A Situation-Specific Smart Retail Service Based On Vital Signs

Completed Research Paper

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Abstract

To compete with online shops, brick-and-mortar stores need to comprehend how to attract customers and keep them in their stores. Smart retail technologies enable a better understanding of customer behavior and thus, can improve customer experience. Such retail services could be realised with wearables as they become more and more part of daily life offering various opportunities for retailers. Perceived stress is one key factor having negative impact on customers' shopping experience. Therefore, shedding light on stress in the context of stationary retail is crucial. This paper aims to do so by analysing customers' behavior from a neuroscientific perspective through the use of unobtrusive measurements. A laboratory experiment was conducted using heart rate sensor and smartphone-based accelerometer. Our analysis indicates that heart rate and acceleration can help predicting arise of shopping stress. Furthermore, implications are generated from results showing how these insights might be used for situation-specific smart retail services.

Keywords: smart retail service, vital signs, heart rate, machine learning, NeuroIS

Introduction

Stationary retail stores have for years been driven by digitalisation and try to adapt the advantages of e-commerce (Farber 2016). However, shopping experience or shopping situation in stationary retail stores itself differs from the one in online shops. Shopping situations are widely recognized as sources of physical and mental stress, with experienced stress leading to avoidance behaviour (Durante and Laran 2016). Therefore, retailers need to think much more carefully about the role of customer emotions emerging during shopping to adjust to the customers' situation and individually react to their needs for creating an enhanced shopping experience (Ceccacci et al. 2018). Many scientists focused on the occurrence of shopping stress and their impact on customers and their purchasing behaviour (Aylott and Mitchell 1998; Duhachek 2005; Moschis 2007; Baker and Wakefield 2012). Zhu and Timmermans have shown that one of the biggest drivers for shoppers to leave the store while shopping is tiredness, which is a result of stress (Zhu and Timmermans 2008). Albrecht et al. (2017) conducted a study for examination of the relationship between consumer shopping stress and purchase abandonment. The results show that increased shopping stress significantly resulted in increased purchase abandonment, i.e. leaving the store earlier, without buying anything or less than planned. Thus, customer's emotion and stress level should be taken into account in the scope of shopping in stationary retail stores (Beasty 2005). In the last years, the use of neuroscientific methods experienced a rapid upswing as the neurosciences provides concepts and techniques, which have been so far disregarded during traditional business decision-making processes (Dimoka et al. 2012). Vital signs can be defined "as a description of a physiological phenomenon", meaning they are signals in living creatures that can be measured and monitored (Crone 2004). The research stream "Neuro Information Systems (NeuroIS)" was initiated in 2007 (Riedl et al. 2014). Since then, researchers conducting research in the field of IS increasingly draw on neuroscience methods and in particular Electrodermal Response measuring skin conductance (EDR), Eye Tracking (ET), Electroencephalogram measuring electric activities of the brain (EEG), and Electrocardiogram (ECG) measuring electric activities of the heartbeat (Riedl, 2014). While there are papers regarding Electrodermal Response measuring (EDR) and Eye Tracking (ET), hardly any paper considers heart rate in particular in the context of consumer behavior in retail stores to measure perceived stress at the point of sale. However, heart rate in combination with movement pattern is an important parameter that can give valuable insights into consumer behavior, as it is suitable to measure behavior related factors (Crone et al. 2004). A focus of this paper is therefore the analysis of customer behavior during shopping from an objective and neuroscientific perspective. More specifically, dynamic parameters (heart rate related data and acceleration) as well as static parameters (age, gender, BMI) were measured in the scope of a laboratory experiment to assess customers' perceived stress level. Therefore, the goal is to analyse sensor-based heart rate measures in combination with movement data to detect perceived stress level. In this way, we intend to tap into an objective and wearable-based data source for analyzing user behavior with respect to its semantic content and its potential for interpretation within the context of retailing. These insights can help to build a basis for mobile smart retail service analysing in-store behaviour of customers and to provide a more situation-specific smart retail services. Smart services are enabled by smart products that are both connected and intelligently aware to enable efficient operation, optimization, analysis, integration and other digitally-enabled business functions (Kagermann et al. 2013). Situation-specific smart retail services describe smart services in stationary retail stores adjusting to the customer's situation and individually reacting to their needs for creating an enhanced shopping experience. The paper addresses two main research questions:

(1) To which extent can customer's stress level in a shopping environment be predicted with the help of dynamic and static parameters?

(2) How can insights from dynamic and static parameters of customers' be used for implementation of a situation-specific smart retail service?

