Hedonic Motivation of Chatbot Usage

Wizard-of-Oz Study based on Face Analysis and User Self-Assessment

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***Abstract*—Ever since, the Internet enabled conversations by supporting interactive features and the presentation of product- or service-related information accumulated on websites, micro pages or portals. More recently, especially user groups of younger generations turn towards messaging applications for communication. Companies adjust to this trend of more messaging-oriented forms of interaction by implementing new channels of customer communication such as chatbots. In this work, a comparative analysis is conducted to uncover the impact of using traditional websites or chatbots for promoting a product in an impulse purchase situation with special attention to hedonic motivation. The aim is to measure the impact of the information delivery option (website or chatbot) on the customers' emotions as expression of hedonic motivation. More specifically, this paper is addressed to answering the question whether chatbot utilization result in a different hedonic motivation and in turn a higher manifestation of positive emotions than tradition website usage. The chatbot-based scenario is implemented by using a Wizard-of-Oz (WOz) experimental approach. The results provide first insights on the effects of chatbot usage on emotions in electronic commerce environments: while the chatbot users showed slightly higher happiness scores, no statistically significant impact could be discovered and there does not seem to be a statistically significant influence of chatbot usage on the purchase decision.**

Keywords–Chatbots; Conversational Commerce; Comparative Analysis; Wizard-of-Oz; Emotion Recognition; Hedonic Motivation.

I. Introduction

In recent years, online communication has shifted from a one-way to a conversational approach [1]. Internet users do not only receive information but also generate content themselves and interact in networks, e.g., via online communication applications. In this network environment, information is not only pushed, but also actively pulled by the users suited to their specific requirements [2]. In doing so, they expect to be treated individually and to be singularly addressed while their questions are adequately answered [3]. Hence, it can be said that the common website behavior of searching and finding transforms into a process of asking and receiving answers. Companies are adapting to this transformation by increasingly offering and sharing information, as well as promotions in online channels allowing for two-way conversations. A current trend is the implementation of chatbots. According to Mittal et al., chatbots are conversational programs for question-and-answer processes, which interact with the users in the form of ever-present assistants. Such systems can be based on pattern matching and natural language processing methods or artificial intelligence (AI) techniques [4]. These days, big global players, such as Google and Microsoft are conducting extensive research in order to advance this technology [5], which shows the current interest and importance of the technology.

Within e-business, chatbots can not only be used for focused product inquiries but also for product comparison or to assist users within the product decision-making processes [6]. Currently, more than a hundred thousand unique chatbots are being offered (with the Facebook messenger being the most popular implementation platform) [7]. As reported in [8], more than one fifth of the population in the US has used such chatbots offerings already. According to a study by Oracle and Coleman Parks, 80 percent of the queried companies either already have implemented or plan to implement a chatbot into their marketing strategy in order to improve their customer experience by 2020 [9]. Thus, the relevancy of the topic becomes apparent.

In ligth of the above, this article is about the assessment of hedonic motivation within impulse purchase situations focusing on chatbot and website utilization. It proceeds with a research background where conversational commerce and chatbot utilization are examined as well as the according role of hedonic motivation. In Section III, our approach on measuring hedonic motivation based on a Wizard-of-Oz testing scenario is presented. Section IV contains details concerning the experimental study while the results are presented in Section V. There, we discuss general findings, the differences between emotion self-assessment and face analysis, as well as the analysis concerning hedonic motivation. In the last section, a conclusion is given concerning the study at hand.

II. Research Background

The analysis of the hedonic motivation of chatbot usage requires a more comprehensive understanding of the principles of the emerging conversational commerce and the concept of hedonic motivation. For this reason, we will provide a more detailed background on the related fundamentals and related scientifc work for these two topics in the following.

A. Chatbot Usage and Conversational Commerce

Chatbots are dialogue programs in the form of composed pattern matching and natural language processes or artificial intelligence techniques [4], which can effectively be used for interactive question answer processes [10]. There are early examples of such systems that date back into the mid-1960s such as the popular ELIZA system and many more systems that have been discussed in literature (e.g., Albert One, ALICE)

[11]. Pattern matching or rule-based processing of chatbots are searches for key words, word roots and synonyms for example. They are noted in code in order to predefine possible conversation flows to generate answers to questions [11]–[13]. In this so-called retrieval-based approach, the chatbot produces answers from a predefined database according to rules. Artificial intelligence techniques in the form of generative models go beyond this logic of predefinition by allowing for learning processes where the bot program generates unique answers via knowledge assembly and by analyzing the current context [14]. Tailored to interaction with humans –consumers in this case–, they produce and understand written input in natural language. This human interface offers an interesting alternative compared to the traditional information architecture, where information is structured and formatted to interact with screens. Without particular setup requirements, it can be easily interacted with and utilized [15]. Application fields for chatbots can be educational, customer service or e-commerce scenarios for example [16].

