 2012; Mulligan and Scherer, 2012; Hooge, 2014; Mills and D'Mello, 2014). Whether or not we become content or embarrassed about seeing an advertisement for underwear while scrolling through social media on a crowded bus, depends on how the mind interprets the content of the ad, if it is appropriate or not.

2.5.1 Operationalizing Emotion

In the sphere of affective computing, psychology, and physiology, the focus has been on investigating the components of emotions. Many different affect models have been suggested, however not suitable for the design of applications in the field of affective human-computer interaction (HCI), social data mining, and sentiment analysis (Cambria et al., 2012). The concept "emotion" presents an inherent fuzziness as the ambiguity of natural language makes it difficult to define a universal and consensual concept. Consequently, overlapping words are used to describe an emotion. Multiple definitions of the term exist in the field of psychology. Mulligan and Scherer (2012) argue that much of the confusion stems from the semantic overlap of denotations and connotations of the terms "affect," "emotion," and "feeling," as well as adjectives and adverbs, and other words such as "preferences" and "moods" (Scherer, 2005; Cambria et al., 2012; Mulligan and Scherer, 2012). However, a widespread acceptance within the field has emerged that emotion has multiple components, "including physiological arousal, motivation, expressive motor behavior, action tendencies, and subjective feelings." (Spinelli et al., 2014). Cambria et al. (2012) define emotion as "complex states of feeling that result in physical and psychological reactions influencing both thought and behavior." The definition provided is quite general but offers guidance for identifying categories of emotions and emphasize the relation between emotions and user behaviors.

2.5.2 Appraisal Dimensions of Emotions

Researchers have for decades proposed several labels on human emotions and categorizations upon how emotions interrelate. It is due to the ambiguity of natural language and cultural differences that it is still difficult, if not an impossible task to distinguish and label a specific emotion that is considered universal. For practical reasons, researchers define emotions according to emotional approaches rather than categorical approaches since they usually fail to describe the complex range of emotions that can occur in daily communication (Cambria et al., 2012). Some researchers suggest there should be a distinction to understand how emotions influence behavior and decision making, whereas other researchers suggest influence can be predictable with a restricted number of cognitive or emotion appraisal dimensions (Hooge, 2014). The dimensional approach represents emotions as coordinates in multi-dimensional space, such as valence, arousal, certainty, etc.

(Cambria et al., 2012; Hooge, 2014). Dimensional approaches have the advantage of describing emotional states that are more tractable than words but does not account for several emotions to be experienced at once (multiple emotion states). Cambria et al. (2012) developed the Hourglass of Emotions, focusing on the objective inference of affective information with natural language opinions, allowing classification of affective information in both a categorical and dimensional way. Mapping the space of positive and negative primary emotions according to the Gaussian function, G(x) = $\frac{1}{\sigma\sqrt{2\pi}}e^{-(x-\mu)^2/2\sigma^2}$, leads to the hourglass shape of the model (see figure 1) (Cambria et al., 2012). The Hourglass model is a four-dimensional float vector, representing the Pleasantness (how much interaction modalities amuse the user), Attention (how much the user is interested in interaction contents), Sensitivity (how much the user is comfortable with interaction dynamics), and Aptitude (how much the user is confident in interaction benefits). Activation of the independent but contaminant dimensions, when met with different stimuli, makes the distinct emotional state. The model can potentially synthesize the full range of emotional experiences, making it applicable and relevant in the context of affective HCI (Cambria et al., 2012).

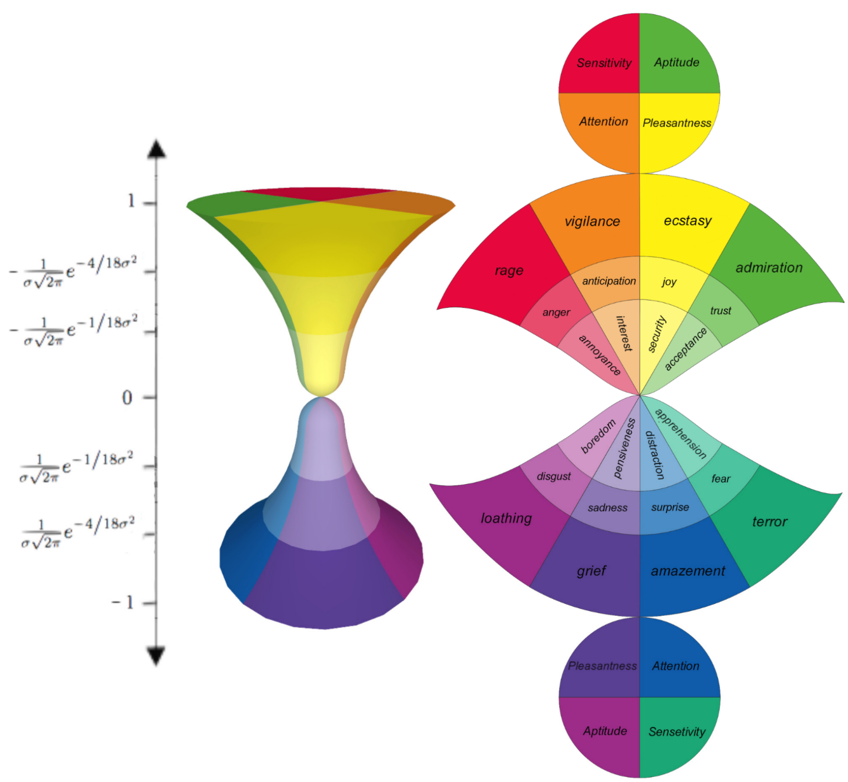

Figure 1: The Hourglass of Emotions by Cambria et al.

2.6 Emotion Detection Technology

Several researchers have talked about technologies that can read and know our authentic emotions and the advantages of using it (El Kaliouby, 2015; Crum, 2018). “Our technology can listen, develop insights, and make predictions about our mental and physical health, just by analyzing the timing dynamics of our speech and language picked up by microphones.” (Crum, 2018). The development of technologies that can detect human emotions is related to the field of affective computing. Knowing how the user is feeling would give businesses an advantage, as the information can be used to enhance experiences and interactions in the digital environment (Garcia-Garcia et al., 2017).

The emotional state of a human being leaves traces on the body, which can be measured with the right tools. The core of emotion detection technologies is an automatic classifier that collects information, extract essential features for the purpose, and train the model to recognize and classify patterns. However, gathering affective information is not always as straightforward because the data needs to be interpreted as the state of the emotion is determined by various dimensions Garcia-Garcia et al. (2017). The emotional state of a person is expressed through the channels like voices, facial expressions, body language, and the physiological states such as breath, pupils size and heart rate (Garcia-Garcia et al., 2017). Emotions are expressed through a primary and secondary channel when people speak. Emotions in speech are detected by what is being said (primary channel) and by the paralinguistic information such as the speaker’s tone-of-voice (secondary channel). Facial expression also reflects a person’s emotions. Eyebrows, lips, nose, mouth, and muscles are identified to process their positions to reveal the person’s emotional status. Emotions can also be detected through text even though the technology faces more obstacles than the previous, such as misspellings, abbreviations, and slang. Even with emerging interest in the field, technologies that detect emotions by reading a person’s body language and physiological states like facial expressions, speech, and text, have yet been developed adequately (Garcia-Garcia et al., 2017). Nevertheless, technologies that can detect body language and physiological states is a probability in the future years.

2.6.1 Review of Existing Emotion Detection Technologies

Garcia-Garcia et al. (2017) reviewed existing technologies that can detect emotions, exploring different sources on which emotions can be read, and technologies that can recognize them. Many tech companies have emerged, focusing exclusively on developing technology that can detect emotions from specific inputs (see table 1) (Garcia-Garcia et al., 2017).

The review of these technologies revealed different limitations. When people talk, information is provided from the primary and secondary channel (also described in 2.6). When someone says: "That’s awesome" (primary channel), what is being said is interpreted with the tone of voice (secondary channel). Emotion detection from speech has yet proven to be effective as the technology cannot detect complex aspects of human speech, such as sarcasm (Garcia-Garcia et al., 2017). Additionally, to extract reliable information from the voice, the technology needs to work in noisy environments, which it still can not.

2017 Emotion Detection Technology List				
Input	**Name**	**API/SDK**	**Difficulty of Use**	**Free Software**
Speech	Beyond Verbal	API	Low	No
Speech	Votukuri	SDK	Medium	Yes
Speech	EmoVoice	SDK	High	Yes
Speech	Good Vibrations	SDK	Medium	No
Facial Expression	Emotion API	API/SDK	Low	Yes (Limited)
Facial Expression	Affectiva	API/SDK	Low	Yes (Limited)
Facial Expression	nViso	API/SDK	–	No
Facial Expression	Kairos	API/SDK	Low	Yes
Text	Tone Analyzer	API	Low	No
Text	Receptiviti	API	Low	No
Text	BiText	API	Low	No
Text	Synesketch	SDK	Medium	Yes

Table 1: 2017 Emotion detection technology list by Garcia-Garcia et al..

With the presence of social media and user feedback, companies have a great advantage to understand what their users are feeling (Garcia-Garcia et al., 2017; Buitelaar et al., 2018). But the current technology for emotion detection from text can only inform if the emotion detected is good or bad. As such, the technology provides minimal insights and conclusions on what the user is feeling. The technology is still in its early phases of development and testing, therefore not considered appropriate for the problem at hand.

The most reliable indicators of emotions are the human face, and Affectiva was found to provide the most information from facial expressions, making it easier to interpret the showed emotion (Garcia-Garcia et al., 2017). Rana el Kaliouby and Rosalind Picard founded Affectiva in the MIT Media Lab in 29. Affectiva has analyzed more than 7.5 million faces and is used by market research firms to measure consumer emotions to digital content (Affectiva, 2018b). Affectiva's AFFDEX Software Development Kit (SDK) uses machine learning and Facial Action Coding System (FACS) to detect and label facial expressions, including age, gender, and ethnicity. FACS is a standardized classification system of facial expressions based on anatomic features and was developed by Carl-Herman Hjortsjö, Paul Ekman and Wallace V. Friesen in 1978 (Imotions, 2017). With this effort, AFFDEX SDK can detect twenty facial expressions, mapped to seven basic emotions: joy, anger, disgust, surprise, fear, sadness, and contempt (Affectiva, 2018a). Although facial analysis technology has shown results with considerable accuracy, it requires sufficient lightning to track facial landmarks. Additionally, large glasses that cover the eyebrows, beards, hats, bangs, etc., can complicate the face detection, leading to only partial results (Garcia-Garcia et al., 2017).

The most significant limitation of current emotion detective technologies is the narrow focus on detecting emotions from only one channel. Human interaction is multimodal, in which emotions are detected from several channels. More than one input is required to get a higher precision of results (Garcia-Garcia et al., 2017). iMotions developed a software suite that connects different biometric devices in one unified software, enabling researchers and marketers to identify emotions from several channels, and increasing the validity and reliability of the results (iMotions, 2018). AFFDEX SDK is one of the biometric devices that is integrated into the iMotions software suite. iMotions offers in addition to automated facial expression analysis, eye tracking, EEG, GSR, ECG, and EMG (iMotions, 2018). Utilizing such software would significantly enhance the validity of the identified emotion.

2.7 Consumer Behavior

The consumer environment is ever-changing, complex, and available everywhere. Researchers have questioned whether online consumer behaviors differ from traditional consumer behaviors. Accordingly, various online consumer models have been defined (Koufaris, 2002). Physiological and environmental factors influence consumers choices which marketers cannot control, but should be accounted for (Wu, 2003). Research in multiple fields have reported emotions to play a significant role in decision making (Lekkas et al., 2009; Kemp et al., 2012; Hooge, 2014; Garcia-Garcia et al., 2017). Some individuals may use consumption or purchasing as a way to manage their emotions. For instance, if the customer is feeling uneasiness, the emotional response of stress could appear, and their interactions with the online environment could translate into faster movements and more mistakes in the buying process. Interfaces that account for these negative emotions could change to more favorable emotional responses, ultimately enhancing the user experience and foster customer satisfaction.

2.8 Ethical Aspects of Personalization

Trust, privacy, satisfaction, loyalty, terminology division, and contextual factors are contested issues often discussed with the implementation of personalization (Salonen and Karjaluoto, 2016). Personalization is reported to have many benefits for both consumers and marketers as it has shown to attract customer attention and foster customer loyalty and lock-ins (Ansari and Mela, 2003). But what implications does it have on the customers? Internet giants like Google, Microsoft, Apple, and Facebook, as well as every existing website, collects data about the users. The reasoning is to provide users with relevant content, tailoring the web around the individual. But the strategies have shifted. Personalization goes beyond targeted advertising – it tailors what news we read, which videos we see and which restaurants we are recommended (Praiser, 2012). The algorithms create our identity, and shapes what we believe and care about. Praiser (2012) describes this as the identity loop where people enter a spiral of reinforcement to existing ideas and opinions. As the media landscape is in constant change, it requires new algorithms that can disprove the idea of who the user is. Clicking on a link could signal an interest in a topic, but not necessary. As such, to avoid misinterpreted identitities, data in real time needs to be interpreted, as well as empowering users to control their user data.