The paper is structured as follows. First, state-of-the-art, related work, and the service design of the situation-specific smart retail service are introduced. Second, the research method is introduced. More specifically, the laboratory experiment with data acquired from wearable sensors and paper-and-pencil questionnaire will be described. Then, collected data is analysed with the help of Machine Learning (ML) methods to predict whether an individual is stressed or not. The results of the laboratory experiment as well as the predictive analytics are presented. Finally the results are discussed and an outlook on future research will be provided.

State of the Art

Heart Rate and Stress Level

There exist several wearable sensors and sensor-based devices such as smartwatches capable to measure and collect heart rate data. Before using these unobtrusive measures for designing a smart retail service, it is important to understand heart rate and its impact on stress. Heart rate is defined as a measure of cardiac activity expressed as the number of contractions or beats per minute (bpm) (Opie and Paterson 2013). Heart rate variability (HRV) measures the specific changes in time (or variability) between successive heart beats (Taelman et al. 2009). The time between beats is measured in milliseconds (ms) and is called an RR-interval (Taelman et al. 2009). Generally, a low HRV (or less variability in the heart beats) indicates that the body is under stress from exercise, psychological events, or other internal or external stressors (Salahuddin 2007). The heart rate is controlled by the autonomic nervous system (ANS), more specifically by its two branches the sympathetic nervous system (SNS) and the parasympathetic nervous system (PSNS) (Salahuddin 2007). Although stress has a psychological origin, it affects several physiological processes in the human body (Salahuddin 2007). When a person is exposed to a stressor, the autonomic nervous (ANS) system is triggered (Kolata 2001). The parasympathetic nervous system is suppressed and the sympathetic nervous system is activated, which leads to increased muscle tension and a change in heart rate (HR) and heart rate variability (HRV). This specific process is known as the 'fight-or-flight' reaction (Taelman 2009). Frequently used time-domain features for stress level are mean value of the HR (mean HR), maximum value of the HR (max HR), standard deviation of the RR-interval (SD RR), Root Mean Square of Successive Differences (RMSSD), and percentage of adjacent NN interval differences referring to the intervals between normal RR-peaks >50 ms (pNN50) (Taelman et al. 2009). There are medical studies showing that mean HR as well as max HR increases when a person is exposed to a stressor (Taelman et al. 2009; Draper and Marschall 2014; McGuire and Beerman 2011) The higher SD RR, the higher the overall heart rate variability, i.e. the better the body adjust and adapt to changes (Sun et al., 2010; Salahuddin 2007). RMSSD is often referred to as a value for the body's ability to recover (Salahuddin 2007). The higher RMSSD the less stressed the individual is (Taelman et al. 2009). The pNN50 value provides information about high spontaneous changes in heart rate (Taelman et al. 2009). The higher the pNN50 value, the less stressed an individual is (Taelman et al. 2009). Sun et al. (2010) also highlights the importance of physical activity as a stressor, since it also increases HR. The maximum heart rate (max HR) is the highest heart rate an individual can attain during the performance of an exhausting activity without experiencing serious problems caused by exercise stress (Handler and Coghlan, 2007). The max HR is influenced by several parameters e.g. age and physical condition of the individual subject (Handler and Coghlan, 2007). The max HR reduces with increasing age, but differs from person to person, as physical active people who are old can also reach a high heart rate (Handler and Coghlan, 2007).