Within e-commerce, one trend gaining interest is conversational commerce [17]. Chris Messina, chatbot industry expert and trend watcher, created the industry-wide accepted definition (e.g., [18][19]) for conversational commerce, which is about "utilizing chat, messaging, or other natural language interfaces (i.e., voice) to interact with people, brands, or services and bots that heretofore have had no real place in the bidirectional, asynchronous messaging context" [20]. Commercial chatbot conversation can be seen as a part of conversational commerce, as the latter can be seen as a combination of messaging apps or rather human-bot chatting and shopping in the form of conversational customer interaction [17]. As such, chatbots transport the previously mentioned idea of asking and and receiving answers into e-commerce allowing consumers to naturally engage with companies in a commercial context like they are used to through common interpersonal conversation. This rather natural engagement capability can be seen as one of the main advantages of conversational commerce alongside the easy accessibility and the already familiar interface within messaging apps [17]. Utilized in such an e-commerce context, chatbots can also improve customer satisfaction [21].

B. Hedonic Motivation in Conversational Commerce

Hedonic shopping can be operationalized through several items, such as joy, excitement, arousal, festive, escapism, fantasy, and adventure, as stated for example in [22]–[26]. A value for the total hedonic motivation can be calculated as the sum of positive and negative emotions [27]. This value is a key element of the consumer experience [28][29]. Emotions are a significant part of the Stimulus-Organism-Response (SOR) process [30][31], which is used in marketing science or to measure hedonic benefits [32][33]. The aim of the consumer is to select hedonic experiences, which maximize positive emotions [34]. The emotional aspect of hedonism can be seen as essential for user satisfaction in information systems [35]. Defined as wish to satisfy a need, hedonic motivation can be specified as emotional experience [31][36], which has been found to directly influence the consumers' positive emotional responses [31]. Further studies examined the aspects of emotions within chatbot usage in general (e.g., [37][38]) or the influence of hedonic values for e-service quality [39] for example. To the authors knowledge, there is no existing study combining these aspects by analyzing emotions and chatbot utilization in an e-shopping situation. In our study, the multidimensional construct emotion is operationalized solely as a physically measurable expression based on the seven basic universal emotions as discovered by Ekman and Heider [40]: Anger, fear, sadness, disgust, surprise, contempt and happiness. Happiness, as emotional aspect, will be focused on in our study. This is because, as per definition, within hedonic motivation positive emotions shall be maximized from consumer side and thus represent an important part of the consumers' hedonic motivation [31].

Impulse purchasing can be seen as hedonic purchase behavior and consumer emotions have been found to influence impulse buying behavior – happiness or excitement being a positive influence [31]. Hence, this study examines the impact of chatbot usage in an impulse purchase situation. For this purpose, a comparative study based on a traditional webpage-based e-shopping scenario and a chatbot enhanced variant is used to analyze for differences in the resulting customers' hedonic motivation.

Different digital offers such as social network sites, social media in general, shopping sites or dialogue systems inherit different content and are set up differently as well thus can be examined individually concerning the influence of hedonic aspects (e.g., [35][41]). In light of the current trend of implementing conversational offers into commerce contexts, we expect diverging manifestations of happiness. Thus, we think that there are different levels of hedonic motivation when consumers interact solely with product webpages or get assistance from chatbots. While previous research already integrated hedonic motivation into impulse buying behavior research and chatbot research in the form of chatbot metrics frameworks (e.g., [31][42]), there is a research gap concerning the combination of these aspects, which this study aims to bridge. Hence, the purpose of this study is to explore the differences in hedonic motivation in the form of happiness scores between traditional product websites and chatbot enhanced customer interaction in an impulse purchase situation. More specifically, the aim of our experimental study is to empirically validate the following research questions:

1) Which levels of hedonic motivation do consumers have when interacting with a chatbot or browsing a website for product information?
2) Can happiness as an operationalization of hedonic motivation be consistently measured by face analysis and self-assessment?
3) To what extent does the use of chatbots as a way to enhance product websites have a measurable impact on hedonic motivation in impulse purchase situations?