The personalization process is contingent on the data collection process. The discussion is often contested to the lack of information, knowledge, and consent (Aguirre et al., 2015; Praiser, 2012; Ashman et al., 2014). Many companies adopt personalization to sell products or services. Although personalization is set as a priority to attract and engage the individual user, the effects of collecting user data can have adverse effects if providers do not inform their customers about their data collection efforts and how their data is treated (Aguirre et al., 2015; Praiser, 2012). Users might perceive that marketers act in their self-interest to enhance click-through intentions and consumption (Aguirre et al., 2015). Before 2018 there were two strategies for data collection: overt and covert. Businesses that adopted an overt strategy made an effort to inform users about the data collection process with the underlying assumption that continued use of the service implies an ad hoc consent to the data collection (Aguirre et al., 2015). Businesses that adopted the covert strategy collected data about the user without their user's awareness (Aguirre et al., 2015). The covert strategy undermines the democratic way of life, as such that it resulted in a new framework the General Data Protection Regulation (GDPR), to protect a fair processing of personal data. GDPR replaced the 1995 Data Protection Directive which was adopted when the Internet was still in its infancy (European Data Protection Supervisors, 2019). A directive allows for individual countries to devise and customize the law, whereas a regulation must be applied in its entirety by all. With the GDPR, strict regulations on how personal data is handled are set. Those who fail to comply are treated with a hefty fine.

With GDPR, consumers hold power over their data. Providers that collects user data must obtain specific consent from the user. Studies have shown that people are becoming more wary of providing data to unknown purposes, in which the personalization is more effective when the users are adequately informed about the data collection process (Ashman et al., 2014; Tam and Ho, 2006; Aguirre et al., 2015). People do not enjoy using a website if they feel deceived or their privacy violated. To ensure an ethical approach to personalization, transparency to the data collection process, user control, and clear intentions would make it easier for users to recognize unethical tactics to persuade them, as well as enabling users to make an informed consent.

3 Methodology

This Master's thesis aims to explore how contextual factors, such as human emotions, can make the user perceive the presented content as more relevant and useful, and the experience more personalized in the situational context. The methodology chosen for this thesis will be used to answer the research questions:

1. Is emotions as contextual information a variable that should be taken into account in web personalization?
   a. Can variables such as the user's emotional state be detected in real time and used as contextual information?
   b. Does emotions affect how users perceive content relevance?
   c. Does emotions affect the total user experience of the product?

To understand whether emotions should be taken into account as contextual information when designing user interfaces (UI) for web personalization, it is crucial to understand the user group, their attitudes toward current personalization strategies, and how they behave online. A combination of qualitative and quantitative methods from HCI will be used to gather insights to user needs and user behaviors during specific emotional states. The investigation of the sub-questions is twofold; the first part addresses the first sub-question and involves identifying emotional states with an emotion detection technology currently available and leading on the market. The second part of the investigation addresses the second and third sub-question. The Autobiographical Emotional Memory Task (AEMT) is used to experimentally induce emotions to measure whether the intended emotion affects how the user perceives content relevance and the user experience.

3.1 Understanding User Needs and User Behavior

Semi-structured user interviews were conducted to get an in-depth understanding of the user's online behavior during specific emotional states. Additionally, a questionnaire was distributed online and manually to get a broader understanding of the topic. Questions in both interviews and questionnaire were pilot-tested with one participant for each. Also, quality assurance was performed by a supervisor, to ensure understandability, and usability in the questionnaire.

3.1.1 User Interviews

A series of user interviews were conducted to understand how users experience personalization on the web, collection of user data, and attitudes towards this process. Four participants (gender= 75% female, 25% male, mean age= 25,5) were recruited to participate, working full time in the field of interaction design (IxD), service design, and artificial intelligence (AI). A semi-structured interview guide was created, tested and questions quality checked before conducting the interviews, ensuring the researcher to ask the same set of questions to each participant (see Appendix A). The structure of the interview enabled the researcher to get an in-depth understanding of the topic, as well as participants to elaborate on new insights, attitudes, and opinions from an expert point of view, and user point of view. Participants were asked to sign a consent form at the beginning of the session (see Appendix B).

3.1.2 Questionnaire

A questionnaire was created in Google Forms and distributed with the intention of getting a broader understanding of user's knowledge about current personalization processes on the web, attitudes toward online personalization, and behavior during specific emotional states (see Appendix C). The user population was targeted between the age of 18-50 years old and recruited through convenience sampling. A total of 110 users (gender=65,6% female, 34,4% male, mean age= 30,78) participated in the survey, but 14 respondents were terminated from the analysis as they did not fit the user profile range.

The questionnaire was designed to be answered in three parts: demographics, general knowledge about personalization, and statements related to user behavior during specific emotional states. To keep the completion threshold low, the questionnaire was designed to take less than five minutes to finish with multiple choices and interval scales. The questions were discussed and checked with a supervisor to ensure clear, non-leading questions, and a pilot test was conducted before distribution. Questions that were unspecific or unclear was rephrased to reduce potential skewness in the data set.

3.1.3 Workshop with Usability Experts

The user interviews and questionnaire resulted in a deeper understanding of user needs and behavior that can occur during certain contextual conditions. A workshop was held with three interaction designers to identify the most important user needs that should be accounted for in contextualized personalization. The workshop was scheduled for two hours, starting with an introduction of the topic before continuing with the core activities. For each activity, participants were asked to write down each idea on a post-it note.

3.2 Study 1: Identifying Emotional State with AFFDEX SDK

The first study of this master's thesis aims to investigate sub-question 1a, if emotions can be detected in real time. Considering all advantages and limitations of current emotion detection technologies (see section 2.6.1), Affectiva was considered appropriate to identify emotions. The AFFDEX SDK can through the use of a web camera detect facial landmarks to classify emotions. Although there is an increasing interest in emotion detection technology, only a small number of peer-reviewed studies have validated these algorithms (Stöckli et al., 2018; Taggart et al., 2016). A validation test would reveal whether the technology can detect natural emotions efficiently in natural environments in real time. The validation study would also determine the effectiveness of AEMT.

As mentioned in the background chapter, iMotions connects several biometric tools into one software, including AFFDEX SDK. The software is not free of charge but offers academic research licenses for educational purposes. The Department of Civil and Environmental Engineering in NTNU in Trondheim is currently testing and using iMotions, in which the researcher was able to utilize the software to investigate if it is possible to identify emotions with such technology.

3.2.1 The Autobiographical Emotional Memory Task (AEMT)

AEMT is a widely used method to experimentally induce emotions, which involves recalling and writing about intense emotional experiences. The validity of the method depends upon whether the intended emotion can be induced without inducing other incidental emotions (Mills and D'Mello, 2014). Researchers have tried to investigate how to most effectively induce emotions experimentally for many years, such as recalling and writing about emotional memories, watching emotional video footages, listening to emotional music, and many more. Some argue that inducing emotions is an unreliable method, although this has not been deterrent for continuing to use this method to make claims about the effects of a specific emotion (Mills and D'Mello, 2014). However, numerous of advantages have been reported of using the AEMT as an induction tool, as it does not require any technology, and can scale up to group administration (Mills and D'Mello, 2014). With appropriate manipulation checks in place, in this case, whether intended emotion is identified by AFFDEX SDK, the AEMT method should enable the researcher to assess the effects of the intended emotion.

Experimental Variables and Hypothesis

Independent variable: Emotion
Dependent variables: Joy, anger, disgust, surprise, fear, sadness, contempt, and valence

The following hypothesis is proposed for examination:

(a) H_1: The emotion can systematically be detected with facial analysis software.
H_0: The emotion cannot be detected with facial analysis software based on intentional emotion.

3.2.2 Equipment

Facial analysis is accomplished in real-time by using a web cam for monitoring and recording facial expressions, or offline by processing pre-recordings. The iMotions software suite was installed on a Dell Latitude E7440 laptop with integrated web cam (0,9 MP) and microphone. At a sampling rate of 102.4 Hz, joy, anger, surprise, fear, contempt, disgust, and sadness could be detected and measured. The laptop camera placement was fixed to each respondent to capture the face angle at ± 20 degrees. The brightness and color distribution was set at 100%.

A Galvanic Skin Response unit (Shimmer3 GSR+) was used in one experiment to detect the intensity of the emotional arousal. A video stimulus was applied instead of the AEMT method. The GSR+ has been validated for use in a biomedical-oriented research application. Though both positive and negative stimuli can result in increased arousal and skin conductance, the GSR result is just representative of the intensity of arousal, not the type of emotion (Farnsworth, 2018). Sensors included with the GSR+ was an Optical Pulse Sensor, GSR Velcro Finger electrodes, and Biophysical 9" leads.

3.2.3 Experimental Setup

The validation test was performed at the Norwegian University of Science and Technology in Trondheim. The computer running the iMotions software suite was placed in an office with natural lights and busy environment to see if emotions could be detected in natural settings. Anger, fear, happy and sad were the intended emotions for the test as they represent different intensities and activation of the affective dimensions in the Hourglass model (see figure 1). The following tasks identical to those used in previous studies (Mills and D'Mello, 2014) were performed: "Please describe in detail the one situation that has made you the most angry/afraid/happy/sad you have been in your life and describe it such that a person reading the description would become angry/afraid/happy/sad just from hearing about the situation." However, considering the time limitations to set up and test the equipment, as well as preserving user's right to privacy, participants were asked to just think about the one situation rather than writing it down for evaluation. A total of six people participated in this experiment (gender= 33,3% female, 66,7% male, mean age= 32), including the researcher. The mean time participants used to finish the experiment was 3:38 minutes. The researcher guided the participants through each task, recording the induced emotions separately for each participant.

For the experiment with GSR+, video stimuli were used to induce emotions. This experiment was only performed by the researcher with two emotions, sad and happy, as a further experiment to investigate the effects of AEMT compared to other induced stimulus. The videos chosen for the experiment were titled "This Video Will Make You Cry" and "Try Not to Laugh". The researcher watched approximately five minutes of each stimuli.

3.3 Study 2: Understanding the Emotional Impact on Content Relevance and User Experience

The second study of this master's thesis aims to investigate sub-question 1b and 1c, whether emotions affect how the users perceive the content relevance and the user experience of a website. Results from Study 1 revealed that even though inducing emotions with AEMT is weaker than other types of stimuli, AFFDEX SDK was able to identify and label the emotion as the intended one systematically. As such, AEMT will be used for inducing emotions to participants in the experiment before evaluating the content relevance and user experience of a website.

3.3.1 Operationalizing Content Relevance and the User Experience

In order to verify whether the emotional state mediates the perception of content relevance and user experience, the variables need to be operationalized to ensure that participants have the same understanding of the terms. Relevance in web environments refer to how well the content fits the user's interest and goals (Kim et al., 2017), how well the content fits the context of use, and the content retrieved from explicit use (Kalyanaraman and Sundar, 2006). Measures of relevance are adapted from items by Thorson and Zhao (1989) with modifications to fit the context, e.g., "the content was meaningful for me at the moment." The content relevance will be measured on a 7-point Likert scale (see table 2).

Measuring Content Relevance							
	1	2	3	4	5	6	7
The content was meaningful for me at the moment							
The content was useful and relevant							
The content was useful but not relevant							
The content was relevant but not useful							
The content neither relevant nor useful							
The content was too general							

Range: 1 - Strongly disagree, 2 - Disagree - 3 - Somewhat disagree, 4 - Neither agree nor disagree, 5 - Somewhat agree, 6 - Agree, 7 - Strongly agree.

Table 2: Content relevance form.

There is still not an agreed definition of user experience in the field of HCI, which could be related to a non-standardized method and metrics for assessing user experience (Väätäjä et al., 2009). ISO 9241-210 defines user experience to include "all the users' emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviors, and accomplishments that occur before, during and after use" (International Organization for Standardization, 2010). Norman and Nielsen

(2018) define user experience to "encompasses all aspects of the end user's interaction with the company, its services, and its products". The UI is an essential part of the design process, and therefore an essential part of determining the user experience. The AttrakDiff questionnaire Hassenzahl (2001) will be used to assess the usability and design of a product for the experiment. The AttrakDiff measurement tool makes it possible to assess and compare two groups perception of the same or different products. The questionnaire uses a semantic differential scale composed of 28 items, ordered into a scale of intensity. Each item is expressed with bipolar word anchors, e.g., Dull – Captivating, Confusing – Clear, Good – Bad (see Appendix D). Each of the middle values of the items groups creates a scale value for Pragmatic Quality (PQ), Hedonic Quality (HQ), and attractiveness (ATT) (AttrakDiff, 2013). PQ refers to the usability of the product related to task-oriented goals. HQ include HQ-I (Identification) and HQ-S (Stimulation) which measures to what extent the product allows users to identify with it, and how the product stimulates users and provides encouragement, interest, novelty, and content. ATT measures the aesthetics of the product (Hassenzahl, 2001; Väätäjä et al., 2009; AttrakDiff, 2013).