Application of Neuroscience Methods in Retailing Research

The most frequently used neuroscience methods in the context of retail environment are Electrodermal Response (Gröppel-Klein 2005; Gröppel-Klein et al. 2005; Gröppel-Klein and Baun 2005; Alajmi et al. 2013) and Eye Tracking (De Balanzó et al. 2010; Gidlöf et al. 2013; Young 2011). Studies using Electrodermal Response mostly measure arousal or emotions at the point of sale as EDR turned out to be one of the most valid and appropriate indicators for measuring arousal and emotions (Gröppel-Klein 2005a; Gröppel-Klein et al. 2005b; Gröppel-Klein and Baun 2005; Alajmi et al. 2013). Gröppel-Klein (2005), for example, showed that the way a retail store is decorated has an influence on consumers' arousal during shopping. Accordingly, a store that has bright electric light or uses eye-catchers such as exotic fruits and flowers leads to higher arousal than a store that is not decorated that way. Alajmi et al. (2013) used EDR to measure consumers' emotion responses and NFC technologies for detecting consumer's location at the point of sale in a shopping mall environment. They showed a relationship between Electrodermal Response curves and emotional states, i.e. Electrodermal Response curves of frustrated participants show a pattern with fast changes, while EDR curves of happy participants demonstrate a phasic pattern. Eye Tracking studies (De Balanzó et al. 2010; Gidlöf et al. 2013; Young 2011) analyse what customers register and what they ignore during shopping and buying decisions (which brands, information, products) as well as how they orientated themselves in a store. Lee et al. (2020) used Functional Magnetic Resonance Imaging (fMRI) to identify the neural representation of the "green logo effect" as significant brain activations. The goal was to explain how environmental priming can increase consumer preferences for fashion products with green logos for "nudging" consumers toward sustainable fashion consumption. Rosenbaum et al. (2019) conducted a study to assess consumers' neural activation in response to natural elements, present in a lifestyle center, as measured by Electroencephalography (EEG). Meyerding and Melhose (2020) measured brand- and label-related brain activation using Functional Near-Infrared Spectroscopy (fNIRS). As fNIRS is mobile and allows for experiments outside the laboratory, this considerably expands the field of usage of neuroimaging processes in the context of marketing. Despite the fact that heart rate generates valuable information about the physical and mental effort, there are no scientific studies focusing on this aspect with respect to stress in the context of shopping.

Related Work

Sensor-based Smart Retail Services

Since several years, organizations collect (sensory) data in physical stores for in-store analytics to get new insights into customer behavior during shopping for creating decision support systems and providing superior retail services (Linzbach et al. 2019). Sensor- and vision-based technologies such as cameras, smart devices, wireless communication, and robots can be individually combined to personally identify individual traits, and his or her in-store shopping activities (Bertacchini et al. 2017; Kamei et al. 2012, Mancini et al. 2013; Chu et al. 2013, Hwangbo et al. 2018). Retailers count the number of shoppers in a store at any given time through small devices such as light curtains placed at the entrance and exits of stores to ensure an adequate number of staff to prevent stressful situations caused by lack of service persons (Oosterlinck et al. 2016). Additionally, using facial recognition technologies empowers the brick-and-mortar retailers to acquire intelligence about store traffic, the gender or age composition of their customers, and their in-store movement pattern (Newman et al. 2002). Newman et al. (2002) used camera-based technologies to detect patterns of customer in-store behavior from the moment of their arrival at the entrance to the minute they leave the store. Customers that already have a relation to the retailer can actively identify themselves at self-service terminals or the point of sale (PoS) using barcodes, QR-codes, loyalty cards, and NFC-equipped smart devices (Ravnik et al. 2014; Lee et al. 2014; Zhou et al. 2009). Cameras with biometric face recognition capabilities that monitor the shop floor can identify inter alia the customer's face, emotion, gestures, speech, and sentiment (Chu et al. 2013; Hwangbo et al. 2018) Sensor-equipped robots directly interact with the customers and adapt to their behavior w.r.t. the customer's reactions (Bertacchini et al. 2017). Manifold options exist to capture the customer's location and movement patterns using satellite navigation, Bluetooth-based beacons, WiFi, and cameras (Kamei et al. 2012; Mancini et al. 2013). RFID-tags (radiofrequency identification) can be attached to products (Zhou et al. 2009), loyalty cards (Chu et al. 2013), and shopping carts (Karmouche et al. 2012), to track customers and their purchases, and interaction with digital product information and the products itself (Huang et al. 2014). Vision-based systems identify, how long customers look at a specific product for performing shelf analysis. While most of these retail services focus on customer tracking and movement patterns, there are only few approaches making emotions a subject of discussion and no papers focusing on the customers' level of perceived stress during shopping, which is proven to have a negative effect on customer purchase behaviour, perceived shopping experience and consequently on the success of the retailer. Furthermore, sensor-based smart retail services on mobile devices, which would provide more individual and situation-based solutions are rarely discussed.

Recommendation Systems in Stationary Retail Stores

Kowatsch and Maass (2010) have shown that mobile recommendation agents (MRAs) increase the value of product information in bricks-and-mortar stores. Among high usability scores, results indicate that perceived usefulness of an MRA influences product purchases, predicts usage intentions and store preferences of consumers (Kowatsch and Maass 2010). There already exists scientific work introducing recommendation systems for fashion stores, supermarkets, but also in the electronic stores (Keller and Raffelsieper 2014; Christidis and Mentzas 2013; Landia 2017). However, existing recommendation systems in stationary retail stores are mostly based on product purchase history and demographics of customers and neglect the receptiveness or stress level of the customer during the shopping process in order to optimize the placement of product recommendations on mobile devices (Keller and Raffelsieper 2014). The differences between the recommendation systems lay in the methods used to analyse historical purchasing data. All solutions disregard the mood, i.e. the stress level of the customers during shopping. Adomavicius and Tuzhilin (2011) have already stressed the importance of incorporating contextual information such as stress level into the recommendation process to create context-aware recommender systems.