III. Approach

The study at hand uses a Wizard-of-Oz testing approach to simulate the integration of an advanced chatbot system on an e-commerce website. Emotional self-assessment and a face analysis software for video files are used to measure the user's state of happiness in our experimental scenario. Before we describe the configuration of the study in more detail, some methodological details of our approach will be described in this section.

A. Wizard-of-Oz (WOz) Testing in Chatbot Research

The WOz method does not only represent a way to investigate immature technology in a prototypical manner but it is also a way to avoid prohibitively high costs and time efforts [43] and to enable a testing environment without the need of coding is the utilization of a Wizard-of-Oz approach. The approach is defined as a kind of simulation where researchers "conceal themselves from research participants and use communications technology to pretend that a prototype or incomplete computer-based conversational system is fully functioning" [43].

In order to conduct a WOz-study, several aspects can be taken into consideration according to Eynon et al. [43]:

- Prototype functionality and fidelity of the prototype,
- technical handling of the prototype by the wizard,
- wizard visibility and control,
- user knowledge concerning the WOz setup,
- research design (Controlled experiment vs. uncontrolled exploration).

Wizard-of-Oz dialogues as utilized for chatbot examinations hold the advantage of resembling realistic behavior, which can appear to be more capable than already existing dialogue systems [6]. They can be seen as a feasible way to cope with the lack of technological advantage in order to assess chatbots as a suitable way of product promotion [10]. They become relevant because rule-based Chatbot dialogue systems as developed until today are limited in functionality since they are bound to a pre-defined database [14] and not able to learn. AI-based chatbot solutions are in an early stage [14] and the implementation of such systems can be a challenging task requiring comprehensive technical knowledge. Hence, this study made use of a WOz approach to simulate an advanced chatbot solution without the need for a complex technical implementation.

Commonly used in chatbot research, for example when setting up interactive question answering systems in the form of a chatbot [10], when examining the role of memory in goal-oriented dialogue systems [6] and when studying non-verbal processing in general [44], the method is being utilized for the study at hand as well. According to the components by Eynon et al., the prototype is set up as a fully functional web-based chatbot with a trained wizard controlling the prototype, who is hidden from the participants in an environment of tight experiment control [43].

B. Measuring Hedonic Motivation

Two methods of hedonic motivation measurement are utilized in this study: emotion self-assessment by the participants and face analysis via a cloud-based face analysis tool. Both practices are being explained in the following.

1) Emotion Self-Assessment: Hedonic motivation can be measured on the basis of different aspects such as the levels of excitement, arousal or escapism (e.g., [22]–[26]). For the study at hand, emotions and within this construct happiness in particular is the relevant aspect to consider. One way of assessing emotions within a research study is the distribution of suitable questionnaires before, during and/or after the session [45]. This written-down method of emotion self-assessment is applied in this study in order to control for possible mismatches

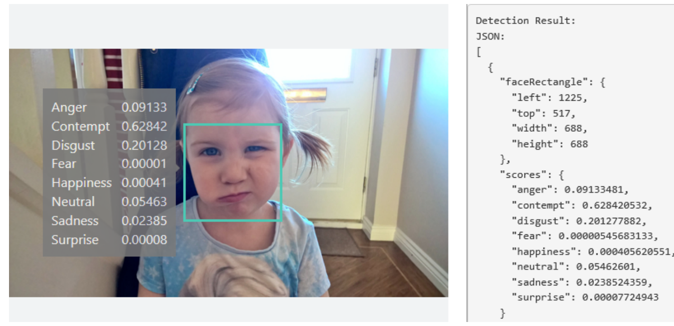

Figure 1. Exemplary Microsoft Emotion API face analysis result. Reprinted from Kearn [49]. Copyright by Microsoft [2016].

in comparison to the face analysis results – the participants conducted it prior to the session and immediately after pre-defined stimuli or impulses. The individual manifestations of the basic emotions as defined by Ekman and Heider [40] were requested via a ten-stage rating scale before converting them to values between zero and one. This was necessary in order to be consistent with the value range of the emotion data derived from the face analysis tool.