From the evaluation of data, it will be possible to assess how well the product tested in the experiment scores on usability and appearance, dependent on the users' induced emotional state.

3.3.2 Pilot Study of the Experiment

A small pilot study was carried out to determine the feasibility of the initial experimental design, a between-subjects design, in which only the experimental group was exposed to AEMT before interacting with a prototype (see table 3). The control group interacted with the prototype without being exposed to the AEMT treatment.

Experimental Design				
Group 1	AEMT	User Interface	Content Relevance Evaluation	User Experience Evaluation (AttrakDiff)
Group 2	–	User Interface	Content Relevance Evaluation	User Experience Evaluation (AttrakDiff)

Table 3: Experimental design of posttest-only control-group design.

Participants were invited to test a prototype of a website for planning activities to do on vacation (see Appendix E), to measure the content relevance and the user experience. As such, participants were not informed before the test that the actual goal was to investigate if an induced emotion affected the user experience and perception of content relevance. Participants were informed about what participation involved regarding tasks and duration. The experiment was set in the same or similar environments to account for confounding variables. Seven people (gender= 71,4% female, 28,6% male) participated in the pilot study within the age of 18-40 years old and recruited through convenience sampling.

Both groups were asked to interact with the interface, following a structured task list:

1. You have booked a vacation in Thailand this summer. During this vacation, you want to find different activities or attractions you can visit. Your journey lasts from April 11th to June 30th.
2. Explore different activities or attractions that you want to visit during your stay. Save the activities, so you can easily access them during your vacation.
3. In addition to traveling to Thailand, you want to extend your vacation and travel to Vietnam as well. Find other activities or attractions that you want to visit there and save them for later.

After finishing all tasks, participants were asked to evaluate the content relevance and the user experience. Participants in the experimental group were asked which emotion they felt before and after interacting with the prototype, while the control group was only asked about which emotion they felt after interacting with the prototype.

Results

The pilot study revealed several flaws to the experimental design that needed to be addressed:

1. The limited number of content and wireframes in the prototype was not sufficient to evaluate the content relevance. The average time spent on all tasks was 4:57 minutes for the control group and 4:03 minutes for the experimental group. Participants only skimmed through the content to finish the task at hand. When the researcher asked for the name of the temples they had saved for later, only two participants could answer.
2. The experimental group is exposed to AEMT, the control group not. The main reason for choosing the posttest-only group design was because pretesting could influence the results of the experimental manipulation. However, people are always in an emotional state, as there is never a total absence of emotion (Cambria et al., 2012). But as the control group was not exposed to AEMT, it would be no way of knowing if the induced emotion actually causes a difference between the groups.
3. A product or service must be perceived as useful to its users to conduct a true assessment of user experience. However, as the product tested was a prototype with limited clickable functionality and elements, participants did not perceive the product as very useful. Some participants became so frustrated with the prototype that they completely lost focus on the task at hand.

As such, after assessing the impact the experimental design would have on the validity of the data, changes were made to the design which is described in following section.

3.3.3 Revised Experimental Design

A within-subjects design was applied for the experiment to examine whether the consumer's emotional state as contextual information could make the user perceive content as relevant and personalized and improving the user experience of the service. Time usage on the provided tasks will provide insights into whether emotions affect learning and problem solving. Both groups will receive the AEMT treatment in the study, with two conditions: positive or negative emotion (see table 4). Happy and anger were the emotions chosen for testing as they represent contrasting emotions, but with corresponding intensities and activation in the Hourglass model (see figure 1). Happy was also the emotion that proved significantly to be detectable in Study 1. A total of 20 people within the age of 18-40 years old participated in the experiment (gender= 50% female, 50% male), randomly assigned to either of the groups. The experiment was conducted for three weeks during the final weeks of the project. Participants were recruited through convenience sampling and held in Oslo and Gjøvik.

Experimental Design				
Group 1	AEMT positive (happy)	User Interface	Content Relevance Evaluation	User Experience Evaluation (AttrakDiff)
Group 2	AEMT negative (angry)	User Interface	Content Relevance Evaluation	User Experience Evaluation (AttrakDiff)

Table 4: Within-subjects design in which both groups receive treatments.

3.3.4 Experimental Variables and Hypothesis

Independent variable: The user's emotional state
Dependent variables: Time usage, content relevance, and user experience

The following hypothesis is proposed for examination:

(a) H_1: The user's emotional status affects time spent on problem solving.
H_0: The user's emotional states does not affect time spent on problem solving.

(b) H_1: The user's emotional status affects how relevant the content is perceived.
H_0: The user's emotional status does not affect how relevant the content is perceived.

(c) H_1: The user's emotional status affects the total user experience of a service.
H_0: The user's emotional status does not affect the total user experience of a service.

3.3.5 Experimental Setup

Participants were invited to participate in user testing, evaluating the usability of a website. Several websites for travel planning were assessed for the experiment. The websites were evaluated on the complexity and usability of the site to get valid data on the assessment of the content relevance and user experience. Only a few participants had visited the site before but only as coincidence from other searches. Participants were randomly assigned to either group, being induced with either happy or angry emotion using AEMT. The tasks to be performed followed the one in the validity study of AFFDEX SDK, as well as those used and tested in previous studies (Mills and D'Mello, 2014). Earlier studies with AEMT have collected and rated participant's responses as having no relevance, some relevance, or considerable relevance to the intended emotion to ensure that the intended emotion was properly induced (Mills and D'Mello, 2014). No previous studies have rated a response as having no relevance. Evaluating the participant's right to privacy, as well as considering the sensitivity of personal stories could impact the effectiveness of AEMT, the researcher assumed responses to having some or considerable relevance to the intended emotion.

An introduction to the use case and the tasked followed. Both groups were asked to interact with the interface, following a structured task list:

1. You plan on traveling in Norway this summer. Explore at least 3 activities, attractions, events, or places you would like to visit or do during your vacation.
2. As you continue planning your vacation, you also want to add activities to your travel planner. Add at least three different activities, attractions, or events that you want to do during your vacation. *(These can be different from the activities you explored in task 1)*
3. You have decided to go on a hike, but are unsure of what you should prepare beforehand. Find useful tips for your hike.

After they had finished interacting with the website, participants were asked to evaluate how relevant the content on the prototype was (see table 2), as well as the user experience with the AttrakDiff questionnaire (see Appendix D). Both groups reported which emotion they felt before and after interacting with the website to enable comparisons of the groups.

4 Results

The following sections present the results from the qualitative and quantitative analysis of user needs and user behaviors, the validity study of emotion detection technology, and the experimental study. The quantitative data was analyzed using SPSS.

4.1 User Research: User Needs and User Behavior

4.1.1 User Interview Results

The user interviews revealed that professionals in the field of IxD, service design, and AI consider contextual personalization to have a significant advantage for the total user experience of a product or service, but only if it serves to benefit the users and not the providers. Concerns toward privacy and security were the most discussed topics during the interviews. The participants argue that providers are to have benefits as well, but it should not be on account of user privacy. In today's digital economy, people are more willing to provide companies access to cameras and microphones, and to track online behavior if the trade-off is considered beneficial. The AI expert emphasizes that this cost-benefit trade-off is not something most people consider when using a website or an application. Most users have a specific goal when using a service or product, in which people accept to terms and conditions without giving it a second thought. Nevertheless, if the purpose of collecting personal data adds value to the user, they are more willing to accept even if they have concerns about privacy and security.

Today's personalization algorithms can predict what the user might be interested in, but the line between relevant, interesting and annoying content is blurred as no real-time information is collected. Even though the professionals express an inherent skepticism to current personalization algorithms and strategies, they believe it can be of advantage to consider emotions as contextual information. But what the provider's intentions of collecting user data and how this information is collected and secured are essential variables that need to be addressed for them to consider contextual personalization as beneficial and valuable to the user.

4.1.2 Questionnaire Results

Respondents can be divided into two populations: online consumers and traditional consumers. Traditional consumers prefer shopping in physical stores and being asked if they need help from store employees than online consumers. This population also reports to be more annoyed with existing personalization strategies online, mainly because of the large number of advertisements on several platforms, and inadequately assumptions made about their style and interests.

The general opinion about personalization is that it is used to deliver targeted advertisements to users, filtering the search results, and changing the UI based on previous purchases (see figure 2). Less than a third report that personalization is used to tailor the content to the individual user, or to create for better user experiences on a site, which could indicate that current personalization strategies do not work efficiently in tailoring content nor changing how people experience the web site. Product suggestions are favorable if it is similar to products they have purchased earlier, but when the product suggested is one of the previous purchases, people report it to be irritating. Figure 3 shows what data people think is collected about them on the web. The results were as expected to the context of online retailing, where the number of clicks, location, and previous purchases affects targeted advertising.

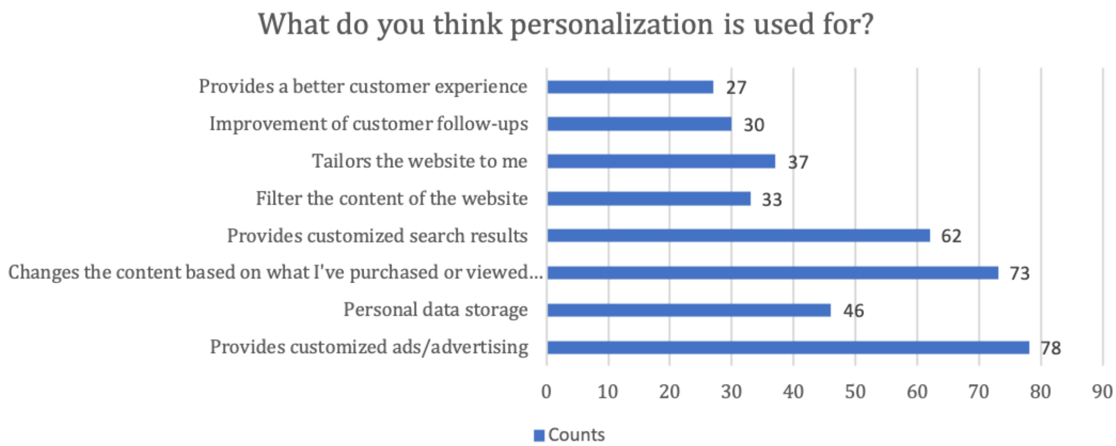

Figure 2: The bar chart shows what the user population think personalization is used for.

Topics concerning data privacy and allowing web providers to obtain user information, respondents are willing to blindly accept cookies, terms and conditions, as well as letting many providers access their camera and microphone. The data set indicates that individualization could be useful for some people, but not all. Depending on the purpose of the site, the content, and the users, the cost-benefit of applying personalization strategies needs to be evaluated by the providers. As current personalization strategies collect user data for enhancing the user experience and tailoring the content to the individual user but are not perceived this way by users, removing it might improve the user's perception towards a website.

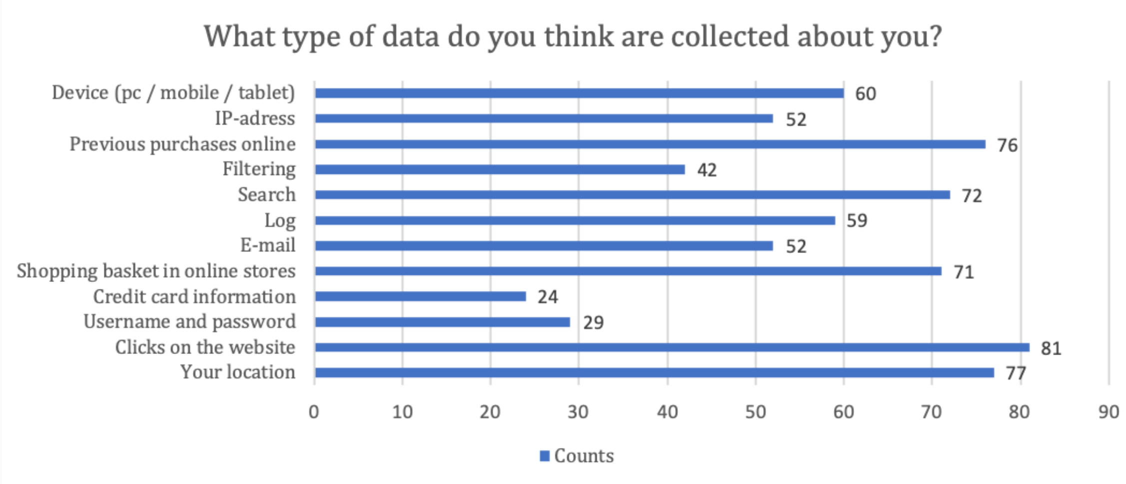

Figure 3: The bar chart shows what type of data the user population thinks web providers are collecting.

4.1.3 Workshop Results

User needs that could occur when interacting with personalized content, and emotions that likely would arise for each user need is presented in table 5. The most critical user needs to account for in personalized environments are: (1) increasing knowledge and learnability, (2) more efficient problem solving, and (3) easier information seeking.

With current personalization strategies, the experts emphasized that feeling of creepiness, frustration, and deceit could occur when interacting with different platforms, because of the little transparency of how the user information is collected, stored, and used. It becomes prominent that the user is trapped in a filter bubble. As with previous findings from both user interviews and questionnaire, the experts agreed that the content is more than often not relevant to the user's interests. Users are not one-dimensional, but the collected information about the individual user is treated this way. As such, the usability experts emphasize that to design personalized experiences and account for the user needs and emotions that occur, providers should:

- Collect real-time data about the user, as well as put more effort into developing algorithms that can make more accurate predictions about what the user might be interested in based on their online behavior. If they already have purchased the product, recommend similar, not the same product.
- Reduce information clutters. For instance, online shopping user profiles should know the user's preferable size and style based on previous purchases. If the user has purchased clothing's in size S and M, it could be of advantage to filter this beforehand.
- Personalization should not be restricted to system-initiated information but also allow for more user-control. When the content does not fit the user's interests they should be able to change or remove the information.

Affinity Diagram Results		
User Need	**Attributions**	**Emotions**
Knowledge and learnability	Learning, teaching, increased awareness	Inspired, passionate, happy, frustration, annoyed with changes, deceived/cheated, angry with outcome or content
Problem solving	Efficiency, spend less time on task, faster problem solving, planning, easy navigation	Relieved, happy about outcomes, antsy, angry, cognitive overload, tired, stressed, angry with outcome or content
Information seeking	Find what you're looking for, help to find things, compare items, filtering unnecessary items, sufficient information to make a choice	Inspired, happy about outcomes, excitement, bored because of repeated content/items, scared, annoyed with changes, misunderstood, confusion, scare of the amount of information
Self-involvement	Find identity, become a better person, increased user satisfaction	Inspired, happy, misunderstood, insecure, confusion
Relations	Make friends, communicate, spend more time with friends and family	Happy, intrusive, deceived/cheated, suspicious "how did it know this?", scared, offended, dispassionate

Table 5: Affinity Diagram results presented as a table.

- Information flow across devices needs to be consistent in order to enhance learnability.
- The industry needs to be transparent in how user data is collected, how they are used for personalizing content and by whom.

From the user research, it is prominent that emotions play an essential role in how people interact with the web environment, as well as influence user satisfaction. Suggestions for improvements of current personalization strategies are provided, but the emotional affect on user interaction has yet been examined. As such, the user research provided the basis for the proposed sub-questions.

4.2 Study 1: AFFDEX SDK Data Analysis and Effectiveness of AEMT

Half the data set was removed from the analysis as it did not contain any information, mainly because AFFDEX were unable to observe or detect the participant's face when they were looking to the side. An independent samples t-tests were performed for each induced emotion (anger, fear, happy, sad). The t-tests investigated whether the evidence value (EV) associated with each emotion is present in the participant's facial expression, based on intentional emotion, compared to the neutral state (EV=0).

The t-values for each induced emotion to the independent variables are presented in table 6. The independent t-tests found that when inducing fear, t-value of disgust, surprise, fear, and contempt increased. When inducing anger, the t-value increased highly for sadness and anger. As the emotion happy were induced, the t-value of joy significantly increased. Sadness scored with the smallest EV with only minor changes in contempt and sadness. The data revealed no significant evidence of identifying the intended emotion. Garcia-Garcia et al. (2017) argues that emotion is not just "happiness" or "sadness." An emotion is determined by various dimensions like valence and arousal, creating a multiple emotion state. As the results indicate, it is not evident that there exists one true emotion, but occurrences of several can happen at the same time.

As the t-value of valence increases for happiness, the t-value decreases for afraid, angry, and sad. With a lower value of valence, negative emotions such as fear, anger, and sadness can be detected as the absence of joy. The data reveals it is possible to detect and distinguish between a positive and negative emotion, as well as categorizing the identified emotion to the intended one. Conclusively, the null hypothesis (the emotion cannot be detected with facial analysis software based on intentional emotion) can be rejected.

Independent Samples t-values								
	Anger	**Sadness**	**Disgust**	**Joy**	**Surprise**	**Fear**	**Contempt**	**Valence**
Afraid	-8,01	-11,19	4,38*	-12,56	2,82*	2,47*	1,59*	-13,60
Angry	11,78*	17,78*	-3,11	-20,57	0,01*	-0,74	3,53*	-24,99
Happy	-11,79	-19,89	-0,41	35,94*	2,17*	-3,70	-4,60	48,69
Sad	-5,07	1,77*	-5,23	-39,63	-6,19	-2,59	3,31*	-28,45

*Positive t-values indicate presence of the emotion.

Table 6: AFFDEX independent samples t-test t-values for each intended emotion.

An independent samples t-test were performed for the GSR+ as well, comparing the two conditions of sad and happy. As with inducing emotions with AEMT, the face analysis software can detect emotions with other stimuli. The data results show that there is a difference between the two conditions, as the GSR+ monitors more change in skin conductance when the emotional arousal increases. Though the AEMT method for inducing emotions proved weaker than video stimuli, AFFDEX SDK can systematically identify and label the emotion as the intended one.

4.3 Study 2: Part 1 – Content Relevance Analysis

The data set was analyzed with an independent samples t-test to investigate whether the induced emotion affected the time spent on each task (see table 7). The results revealed there was a significant difference in time used with the AEMT method. Group 1 (happy) performed the task using a mean time of 2:15 minutes (SD=1:17 minutes), whereas Group 2 (angry) used a mean time of 4:26 minutes (SD=2:52 minutes). Several people in Group 2 reported it was difficult to recall one specific memory that had made them angry, which could have had an implicit influence on the time spent. Although the findings reveal no significant difference in the induced emotion and how fast they finished a task, Group 2 spent, on average more time during interaction of task 2 and 3. As such, the null hypothesis (the user's emotional states does not affect time spent on problem solving) is rejected.

Descriptive Statistics					
	Group	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**
AEMT	Happy	10	02:14	01:17	00:24
AEMT	Angry	10	04:26*	02:52	00:54
Task 1	Happy	10	04:31*	01:46	00:33
Task 1	Angry	10	04:05	02:02	00:38
Task 2	Happy	10	03:20	01:07	00:21
Task 2	Angry	10	03:42*	01:23	00:34
Task 3	Happy	10	01:23	00:42	00:13
Task 3	Angry	10	01:48*	00:39	00:12

*The highest mean time used on each task.

Table 7: Descriptive statistics of the time spent on each task.

All participants were asked which emotion they felt after performing the AEMT task, as well as the emotion they felt after interacting with the website. Seven participants reported they felt happy after AEMT, whereas only five participants said they felt angry after AEMT. Eight participants felt no strong emotion to either of the induced emotions and reported a neutral emotional state after AEMT (see table 8). The results can imply that the implementation of AEMT was not as effective as assumed. Recall bias is the reconstruction process likely to distort past experiences, which could explain why some reported feeling a neutral state.

A one-way ANOVA was used to determine whether there was any statistically significant effect between the induced emotion and the dependent factors (meaningful, relevant, useful, and general) between the groups (see table 9). Although the analysis reveals no significant differences in the perception of content relevance, minor observations can be found. The null hypothesis (the

Group Statistics of AEMT and After Interaction				
Group	**Emotion After AEMT**	**N**	**Emotion After Interaction**	**N**
1	Happy	7	Happy	2
			Neutral	5
			Confused	0
2	Neutral	8	Happy	2
			Neutral	3
			Confused	3
3	Angry	5	Happy	1
			Neutral	3
			Confused	1

Table 8: The table shows the groups emotional state after AEMT, and the emotion felt after interaction.

user's emotional status does not affect how relevant the content is perceived) is as such retained. Group 1 that reported to be happy after AEMT found the content more relevant (M=4,86) and meaningful (M=5,57) than the other groups, which could indicate that when in a positive emotional state, the user is more attentive to the content. This finding could also be related to the time spent on exploring the website's content in task 1. Group 2 and 3 reported the content to be more useful (Neutral M=3,75, Angry M=3,65), and more general (Neutral M=4,75, Angry M=4,25). This result is intertwined with the perception of user experience, which is presented in the next section.

Descriptive Statistics Content Relevance						
Group	**Emotion after AEMT**	**N**	**Useful**	**Relevant**	**Meaningful**	**General**
1	Happy	7	2,86	4,86*	5,57*	3,57
2	Neutral	8	3,75*	2,25	5,25	4,75*
3	Angry	5	3,65	3,55	5,30	4,25

*The highest mean score for each parameter.

Table 9: Descriptive statistics of the content relevance compared with the induced emotion.

4.4 Study 2: Part 2 – User Experience Analysis

The AttrakDiff questionnaire was used to compare how the two groups induced with different emotions perceived the pragmatic quality, hedonic quality, and the design of the website. The results show that both groups scored similarly in both HQ and PQ regardless of the induced emotion (see figure 4). The confidence rectangles imply that Group 1 (A) were more at one in their evaluation of the website. Group 2 (B) showed a bigger confidence rectangle, showing more variable evaluation ratings within the group. But the data indicates too little difference to determine any significant differences between the groups. As such, the null hypothesis (the user's emotional status does not affect the total user experience of a service) is retained. The data still lays out observations correlated to the perception of content relevance presented in the section above.

Figure 5 shows the mean score of the AttrakDiff dimensions, where HQ distinguishes between HQ-I and HQ-S. Group 1 scores higher on HQ (=1,08, confidence=0,28) and HQ-I (=1,36) which correlated with how meaningful and relevant the content was perceived by the participants in the situational context. HQ is caused by the stimulation of the product's challenging and novel character, or by personal identification, finding the content directly related to the context of use. Group 2 scored higher on PQ (=0,29, confidence=0,57) than Group 1 (PQ=0,13, confidence=0,60), which fits the result that Group 2 finds the website to provide useful information and functionality to reach their goals. On attractiveness, only a slight difference is observed. The average score for each of the word-pars is shown in figure 6.

No participant that reported to be happy after AEMT felt confused or in a negative emotional state after the interaction, but several from the other groups felt confused (see table 8). Although the data from study 2 does not show any statistical difference in perceived content relevance and user experience, and several hypotheses were retained, findings imply that emotions affect user interaction.

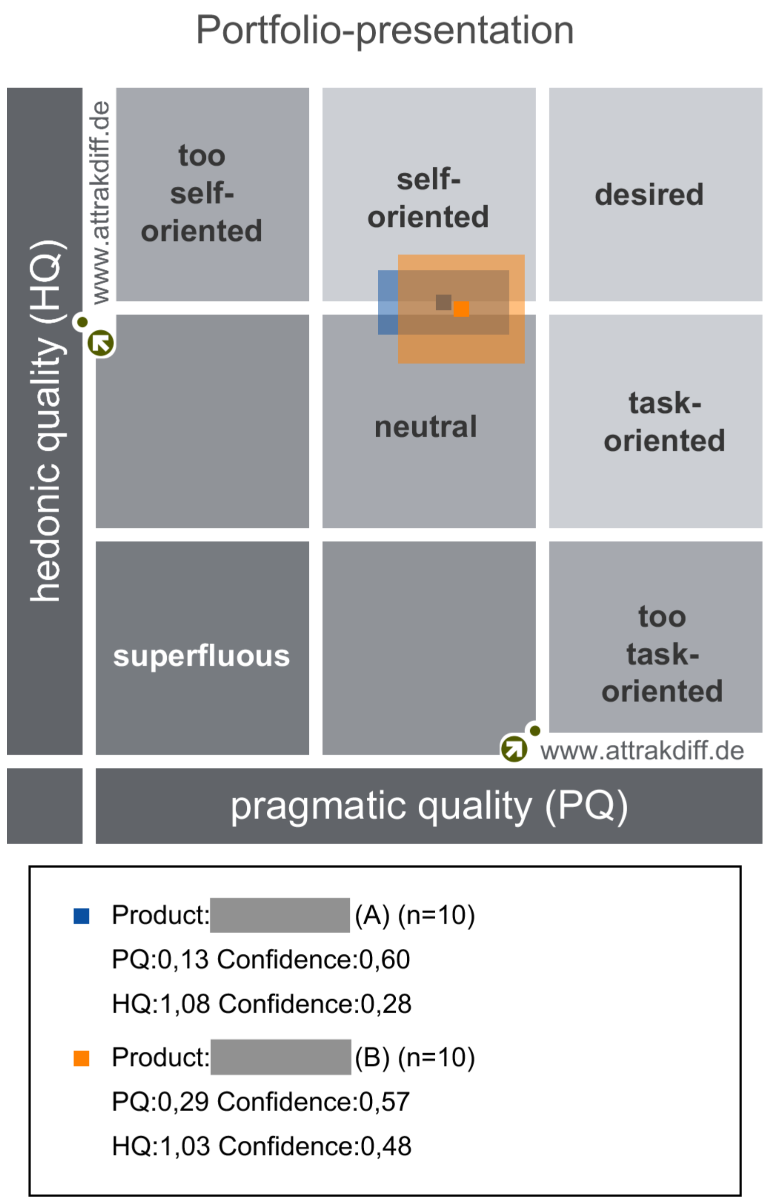

Figure 4: AttrakDiff portfolio of results.