2) Emotion Tracking and Face Analysis: On a physical level, the emotions as the individual manifestations of the different emotional values according to Ekman and Heider [40], can be assessed via face analysis. On basis of this emotion classification, the face muscles and the according mimic manifestations are being analyzed and categorized into the seven distinct emotions [46]. Such an analysis can be conducted based on video material of the participants' faces recorded during experimental sessions where individuals are exposed to defined impulses to stimulate the expected reaction or emotion. Face analysis requires complex algorithms and massive data processing but is also available by cloud-based services like the Microsoft Cognitive Services. The service used in this paper is the Microsoft Emotion API, which provides emotional scores based on the seven basic emotions fear, anger, sadness, disgust, surprise, contempt and happiness. Additionally, the service calculates a neutral score indicating an absence of the other seven emotions within the measurement out of face recordings of the participants. The scores are to be interpreted as normalized scores ranging from zero to one – thus, the program shows the relative scores of the eight different emotional states indicating the predominant ones. This information is not to be confused with emotion intensity, which no information is given for within the tool results [47]. According to Microsoft, the two emotions contempt and disgust are only experimental for now [48]. Since neutral can be seen as the absence of the other emotional scores, the focus will be on those other scores rather than on neutral.

IV. Experimental Study

Based on the theoretical and methodological foundation above, an experimental study on the hedonic motivation of chatbot usage is presented in this section. The study is a work-in-progress and was based on an experimental setup with a convenience sample. Besides validating the research questions presented in Section II, the aim of the study is to derive some more insights on the applicability of the discussed test setups and tools for chatbot prototyping and emotion measurement.

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A. *Wizard-of-Oz Setup*

Starting point of the experimental study was the development of a chatbot concept. The utilized chatbot prototype for our WOz study has been designed as a web-based bot. This means that it searches for key words in the form of full words, their lemmas, roots and synonyms. The according information needs to be fed into the chatbots database prior to utilization. Based on this data and the defined rules, the chatbot responds with a preset answer. A fallback answer has been defined to handle questions new to the chatbot to ensure consistency concerning the user experience ("Unfortunately, I did not entirely understand you. How exactly can I help you?"). This inquisitive aspect can be built in in case of insufficient information in order to be able to give an adequate answer [12]. Such a response does not only inform the user that the system cannot process his question but also prompts the user to rephrase or state his question more clearly. Figure 2 shows an exemplary chat snippet from the study, which has been translated from German into English language.

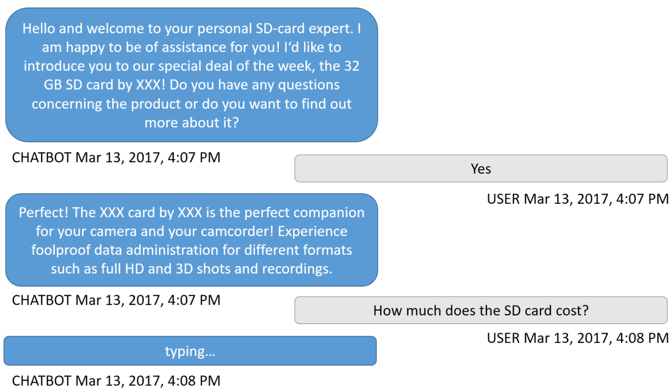

Figure 2. Exemplary chatbot dialogue snippet

For reasons of simplification, our concept does not adapt its behavior and answers based on previous customer input. This means that there are no adaptable templates defined but a static set of predefined responses. Based on the concept above, the chatbot was set up with the Wizard-of-Oz method, where no program converses with the user. The response is controlled by a human counterpart —the wizard—, who applies pre-set rules implemented prior to application. The WOz setup of this study is an own web solution running via the chatserver Arrowchat [50] filled with predefined JavaScript commands, which are elicited by a human via a control board. The wizard can respond to the participants interaction by selecting pre-defined phrases from this control board. According to these commands, answer sentences are being shown to the participant through a chat interface. The wizard could also type in text as a fall-back feature if the set of predefined phrases is not sufficient. However, this option was only used as an exception to cope with unpredicted user behavior.