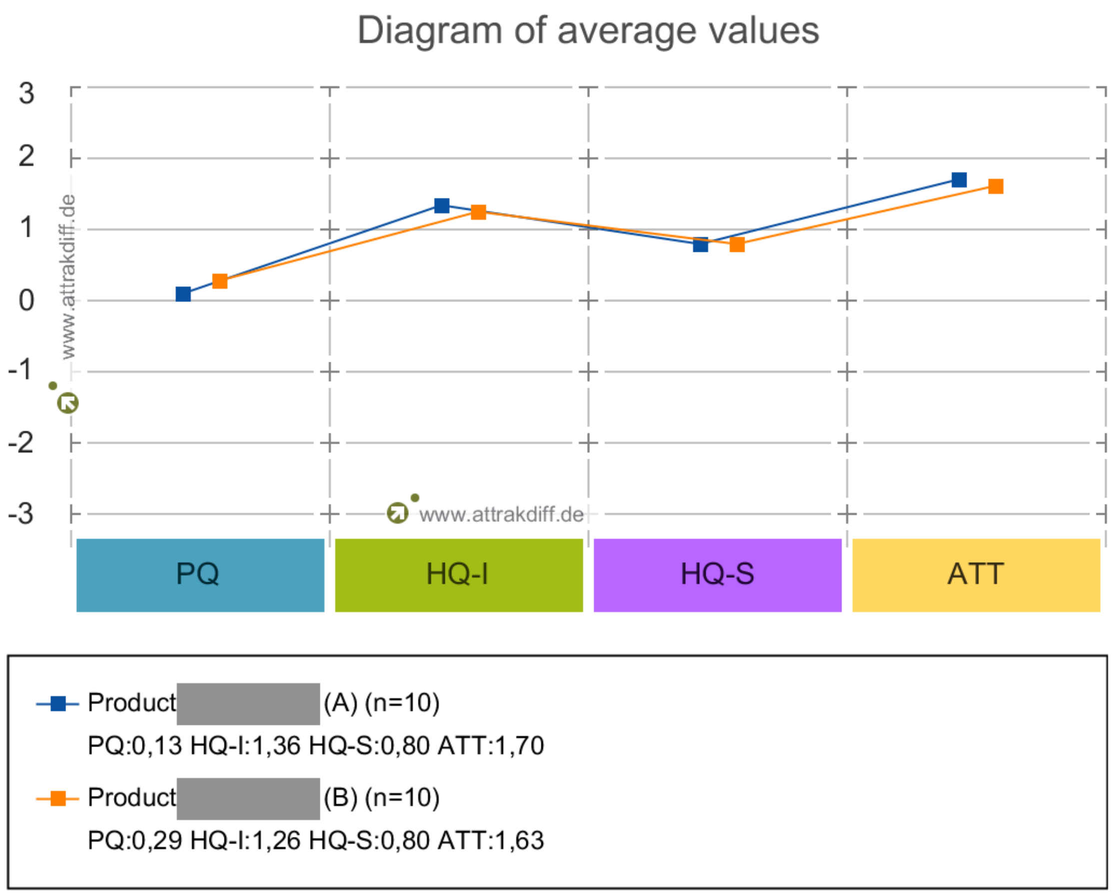

Figure 5: Diagram of average values of the AttrakDiff dimensions.

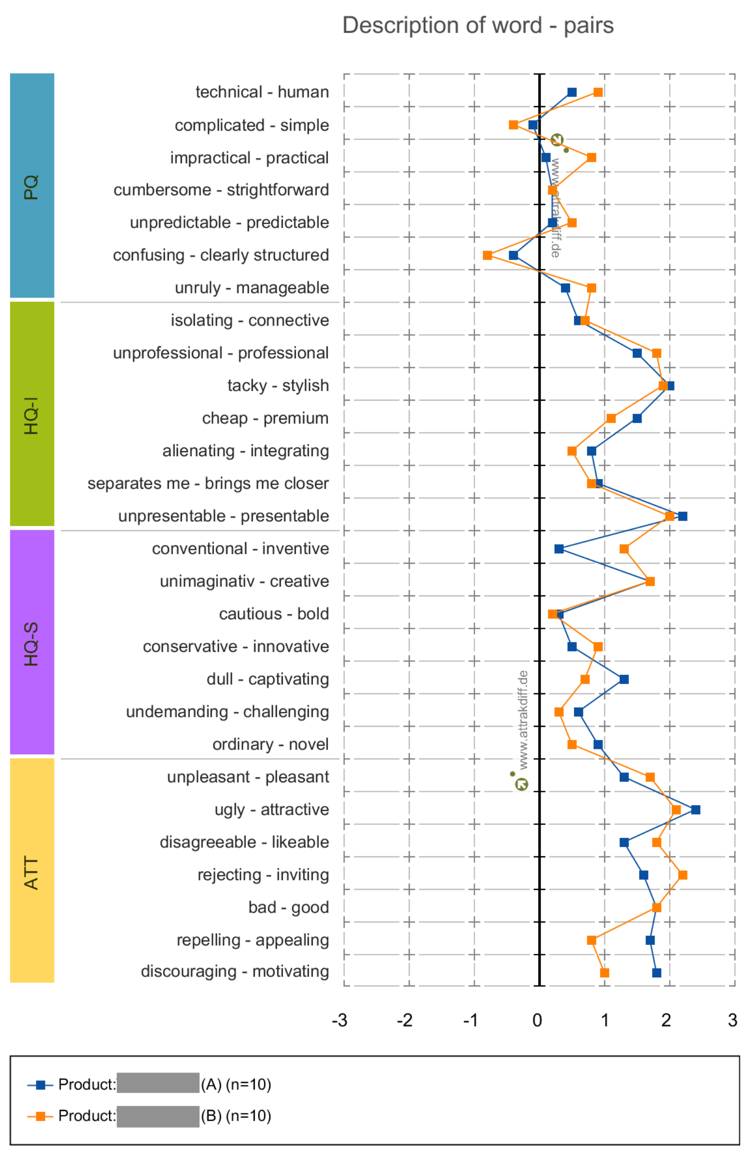

Figure 6: AttrakDiff description of wordpairs.

5 Discussion

5.1 Understanding User Needs and User Behavior

Considering emotions as contextual information adds to the discussion whether it will have an adverse effect on the user's beliefs and open-mindedness, or create more accurate and fitting user experiences. Most of our time spent online is guided invisibly by recommendation algorithms, creating a filter bubble. This filter bubble can lead to partial information blindness, but also more effectively help users reach a goal, widen their interests, and create a commonality of interests. The findings from the user interviews, survey, and workshop, is consistent with similar results from previous studies. While some people are more concerned about user privacy and data security, data reveals that personalization could be useful for some people, but not all. How we feel about an advertisement, a song, a product, a brand, or a website influences what we decide to do next. An employee in a physical store would be able to adapt to the customer by interpreting the facial movements, tone of voice, body posture, etc.. But, people are disengaged from human interaction online in which inconsistent conclusions are made about the user needs. It is therefore not sufficient anymore to only obtain information about previous preferences and behavior – it also needs to adapt to the immediate information about the user. Only then, appropriate guesses can be made about the actual user needs in the specific context. As such, designing websites that can arouse emotional responses in users like enjoyment and involvement could ultimately foster customer satisfaction and loyalty.

Some people like to get suggestions or recommendations that are similar to what they have looked at or purchased before, but some people find personalization annoying, limiting their searches and missed opportunities. This suggests that the industry need to change their approaches to personalization by creating new standards and being transparent about how user data is handled, and empowering people to protect their personal information. Personalization should not be restricted to system-initiated information but allow users insights to what data is inferred about them, how they are used, by whom, and allow them to modify or turn it off and still be able to use the site.

5.2 Study 1: The Validity Study of Emotion Detection Technology

Research question 1a asks *Can variables such as the user's emotional state be detected in real time and used as contextual information?*, and through a validity study of AFFDEX SDK, the results revealed it is possible to detect and distinguish between a positive and negative emotion, as well as categorizing the identified emotion to the intended one.

Considering all reported advantaged and limitations of current emotion detection technology by Garcia-Garcia et al. (2017), Affectiva's AFFDEX SDK was chosen for the validation study as it is one of the leading emotion detection technology available on the market. The reliability of the AFFDEX SDK has already been confirmed in a preliminary study by Taggart et al. (2016), but the comparability to this study is not possible as the emotion detection was not performed in real time. The preliminary study analyzed prerecorded videos that were exposed to video stimulus. Hence, as the goal was to research whether the user's situational context could be detected with such software in natural environments, the researcher decided it would be necessary to perform a validation study of the software, as well as determine the effectiveness of AEMT. Using AEMT as an emotion induction tool has several advantages, both in the lab and in natural environments: it is effective in inducing the intended emotion in short times (<10 minutes), requires no technology in contrast to methods such as video stimuli, and can scale up to group administration. Though there have been raised critical concerns that threaten the internal validity of experiments that utilize AEMT without appropriate manipulation checks, AFFDEX SDK would address this concern if the intended emotion is identified.

Affectiva's software is not free of charge, but they offer academic research licenses through their partner iMotions. As the Department of Civil and Environmental Engineering in NTNU in Trondheim are currently testing and using iMotions for other research projects, the researcher were able to utilize the software and conduct the validity study. One of the most significant limitations of this study was the time constraints for conducting it. The license was not transferable even for a short time, in which the researcher had to travel to conduct the study. The software had only been tested briefly by the license manager before the visit, in which the researcher spent quite some time to set up the equipment properly. Also, access to participants in this study was limited due to time constraints. Only six people participated in the study, including the researcher, which could raise questions if the findings are leaning toward a certain positive outcome. However, it was done to test whether the equipment worked properly and recorded data as expected. The data results were as such not influenced by the researcher's participation.

The data results revealed that the user's emotional state in the contextual situation could be detected with AFFDEX SDK, though the effectiveness and significance of the data set could have been more valid if the AEMT method were performed accordingly with the proposed procedure. During the validation study, it was decided that participants would not need to type in the specific situation for each emotion and evaluated by the researcher as it would require too much effort and time by each participant. Participants were therefore asked to think about that one situation for each emotion instead of writing it down, which could have affected the effectiveness of inducing that particular emotion compared to using video stimulus, as the total mean time for all participants were less than previous studies have used per emotion.

It was expected that the intended emotions would be significantly higher in their respective conditions, although in addition to the intended emotions, other emotions increased as well (e.g., induced anger also increased sadness). Multiple emotion states have been discussed as a limitation in previous research as emotions are unlikely to occur in isolation with AEMT compared to an emotion that arises naturally. Multiple emotion states bring to the discussion of whether facial analysis software such as AFFDEX SDK is good enough alone to identify the user's real emotion correctly.

Human interaction is multimodal, in which emotions are detected from additional channels such as body language, speech, and dynamic temporal changes. Comparing the AFFDEX scores with GSR+ showed that the measures significantly correlate with the arousal of the emotion. As such, detecting emotions from additional channels would further enhance the precision of results, although the facial analysis software alone is sufficient to pick up even a microexpression that tells what the user is feeling.

Although it was not investigated nor accounted for in this thesis study, cultural differences and ethnicity could be confounders. Despite the similarities of facial expressions and neural architecture across cultures, there exist no universal emotions. We are likely to judge facial expressions more accurately from our own culture than others. All participants in the study had different ethnicities which could have influenced the reliability of the facial analysis software.

5.3 Study 2: The Experiment

Research question 1b asks *Does emotions affect how the users perceive content relevance?*, and research question 1c asks *Does emotions affect the total user experience of the product?*. A 7-point Likert scale was used to measure the content relevance and the AttrakDiff measurement tool to assess the user experience, after AEMT. Although the results revealed no significant evidence to support a difference between the two conditions, several interesting observations appeared.

When participants were asked to describe a negative situation that had made them the angriest, several reported it was difficult to recall one, compared to the happy group. This correlates to the average time spent on the AEMT. Recalling memories depends on a variety of cues that help them draw inferences about past experiences (Aaker et al., 2008). All participants were asked which emotion they felt after performing AEMT, in which eight out of twenty reported a neutral feeling. Compared to other types of stimuli, AEMT has yet proven to be the most efficient method to induce an emotion experimentally. Asking a person to recall a specific memory is a reconstructive copy of the past, not a direct copy. Our perception and memory are temporarily and slippery, recalling a situation that would make others feel the same way is a difficult task as individual interpretations, attitudes, and beliefs affect our reactions. As such, some degree of response bias is inevitable. However, not collecting nor rating participant's responses may have a reinforced effect on the reliability of AEMT, as participants could have described a more truthful situation. The method calls for further improvements for future implementations. As such, choosing alternative methods or adjunct AEMT to induce emotions, might enhance the effect of the induction, to more easily compare different emotions.

The initial experimental design was to have people evaluate a prototype, allowing people to interact freely and with enough content to measure both the content relevance and the user experience. Creating a prototype and a new context of use would account for any existing biases toward already existing web sites or brands, affecting their overall perception of the content relevance and the user experience. However, creating a prototype with such complexity would require too much effort and time for this study. An initial prototype was designed but failed to account for sufficient complexity and functionality. The AttrakDiff measurement tool can only assess a true evaluation if the product is perceived as useful to its users. With only limited clickable features, design elements and little enriched content, using an already existing website made it possible for participants to fully engage and interact with the content.

By modifying and adapting recommended items to measure content relevance, it was possible to investigate whether there was a difference between the two groups in perceived usefulness and relevance of the content. Some participants suggested that the items were too similar and repeating. The items were carefully chosen and modified to ensure the reliability of the responses. Although there were found no significant differences between the groups, the group induced with happy emotion found the content more relevant than useful, whereas the group induced with negative emotion found the content more useful. These observations could indicate that when a user is in a positive emotional state, the user is more attentive to the content. Comparing this result to the AttrakDiff questionnaire, being in a positive emotional state also affects how stimulated the users are by interacting with the product. This group also found on average the design more attractive. It is worth noting that the AttrakDiff questionnaire is in English. All participants were Norwegian which could have imposed misunderstandings to the true meanings of the adjectives used in the questionnaire. Clarifications of the words were available at all times during the evaluation, but could as well have been lost in translation. It was decided not to translate the questionnaire as it has not been empirically tested to ensure the same results as the original.

A significant limitation to the findings is the small sample size. Only ten observations per group were performed, which is merely sufficient to state any effects of the emotional state to the content relevance and the user experience. The independent variables imposed the between-subjects design, but one of the major disadvantages of choosing this method is that it requires a large number of participants to generate sufficient data. Considering the time left on the project, as well as the timing of conducting the experiments, it would not have been possible to recruit twice the number of participants. Therefore, it is not possible to state a significant difference between the groups, but with additional observations for each group, as well as better manipulations checks to ensure that the correct emotion is induced, a statistically significant difference between the two groups could be detected.

5.4 Discussion of Contextual Personalization

One of the most critical issues with personalization strategies today is the adoption of one-size-fits-all. Not only has it shown to cause frustration to users, but also makes them feel alienated with the content they are presented. People are novices when it comes to persuasive technologies and what it entails. Many people have become more aware that user interfaces and technologies are designed to influence them by manipulating the content they see, but not how to identify, respond or understand what consequences it has on not accepting it (Fogg, 2003). Some strategies are more subtle, but most are not. The same product that the user had clicked at some point or similar ones follow the user on several platforms. The repeated request for compliance never ends, no easy way to turn it off, which ultimately may lead to some users to finally give in.

It is prominent that age, gender, and the location is not accurate information about people's interest and needs. For instance, not all twenty-four-year-old women are interested in dating websites, tips on how to lose weight for the summer, or pregnancy tests. A salesperson uses emotional cues to persuade customers and can sense when you like a product that is being proposed or when you dislike it, to modify their tactics to finalize a sale. Although facial analysis technology detects and interprets even the most subtle cues in the human face, it is the technology that ultimately controls how the interaction unfolds (Fogg, 2003). It simply cannot account for interactions it has not been programmed to accept. But with the immense interest in creating more sophisticated technology, accounting for human emotions as contextual information could create for more interesting interactions. Many brands account for what the user is feeling, such as mood playlists. But these require active input from the user. The user has to identify what emotional state they are in before choosing the appropriate playlist. With contextual personalization, the technology can identify what the user is feeling and say, "I sense you are feeling sad. Should I play your favorite song?" or, "You did not express satisfaction with this product. Would you prefer something similar instead?" Processing information about the user in real-time will benefit users as the interaction becomes more human, engages the users more effectively, and adjusts the marketing dynamically.

6 Conclusion

The work done in this thesis project has aimed to answer whether human emotions should be considered as contextual information in personalization processes by assessing the validity of an emotion detection technology, and the effects emotions have on perceived content relevance and user experience. Although no significant difference was found on perceived content relevance and user experience between different emotions, the data still yields indications that there is an emotional affect.

Both academia and industry have shown an increasing interest in personalization strategies and emotion detection technologies. The technology and algorithms are becoming more sophisticated, yet fail to create value to the users, making faulty assumptions about what the user wants and needs. Current personalization strategies are limited to only consider entities such as historical data, time, location, and devices as contextual information. Deriving from existing work that has shown that emotions affect consumer behavior, decision making, attention, and perception, it becomes prominent from observations in this thesis that considering emotions as an entity in real-time could increase the value of personalization in web environments. Contextual personalization is far from simply adding a name in an e-mail or website, nor is it just educated guesses about the user's interest. The potential is invaluable when considering real-time information in combination with in-depth analysis of consumer behavior. Implementing contextual personalization can increase the brand's ability to deliver interesting and relevant experiences, dependent on the exact user need during a specific mood at a particular time. The ultimate goal is to give what the user wants when they want it, where they want it. Conclusively, the answer to the research question *Is emotions as contextual information a variable that should be taken into account in web personalization?*, the prominent answer is yes. Technology is an inevitable part of everyday life, with complex algorithms that can detect even microexpressions in the face and make decent guesses about interest and user needs. Utilizing such technology and understanding context will further improve the focus on keeping users as the core of interests, dynamically tuning and refining content to the individual's needs and preferences.

6.1 Future Work

Personalization has been used and implemented by marketers for years, and each strategy has its own advantages. But the research is divided and no strategy has shown to proven effective to attract and engage the majority of users, which leaves significant room for future work.

Not all technology or web applications call for personalization, which has repeatedly been suggested from the qualitative research, as well from existing literature. Proposedly, one reasonable approach to assessing the value of applying contextual personalization is to develop a framework for evaluating the intentions of the brand, and ethical strategies to the data collection process. Technology aiming for contextual personalization should establish a transparent relationship between the brand and the user, to make it easier for people to recognize unethical tactics of persuasion, as well as enabling people to make an informed consent.

Another aspect of future research is to which degree contextual personalization should be implemented. Providing the right content at the right time has yet been proven efficient because suggestions are based on what the user potentially would want, not what they want right now. It is as such proposed that the timing of personalization is investigated, related to contextual factors such as emotion, time, and location. A suggested approach is to explore how changes in the web environment based on such contextual data influences user behavior and user experience. Designing user interfaces that respond to the context could account for the currently fragmented and disengaged user interaction.

As this thesis project could not conclude with significant results on the effects of emotional influence on content relevance and user experience, the researcher hopes that future research continues to examine this topic. The experimental design proposed in Study 2 (see section 3.3.3) can be used as a basis for further research on the subject, with other types of stimuli for inducing emotions. It is a necessity for the validity of future research to obtain data from more participants.

Finally, it would be highly interesting to research the topic with wearable technology. The market continues to expand as the interest increases. Multiple contextual information is collected, from entities as time and location, but also data about the user's sleeping habits, heart rate, calories burnt, and steps walked. It is almost inevitable that wearable technology will create a full experience, perfectly customized to the user's daily preferences. A suggested approach for future research is to test how users respond to personalized messages and nudges over a more extended period. Privacy issues regarding such data collection should be researched as well.

6.2 Contributions

The researcher has with this thesis aimed to combine several research approaches to advance web personalization to focus on contextual factors. The literature on web personalization is prominent in the field of information systems. The focus has been on technological applications, even when considering user-centric issues. This master's thesis contributes to a multidisciplinary approach where technology is tested with models from user-centric approaches and consumer psychology. The results further support the general notion that the user's situational context are essential variables in web personalization. Real-time data about the user's situational context, as well as historical data, can account for misinterpreted identities about the user. Recognizing emotions as contextual information, and utilizing technology that can detect such information would significantly enhance the interaction, engage the user more effectively, ultimately creating for better user experiences. The experimental designs laid out in the thesis can be employed to further evaluate the effectiveness of contextual personalization to content relevance and user experience.

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Appendices

A Interview Guide

Dato og lokasjon: Januar-februar 2019. Oslo og Gjøvik.
Tid: 25-30 minutter.
Utstyr: Samtykkeskjema, printet format av intervjuguide, båndopptaker, penn og papir.

1. Oppvarming / introduksjon (5 minutter)
Hilse på deltaker og fyll ut samtykkeskjema. Introduser prosjektets formål.

2. Nøkkelspørsmål (20 minutter)
Erfaringer med personalisering

- Hva forbinder du med personalisering?
- Hva tenker du om personalisert reklame?
- Hva tenker du om «anbefalt for deg»?
- Mener du personalisering gir nytteverdi?
    - Eksempler på gode og dårlige nettsteder som personaliserer innholdet?

Brukeratferd og behov på nett

- Blir du mer eller mindre informasjonssøkende når du er glad/sint/trist?
- Handler du mer eller mindre når du er glad/sint/trist?
- Opplever du at du endrer atferd på nett når du er glad/sint/trist?
- Oppstår det nye behov når du er glad/sint/trist?
    - Behov for mer/mindre informasjon?
    - Behov for å fullføre oppgaven så raskt som mulig?
    - Behov for hjelp? Finne på egen hånd/kontakte kundeservice?
- Hvordan opplever du tekst og informasjon på nett når du har en spesifikk emosjon, som for eksempel når du er glad, sint, trist eller kjeder deg?
- Blir du ofte irritert når du bruker en nettside? Hvorfor?
- Hva gjør at du endrer holdning til en nettside/applikasjon?
- Har du opplevd en følelse av å bli lurt til å kjøpe et produkt fordi det «passer bedre» til deg?

Informasjon og samtykke

- Leser du om informasjonskapsler og hvilke informasjoner som blir samlet om deg?

- Ignorerer du cookie-banners eller aksepter du dem når du besøker en nettside?
- Ville du trukket tilbake samtykke hvis du var klar over hvilken informasjon som ble samlet om deg?
- Hva er dine tanker om smart-assistenter som Google Home, Alexa og Siri?
- Hva tenker du om at denne typen teknologi alltid har tilgang til mikrofonen din?
- Tror du produkter og tjenester kunne vært bedre tilpasset brukerne dersom man forstod og tok hensyn til brukernes emosjoner?

3. Avrunding og avslutning

Oppsummer intervjuet og takk deltakeren for å ha deltatt i intervjuet.

B Interview Consent Form

Intervju samtykkeskjema
Kontekstuell personalisering av brukergrensesnitt

Formål
Formålet med intervjuet er å få en større forståelse av hvilke brukerbehov og brukeratferd som oppstår under bestemte emosjonelle tilstander, og hvordan det påvirker hvor relevant en bruker opplever innholdet samt brukeropplevelsen. Intervjuene vil gi en indikasjon på hvorvidt emosjoner bør tas med som en del av den kontekstuelle informasjonen som samles inn av brukere på personaliserte nettsider.

Brukerintervjuet utføres som en del av en masteroppgave. Hvis du har spørsmål eller bekymringer om denne studien, vennligst kontakt:

Intervjuer
Mai Thao Nguyen, maitn@stud.ntnu.no
Master i interaksjonsdesign
Fakultet for Arkitektur og Design
NTNU i Gjøvik

Akademisk veileder
Frode Volden, frodev@ntnu.no
Førstelektor
Fakultet for Arkitektur og Design
NTNU i Gjøvik

Deltakelse
Det er frivillig å delta i prosjektet. Alle opplysninger om deg blir anonymisert. Hvis du velger å delta, kan du når som helst trekke samtykke tilbake uten å oppgi noen grunn. I dette tilfellet vil alle opplysninger om deg bli slettet. Det vil ikke ha noen negative konsekvenser for deg hvis du ikke vil delta eller senere velger å trekke deg. Prosjektet skal etter planen avsluttes 31.juni. Personopplysninger vil bli slettet. Anonymiserte utdrag fra intervjuer og andre resultater vil bli lagret frem til utgangen av året 2019.

Dine rettigheter
Så lenge du kan identifiseres i datamaterialet, har du rett til:
- innsyn i hvilke personopplysninger som er registrert om deg,
- å få rettet personopplysninger om deg,
- få slettet personopplysninger om deg,
- få utlevert en kopi av dine personopplysninger (dataportabilitet), og
- å sende klage til personvernombudet eller Datatilsynet om behandlingen av dine personopplysninger.

På oppdrag fra NTNU har NSD – Norsk senter for forskningsdata AS vurdert at behandlingen av personopplysninger i dette prosjektet er i samsvar med personvernregelverket.

Samtykke
Jeg har mottatt og forstått informasjon om prosjektet, og har fått anledning til å stille spørsmål. Jeg samtykker frivillig til å delta i dette intervjuet.