The experimental setup of the study is shown in Figure 3. Two separated rooms were used. The survey, briefing of the participant on the course of the study, as well as an interview were conducted in room 1. After the study preparation the wizard left room 1 to operate the control panel and supervise the experiment from room 2. The participants were left unattended to complete the defined task the chatbot system. They were not informed to participate in a WOz scenario and did not know that they interact with the wizard in room 2. Two

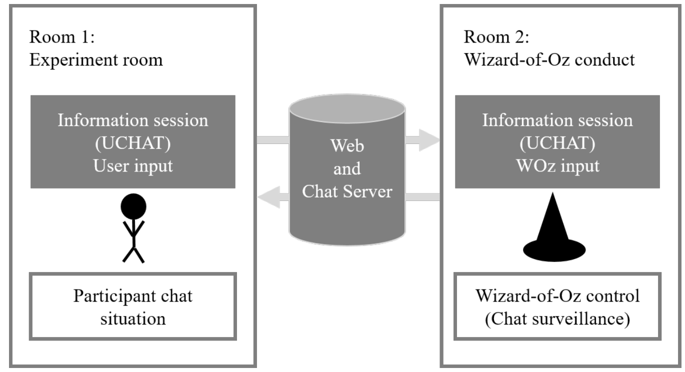

Figure 3. Wizard-of-Oz experiment setup

laptops have been utilized – all participants were positioned in front of the first to be recorded and to interact with the chatbot or the product webpage under the same conditions. The second laptop has been used by one of the authors to act as the chatbot wizard.

B. *Study Procedure*

For the laboratory situation, the participants were randomly assigned to conduct a product information process either via chatbot (UCHAT) or via a product information detail page (UPAGE). The sessions were divided into five procedural steps:

1) Introduction to the study with its purpose and signing of the consent form concerning the recording and data processing method via the utilized cloud-based face analysis tool.
2) Questionnaire with socio-demographic aspects such as age, job position and education as well as personality traits according to the Big Five approach (the five dimensions of personality: openness, conscientiousness, extraversion, agreeableness and neuroticism) by Rammstedt et al. [51].
3) Screen capturing and emotion tracking while accomplishing the task of browsing a product overview website for a specific product (digital cameras).
4) Simulation of an impulse purchase situation by displaying a product promotion in a pop-up window on the webpage.
5) Structured interview with detailed questions concerning the experience during the session.

Steps two to four were time-constraint by preset appearance times set on the utilized laptop for comparability. The simulation of the impulse purchase situation by the pop-up windows consisted of two defined stimuli or impulses that initiated and ended this phase of the experiment:

- Impulse 1 (I1): Overlay of a specific product promotion (SD card) via a pop-up or product overview website five seconds after accessing the site. Showing an instruction to open the product detail page or the chatbot respectively according to their affiliation (UCHAT or UPAGE).
- Impulse 2 (I2): Exposure to a purchase solicitation with question concerning the purchase decision. Showing an instruction to answer to the according question of the chatbot (UCHAT) or click accordingly within the appearing pop-up (UPAGE).

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The participants were not informed about the precise time constraints in order to simulate a natural product information process situation. Since neutral can be seen as the absence of the other emotional scores, the emotion assessment focus was on those other scores rather than on neutral.

For the analysis of the data, videos, audio files as well as questionnaire responses, several steps were necessary: The video preparation consisted in a (1) systematic filing of the two videos per participant (screen capturing and face recording), (2) the cutting according to the two impulses I1 and I2, thus creation of two 20-second videos per testing person, (3) the appropriate formatting and labeling of the video files for the cloud-based analysis, (4) the retrieval of the emotion data by processing the video files through the Microsoft Emotion API and (5) the transferral of the raw analysis data into the data processing program and statistical analysis. For the audio interviews, the data was transcripted and analyzed. Alongside with the quantitative survey data, the material was statistically analyzed and descriptively evaluated as stated in the following sections.

C. Sample Description

Among the 57 participants, the chatbot was used by 28 (= UCHAT group) while 29 formed the control (UPAGE) group by using the unassisted product webpage only. Table I gives an overview of the demographics of the sample. The sum of the figures does not always add up to 57 because of missing values in the datasets.

TABLE I. DEMOGRAPHIC SAMPLE DESCRIPTION

		Total	*UCHAT*	*UPAGE*
Gender	Female	39	38	21
	Male	16	9	7
Mean age (in years)		25.4	24.6	26.1
Educational level	Student	35	19	16
	Pupil	5	1	4
	Other	15	7	8
Highest educational degree	University level	15	7	8
	A-Level	37	17	20
	High School	3	1	2
Chatbot experience	No	37	14	23
	Yes	19	14	6

Most of the participants are female, in their mid-twenties, A-level (university entry qualification) university students and do not have prior chatbot experiences yet. This is due to the fact that this experiment was conducted in an university environment based on a convenience sample. This has to be considered with regard to the generalizability of the findings. However, as this pre-study focuses more on the general measurability of effects and the applicability of the suggested approach, the composition of the groups is not an issue here.