Deltakers signatur

____

Dato, Sted

____

C Questionnaire

Personalisering på nettsider

Personalisering på nett handler om å identifisere og bruke kundeinformasjon til å levere relevant innhold til brukerne. Målet med spørreundersøkelsen er å kartlegge nettbruk, netthandel og synspunkter om personalisering på nettsider.

Ved å delta i denne spørreundersøkelsen bekrefter du at dine svar kan brukes i en masteroppgave gjennomført ved NTNU i Gjøvik. Du svarer anonymt på denne undersøkelsen og registrert data vil ikke kunne spores tilbake til deg. Deltakelse er frivillig og du kan trekke deg fra undersøkelsen når som helst.

Hvis du har spørsmål, bekymringer om studien eller ønsker å få slettet svarene dine, vennligst kontakt: maitn@stud.ntnu.no.

*Må fylles ut

Generell informasjon

1. **Alder** *

   ____

2. **Kjønn** *
   Markér bare én oval.

   ◯ Mann
   ◯ Kvinne
   ◯ Annet

Personalisering

3. **Har du hørt om personalisering?** *
   Markér bare én oval.

   ◯ Nei
   ◯ Kanskje
   ◯ Ja

4. **Hva tror du personalisering brukes til? (en eller flere)** *
   Merk av for alt som passer

   - [ ] Gir tilpasset annonser/reklame
   - [ ] Forbedring av kundeoppfølging
   - [ ] Gir tilpasset søkeresultater
   - [ ] Skreddersyr nettsiden til meg
   - [ ] Lagring av personopplysninger
   - [ ] Gir en bedre kundeopplevelse
   - [ ] Endrer innholdet basert på det jeg har kjøpt eller sett på tidligere
   - [ ] Filtrerer innholdet på nettsiden

5. **Hvilken informasjon tror du blir lagret om deg? (en eller flere)** *
Merk av for alt som passer

- [ ] Din lokasjon
- [ ] Klikk på nettsiden
- [ ] Brukernavn og passord
- [ ] Kortinformasjon
- [ ] Type enhet (pc, mobil, nettbrett)
- [ ] Handlekurv på nettbutikk
- [ ] E-postadresse
- [ ] Logg
- [ ] Søk
- [ ] Filtrering
- [ ] Tidligere kjøp på nett
- [ ] IP-adresse

Personalisering

6. **Jeg liker å se annonser/reklame av det jeg har kjøpt tidligere** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

7. **Jeg liker å se lignende annonser/reklame som ligner på det jeg har sett på tidligere** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

8. **Jeg liker å få tilpasset annonser/reklame til meg** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

9. **Jeg liker å få forslag til produkter som passer meg** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

10. **Jeg liker at et kjøp gjennomføres på raskest mulig måte** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

11. **Jeg liker å bli tilbudt hjelp når jeg handler** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

12. **Jeg liker å få opp de samme produktene jeg har sett på tidligere, men ikke kjøpt** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

13. **Jeg liker bedre å handle fysisk i butikk enn på nett** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

14. **Jeg blir irritert på for mye personalisering på nett** *

Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

15. **Anbefalinger av produkter på nett passer min stil og mine interesser** *

Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

16. **Jeg liker at innholdet filtreres avhengig av produkter jeg har kjøpt eller sett på tidligere** *

Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

17. **Jeg føler meg presset til å handle et produkt på nett når jeg stadig får opp reklame av produktet** *

Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

18. **Jeg leser sjeldent/aldri bruk og vilkår når jeg bruker en tjeneste eller applikasjon** *

Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

19. **Jeg liker at butikkansatte spør om jeg trenger hjelp** *
Markér bare én oval.

- Uenig
- Litt uenig
- Verken eller
- Litt enig
- Enig

Personalisering

20. **Bruker du smart-assistenter som Google Home, Siri eller Alexa?** *
Markér bare én oval.

- Nei
- Ja

21. **Tillater du applikasjoner å få tilgang til mikrofon og kamera?** *
Markér bare én oval.

- Nei
- Av og til
- Ja

22. **Tillater du applikasjoner å få tilgang til din lokasjon?** *
Markér bare én oval.

- Nei
- Av og til
- Ja

23. **Aksepterer du bruk av informasjonskapsler? (cookies på nettsider)** *
Markér bare én oval.

- Nei
- Av og til
- Ja

24. **Ville du tillatt nettsider å få tilgang til mikrofon for å få mer relevant innhold og produkter?** *
Markér bare én oval.

- Nei
- Kanskje
- Ja

25. **Ville du tillatt nettsider å få tilgang til kamera for å få mer relevant innhold og produkter?** *
Markér bare én oval.

- Nei
- Kanskje
- Ja

26. **Ville du tillatt nettsider å opprette profiler om deg og dine kjøp?** *
Markér bare én oval.

- Nei
- Kanskje
- Ja

Netthandel

27. **Når på dagen handler du på nett?** *
Markér bare én oval.

- Morgen
- Formiddag
- Ettermiddag
- Kveld

28. **Handler du ofte på impuls?** *
Markér bare én oval.

- Nei
- Av og til
- Ja

29. **I hvilket humør impulshandler du mest?** *
Markér bare én oval.

- Når jeg er glad
- Når jeg er sint
- Når jeg er lei meg
- Når jeg er overrasket
- Når jeg er redd
- Når jeg er stresset
- Når jeg kjeder meg

30. **Jeg utforsker og leter etter ny informasjon...** *
Markér bare én oval.

- Når jeg er glad
- Når jeg er sint
- Når jeg er lei meg
- Når jeg er overrasket
- Når jeg er redd
- Når jeg er stresset
- Når jeg kjeder meg

31. **Jeg prokastinerer på nett...** *
Markér bare én oval.

- Når jeg er glad
- Når jeg er sint
- Når jeg er lei meg
- Når jeg er overrasket
- Når jeg er redd
- Når jeg er stresset
- Når jeg kjeder meg

32. **Jeg handler for høyere summer på nett...** *
Markér bare én oval.

- Når jeg er glad
- Når jeg er sint
- Når jeg er lei meg
- Når jeg er overrasket
- Når jeg er redd
- Når jeg er stresset
- Når jeg kjeder meg

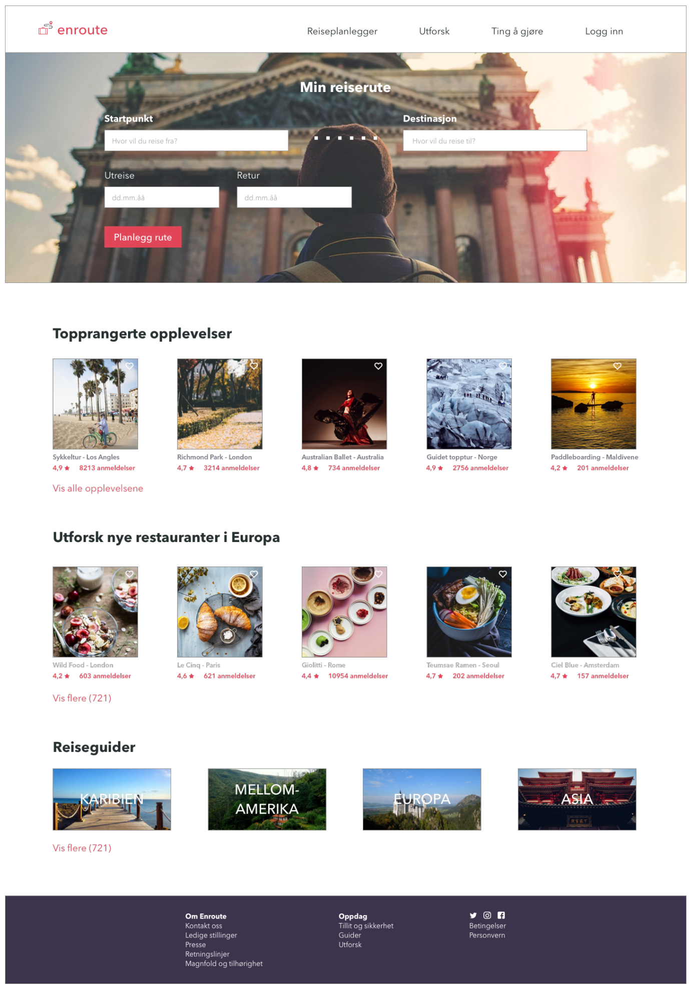
D AttrakDiff Questionnaire

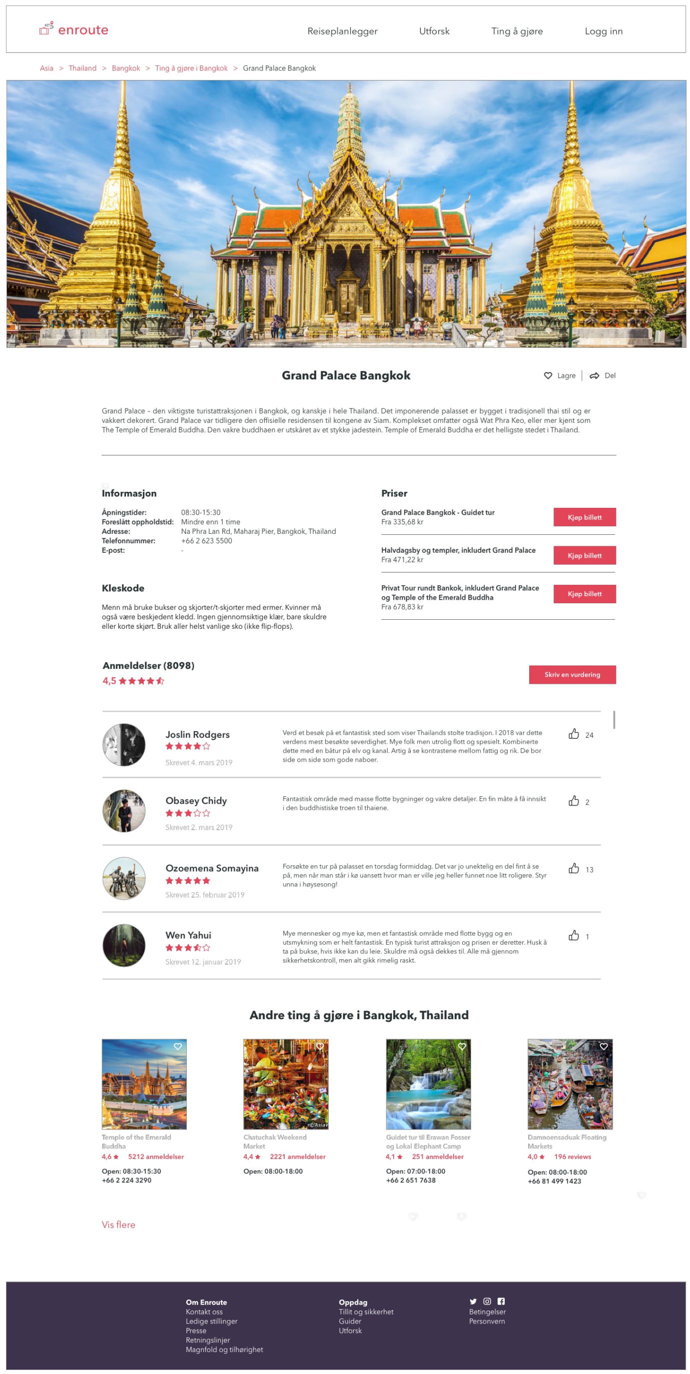
AttrakDiff

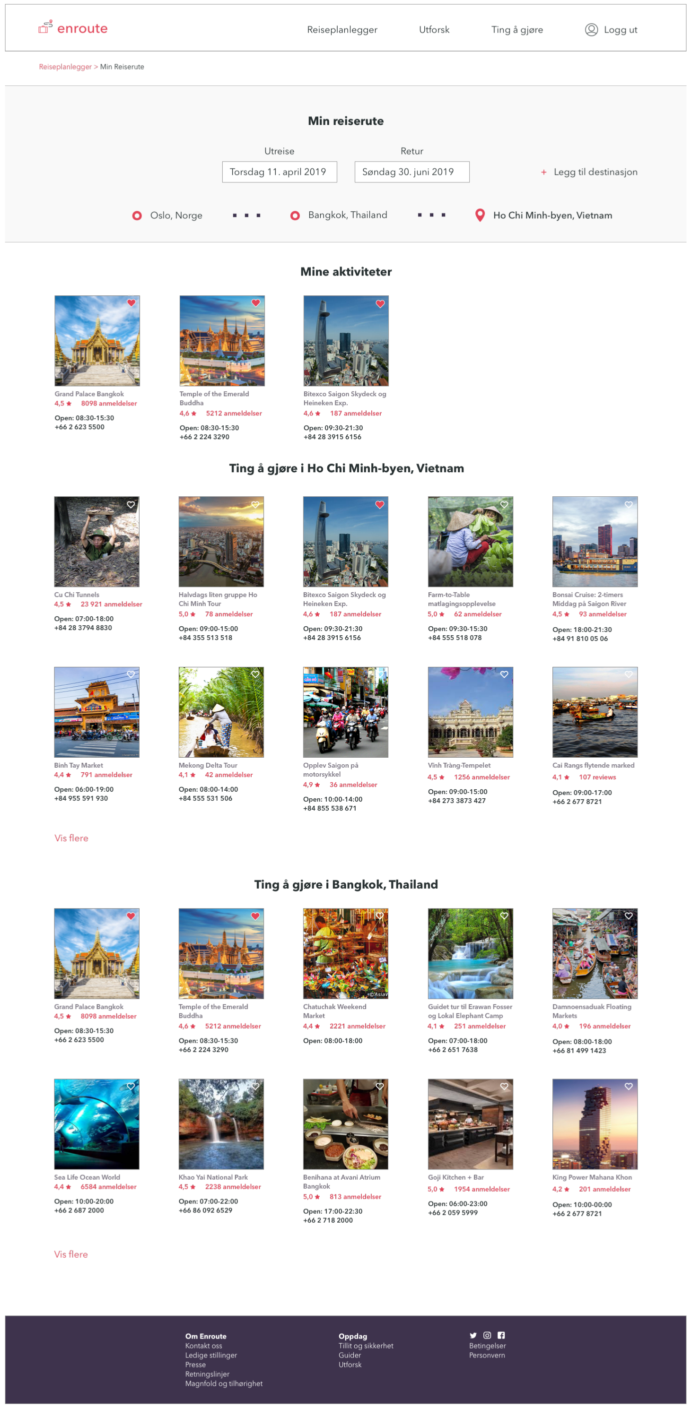
Deutsch | English

human	o	o	o	o	o	o	o	technical
isolating	o	o	o	o	o	o	o	connective
pleasant	o	o	o	o	o	o	o	unpleasant
inventive	o	o	o	o	o	o	o	conventional
simple	o	o	o	o	o	o	o	complicated
professional	o	o	o	o	o	o	o	unprofessional
ugly	o	o	o	o	o	o	o	attractive
practical	o	o	o	o	o	o	o	impractical
likeable	o	o	o	o	o	o	o	disagreeable
cumbersome	o	o	o	o	o	o	o	straightforward
stylish	o	o	o	o	o	o	o	tacky
predictable	o	o	o	o	o	o	o	unpredictable
cheap	o	o	o	o	o	o	o	premium
alienating	o	o	o	o	o	o	o	integrating
brings me closer to people	o	o	o	o	o	o	o	separates me from people
unpresentable	o	o	o	o	o	o	o	presentable
rejecting	o	o	o	o	o	o	o	inviting
unimaginative	o	o	o	o	o	o	o	creative
good	o	o	o	o	o	o	o	bad
confusing	o	o	o	o	o	o	o	clearly structured
repelling	o	o	o	o	o	o	o	appealing
bold	o	o	o	o	o	o	o	cautious
innovative	o	o	o	o	o	o	o	conservative
dull	o	o	o	o	o	o	o	captivating
undemanding	o	o	o	o	o	o	o	challenging
motivating	o	o	o	o	o	o	o	discouraging
novel	o	o	o	o	o	o	o	ordinary
unruly	o	o	o	o	o	o	o	manageable

E Prototype Wireframes




enroute
Reiseplanlegger
Utforsk
Ting å gjøre
Logg inn
Asia > Thailand > Bangkok > Ting å gjøre i Bangkok > Grand Palace Bangkok
Grand Palace Bangkok
Lagre
Del
Grand Palace – den viktigste turistattraksjonen i Bangkok, og kanskje i hele Thailand. Det imponerende palasset er bygget i tradisjonell thai stil og er vakkert dekorert. Grand Palace var tidligere den offisielle residensen til kongene av Siam. Komplekset omfatter også Wat Phra Keo, eller mer kjent som The Temple of Emerald Buddha. Den vakre buddhaen er utskåret av et stykke jadestein. Temple of Emerald Buddha er det helligste stedet i Thailand.
Informasjon
Åpningstider: 08:30-15:30
Foreslått oppholdstid: Mindre enn 1 time
Adresse: Na Phra Lan Rd, Maharaj Pier, Bangkok, Thailand
Telefonnummer: +66 2 623 5500
E-post: -
Kleskode
Menn må bruke bukser og skjorter/t-skjorter med ermer. Kvinner må også være beskjedent kledd. Ingen gjennomsiktige klær, bare skuldre eller korte skjørt. Bruk aller helst vanlige sko (ikke flip-flops).
Priser
Grand Palace Bangkok - Guidet tur
Fra 335,68 kr
Kjøp billett
Halvdagsby og templer, inkludert Grand Palace
Fra 471,22 kr
Kjøp billett
Privat Tour rundt Bankok, inkludert Grand Palace og Temple of the Emerald Buddha
Fra 678,83 kr
Kjøp billett
Anmeldelser (8098)
4,5
Skriv en vurdering
Joslin Rodgers
Skrevet 4. mars 2019
Verd et besøk på et fantastisk sted som viser Thailands stolte tradisjon. I 2018 var dette verdens mest besøkte severdighet. Mye folk men utrolig flott og spesielt. Kombinerte dette med en båtur på elv og kanal. Artig å se kontrastene mellom fattig og rik. De bor side om side som gode naboer.
24
Obasey Chidy
Skrevet 2. mars 2019
Fantastisk område med masse flotte bygninger og vakre detaljer. En fin måte å få innsikt i den buddhistiske troen til thaiene.
2
Ozoemena Somayina
Skrevet 25. februar 2019
Forsøkte en tur på palasset en torsdag formiddag. Det var jo unektelig en del fint å se på, men når man står i kø uansett hvor man er ville jeg heller funnet noe litt roligere. Styr unna i høysesong!
13
Wen Yahui
Skrevet 12. januar 2019
Mye mennesker og mye kø, men et fantastisk område med flotte bygg og en utsmykning som er helt fantastisk. En typisk turist attraksjon og prisen er deretter. Husk å ta på bukse, hvis ikke kan du leie. Skuldre må også dekkes til. Alle må gjennom sikkerhetskontroll, men alt gikk rimelig raskt.
1
Andre ting å gjøre i Bangkok, Thailand
Temple of the Emerald Buddha
4,6 ★ 5212 anmeldelser
Open: 08:30-15:30
+66 2 224 3290
Chatuchak Weekend Market
4,4 ★ 2221 anmeldelser
Open: 08:00-18:00
Guidet tur til Erawan Fosser og Lokal Elephant Camp
4,1 ★ 251 anmeldelser
Open: 07:00-18:00
+66 2 651 7638
Damnoensaduak Floating Markets
4,0 ★ 196 reviews
Open: 08:00-18:00
+66 81 499 1423
Vis flere
Om Enroute
Kontakt oss
Ledige stillinger
Presse
Retningslinjer
Magnfold og tilhørighet
Oppdag
Tillit og sikkerhet
Guider
Utforsk
Betingelser
Personvern


enroute
Reiseplanlegger
Utforsk
Ting å gjøre
Logg ut
Reiseplanlegger > Min Reiserute
Min reiserute
Utreise
Retur
Torsdag 11. april 2019
Søndag 30. juni 2019
+ Legg til destinasjon
Oslo, Norge
Bangkok, Thailand
Ho Chi Minh-byen, Vietnam
Mine aktiviteter
Grand Palace Bangkok
Temple of the Emerald Buddha
Bitexco Saigon Skydeck og Heineken Exp.
Ting å gjøre i Ho Chi Minh-byen, Vietnam
Cu Chi Tunnels
Halvdags liten gruppe Ho Chi Minh Tour
Bitexco Saigon Skydeck og Heineken Exp.
Farm-to-Table matlagingsopplevelse
Bonsai Cruise: 2-timers Middag på Saigon River
Binh Tay Market
Mekong Delta Tour
Opplev Saigon på motorsykkel
Vinh Tràng-Tempelet
Cai Rangs flytende marked
Vis flere
Ting å gjøre i Bangkok, Thailand
Grand Palace Bangkok
Temple of the Emerald Buddha
Chatuchak Weekend Market
Guidet tur til Erawan Fosser og Lokal Elephant Camp
Damnoensaduak Floating Markets
Sea Life Ocean World
Khao Yai National Park
Benihana at Avani Atrium Bangkok
Goji Kitchen + Bar
King Power Mahana Khon
Vis flere
Om Enroute
Kontakt oss
Ledige stillinger
Presse
Retningslinjer
Mangfold og tilhørighet
Oppdag
Tillit og sikkerhet
Guider
Utforsk
Betingelser
Personvern

F NSD Privacy Note

NSD NORSK SENTER FOR FORSKNINGSDATA

NSD sin vurdering

Prosjekttittel

Personalisering av grafiske grensesnitt basert på kontekstuell informasjon

Referansenummer

821091

Registrert

28.01.2019 av Mai Thao Nguyen - maitn@stud.ntnu.no

Behandlingsansvarlig institusjon

NTNU Norges teknisk-naturvitenskapelige universitet / Fakultet for arkitektur og design (AD) / Institutt for design

Prosjektansvarlig (vitenskapelig ansatt/veileder eller stipendiat)

Frode Volden, fordev@ntnu.no, tlf: 93227262

Type prosjekt

Studentprosjekt, masterstudium

Kontaktinformasjon, student

Mai Thao Nguyen, maitn@stud.ntnu.no, tlf: 48230897

Prosjektperiode

16.01.2019 - 19.07.2019

Status

05.03.2019 - Vurdert

Vurdering (1)

05.03.2019 - Vurdert

Det er vår vurdering at behandlingen av personopplysninger i prosjektet vil være i samsvar med personvernlovgivningen så fremt den gjennomføres i tråd med det som er dokumentert i meldeskjemaet med vedlegg den 05.03.2019, samt i meldingsdialogen mellom innmelder og NSD. Behandlingen kan starte.

MELD ENDRINGER
Dersom behandlingen av personopplysninger endrer seg, kan det være nødvendig å melde dette til NSD ved å oppdatere meldeskjemaet. På våre nettsider informerer vi om hvilke endringer som må meldes. Vent på svar før endringer gjennomføres.

TYPE OPPLYSNINGER OG VARIGHET
Prosjektet vil behandle alminnelige kategorier av personopplysninger frem til 19.07.2019.

LOVLIG GRUNNLAG
Prosjektet vil innhente samtykke fra de registrerte til behandlingen av personopplysninger. Vår vurdering er at prosjektet legger opp til et samtykke i samsvar med kravene i art. 4 og 7, ved at det er en frivillig, spesifikk, informert og utvetydig bekreftelse som kan dokumenteres, og som den registrerte kan trekke tilbake. Lovlig grunnlag for behandlingen vil dermed være den registrertes samtykke, jf. personvernforordningen art. 6 nr. 1 bokstav a.

PERSONVERNPRINSIPPER
NSD vurderer at den planlagte behandlingen av personopplysninger vil følge prinsippene i personvernforordningen om:

- lovlighet, rettferdighet og åpenhet (art. 5.1 a), ved at de registrerte får tilfredsstillende informasjon om og samtykker til behandlingen
- formålsbegrensning (art. 5.1 b), ved at personopplysninger samles inn for spesifikke, uttrykkelig angitte og berettigede formål, og ikke behandles til nye, uforenlige formål
- dataminimering (art. 5.1 c), ved at det kun behandles opplysninger som er adekvate, relevante og nødvendige for formålet med prosjektet
- lagringsbegrensning (art. 5.1 e), ved at personopplysningene ikke lagres lengre enn nødvendig for å oppfylle formålet

DE REGISTRERTES RETTIGHETER
Så lenge de registrerte kan identifiseres i datamaterialet vil de ha følgende rettigheter: åpenhet (art. 12), informasjon (art. 13), innsyn (art. 15), retting (art. 16), sletting (art. 17), begrensning (art. 18), underretning (art. 19), dataportabilitet (art. 20).

NSD vurderer at informasjonen om behandlingen som de registrerte vil motta oppfyller lovens krav til form og innhold, jf. art. 12.1 og art. 13.

Vi minner om at hvis en registrert tar kontakt om sine rettigheter, har behandlingsansvarlig institusjon plikt til å svare innen en måned.

FØLG DIN INSTITUSJONS RETNINGSLINJER
NSD legger til grunn at behandlingen oppfyller kravene i personvernforordningen om riktighet (art. 5.1 d), integritet og konfidensialitet (art. 5.1. f) og sikkerhet (art. 32).

For å forsikre dere om at kravene oppfylles, må dere følge interne retningslinjer og/eller rådføre dere med behandlingsansvarlig institusjon.

OPPFØLGING AV PROSJEKTET
NSD vil følge opp ved planlagt avslutning for å avklare om behandlingen av personopplysningene er avsluttet.

Lykke til med prosjektet!

Kontaktperson hos NSD: Karin Lillevold
Tlf. Personverntjenester: 55 58 21 17 (tast 1)

2/2

NTNU

Norwegian University of
Science and Technology