V. Results

The experimental study generated data that required further analysis to answer the research questions and aims that have been defined above. Before the according results on emotion measurement and chatbot impact are presented, we introduce this section with some more general findings for the UCHAT and UPAGE groups in the sample.

A. General findings

During the session, much information has been obtained concerning the participants' experience with online shopping in general (frequency of online product information searches and purchases) as well as with chatbot dialogues, their opinion on the product search conducted during the session (purchase decision, influencing factors on the decision, their feeling during the conduct, their own preferred way of informing themselves online) and their emotional states prior to the session and after impulses I1 and I2.

Table II shows the manifestations of the aspects stated above for the two groups UCHAT and UPAGE. It can be seen that most are experienced and active e-commerce users. Most of the users in both groups are using the Internet for searching product information more than once a week. The participants are even more active in purchasing online as the majority in both groups purchases products online at least one a week.

TABLE II. UCHAT AND UPAGE ONLINE EXPERIENCE

Aspect		*UPAGE*	*UCHAT*
Frequency of online product search	Fewer than once a month	5	3
	1-2 times a month	11	4
	At least once a week	8	7
	Daily	5	3
Frequency of online purchases	Fewer than once a month	0	2
	1-2 times a month	8	5
	At least once a week	18	18
	Daily	3	1

Missing values occur due to not mentioned aspects within the structured interviews at the end of the session. It can be seen that according to the Spearman correlation analysis, the two differences in online experience between the two groups are not significant ($p = .179$ for the frequency of online information and $p = .864$ for the frequency of online purchases) meaning that both groups did not differ concerning online expertise.

Other interesting aspects seemingly diverging are presented in Table III. It can be seen that differences occured between the two groups with regards to chatbot experience, the perceived feeling of being well-informed, having missed information within the information process, the influence of the received information on the purchase decision and the individual purchase decision.

TABLE III. SELECTED UCHAT AND UPAGE EXPERIMENT RESULTS

Aspect		*UPAGE*	*UCHAT*
Existing chatbot experience	No	23	14
	Yes	6	13
Feeling of being well-informed	No	3	6
	Yes	26	19
Feeling of having missed information	No	23	15
	Yes	6	12
Feeling of a good experience	No	13	7
	Yes	12	19
Positive purchase decision	No	20	16
	Yes	9	12
Decision influenced by information	No	14	9
	Yes	12	12

The differences in feeling of having missed information and the influence of the given information on the purchase decision seem ample – however, none of the differences are statistically significant (Pearson Chi square p-values higher than 0.01).

B. Self-Assessment and Face Analysis

The face analysis of the video material generated time-coded emotion values. We focused the data analysis on 10 seconds before and after the defined impulses I1 and I2. Figure 4 shows an exemplary data flow from the Microsoft Emotion API tool. In this study, this data is compared to the self assessed emotional manifestations of the participants.

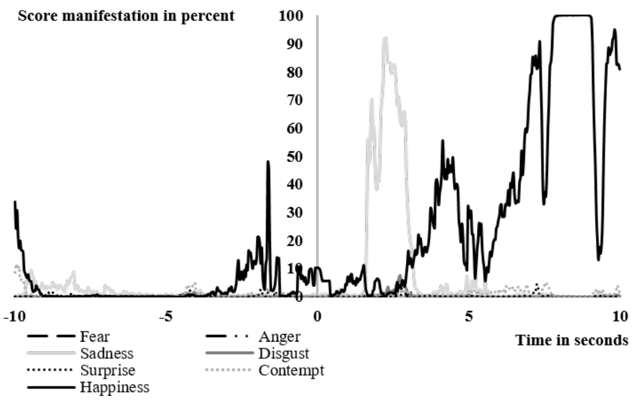

Figure 4. Exemplary happiness score flow around impulse I1

The scores for the happiness value were extracted from the data and mean values for the scores have been calculated to represent the observation time frame for each participant and the respective two stimuli. This data is then compared to the self-assessed emotion manifestations. Table IV shows the specific happiness scores the participants possessed during I1 and I2 of the online face analysis tool and the self-assessment in order to assess the differences the tool measured and perceived hedonic motivation of the participants.

TABLE IV. HAPPINESS SCORES VIA FACE ANALYSIS (FA) AND SELF-ASSESSMENT (SA)

$Stimulus$		FA	SA
Impulse 1 (I1)	Mean	0.234	0.272
	SD	0.353	1.698
Impulse 2 (I2)	Mean	0.278	0.354
	SD	0.382	1.984

The happiness score means presented in table IV are shown as calculated means over the whole timespan across either I1 or I2 and are displayed as values between 0 and 1. SD, the standard deviation, is displayed as percentage points. Both kinds of assessment show significant differences (p lower than .001 for both I1 and I2). Thus, the results of online face analysis and emotion self-assessment diverge. This is a preliminary result and needs more investigation. However, it might give some indication that the self-assessed emotion cannot be represented by a mean value of an emotional status measured over time, additional factors forming the emotional status after the stimulus or different value interpretations (predominance vs. intensity).

C. Hedonic Motivation Analysis

Table V shows the happiness scores the participants possessed during I1 and I2 in order to assess the differences in hedonic motivation of the participants concerning their affiliation to the UCHAT and UPAGE groups. The self-assessed scores have been taken for analysis because of the diverging results as discovered in sub section B and the resulting decision to focus on one of the two methods. When comparing the mean values, the happiness scores are slightly higher in the group of the sample that was assisted by the chatbot. This could indicate that the usage of chatbots has a positive impact on customers' hedonic motivation. However, a more comprehensive analysis reveals, that the difference is not statistically significant (p = .55 for I1, p = .148 for I2).

TABLE V. HAPPINESS SCORES OF UCHAT AND UPAGE

$Stimulus$		$UCHAT$	$UPAGE$
Impulse 1 (I1)	Mean	0.286	0.258
	SD	0.146	0.192
Impulse 2 (I2)	Mean	0.314	0.238
	SD	0.184	0.208

In Table VI, the happiness scores for the groups of buyers and non-buyers can be seen. From a purely descriptive perspective it is interesting, that we could observe (1) a slightly higher increase of happiness within the group of buyers and (2) a higher mean score for happiness of the buyers compared to the non-buyers for I2 (purchase question).

TABLE VI. HAPPINESS SCORES OF BUYERS AND NON-BUYERS

Stimulus		*Buyer*	*Non-buyer*
Impulse 1 (I1)	Mean	0.333	0.236
	SD	0.185	0.151
Impulse 2 (I2)	Mean	0.338	0.239
	SD	0.201	0.190

However, also for the purchase decision there is no significant difference concerning the means when statistically analyzed (p = .036 for I1 and p = .068 for I2).

VI. Conclusion and Future Work

The study applied WOz testing to analyze the impact of chatbot usage on hedonic motivation. Data on the emotional status of the participants was acquired based on face analysis and self-assessment. Levels of hedonic motivation could be measured but the data revealed no statistically significant differences for users with and without chatbot support. Moreover, there was no statistical significant difference between those groups with regard to the purchase decision in a simulated impulse purchase situation.

This does not mean that chatbots do not have an impact on purchase behavior as our observations depend very much on the study sample and setup. However, our results could give some first indication, that the value add generated by implementing chatbots must address aspects beyond pure enjoyment or producing ”happier” customers. Another interesting finding of the study is that measures of happiness as operationalization of hedonic motivation by face analysis and self-assessment did not produce consistent results. As mentioned before, the reasons can be manifold. Obviously, there is a difference between the analysis of facial expressions within a specific time-frame and self-assessments that are based on perceptions and experiences. Additionally, commercially available tools are somehow "black boxes" with regard to the algorithms involved or the calculation and interpretation of resulting scores. Thus, researchers must be careful when using an appropriate approach for emotion detection and measurement.

The study exhibits several limitations. The results may not be generalizable as the study was conducted based on a convenience sample as mentioned before. Furthermore, the impulse purchase situation was simulated with preselected products and defined impulses, which might have influenced the participants' emotional states. Their opinion of the product might have overshadowed the potential impact they might have been exposed to when being assigned to the UCHAT or UPAGE group. Being limited to the emotional state of happiness as representative of the aspect of joy as defined by [22] for example, future research might investigate other aspects of hedonic motivation in online shopping such as arousal or escapism.

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