A Design of Situation-specific Smart Retail Service

Figure 1 illustrates the device and backend components of the envisioned situation-specific smart retail service, as well as the typical flow of the data and analytics pipeline. Each individual shopper carries an own smartphone, where the envisioned smart retail service is installed in the form of an app, and an unobtrusive on-body heart rate sensor or smartwatch of daily use, whose sensor streams capture the individual's heart rate with the timestamps over an entire shopping episode. Additionally, acceleration (x-, y-, z- values) is measured during shopping (e.g. through accelerometer inside smartphones). Over the app through a customer account, several static parameters, e.g. age, gender and BMI can optionally be typed in. The app recognizes as soon as the customer enters the store (e.g. with the help of Beacons or visible light communication (VLC)), the heart rate data and acceleration data is constantly sent to the backend in an encrypted and anonymised format to guarantee an adequate level of privacy protection of the customer. At the backend, the heart rate stream as well as acceleration data is collected with the timestamps and processed with the help of machine learning models to find patterns in the data and help to classify the customer into "stressed" and "not stressed". Based on the results, the smart retail system react to the changing behaviour and generate preventive measures by providing individual situation-specific services. If the shopper is classified as being stressed, additional help during shopping such as finding products or help during checkout can be provided. If the shopper is classified as being not stressed, the service could introduce new product launches or recommend products fitting to the customer's preferences. Data security and the ethical aspect of such a situation-specific smart retail service are important aspects and should be taken seriously. The increased risk perception is mainly driven by fear of privacy violations and concerns about data security (Wünderlich et al. 2018). Thus, retailers have to ensure data security by e.g. newest encryption technologies. Another option could also be an architecture that makes use of the local processing power of mobile edge devices in order to come up with high complex AI pipelines processing data in real-time instead of using cloud-based systems (Pyrtek et al. 2019). Such architecture could give users full control over their personal information and physically store and evaluate it on their devices through analysis applications that operate on that data. This eliminates the need to store and evaluate the data in a central cloud environment (Pyrtek et al. 2019).

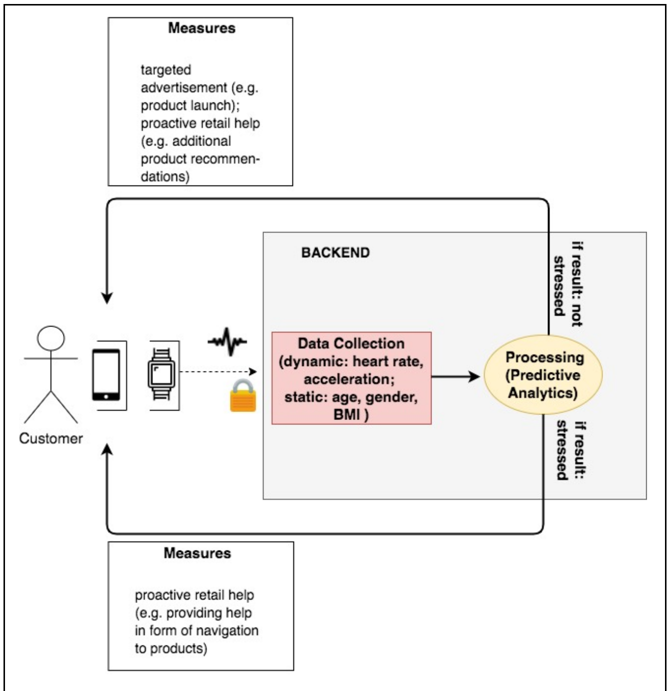

Figure 1. Functionalities and Components of the envisioned Smart Retail Service

Research Method

In this section, the data collection for the predictive analytics by conducting a laboratory experiment is described. The experiment consists of two parts: (1) collecting heart rate and acceleration data during shopping (input data for the ML models), and (2) a paper-and-pencil questionnaire to analyse the perceived stress during shopping (output data for ML models). Details on how useful ML models for predicting perceived stress ("stressed" vs. "not stressed") are obtained, is provided. Then out - of - sample evaluation of the performance of these models will be discussed.

Data Collection

In order to be able to produce predictive models regarding stress prediction, a data collection study in a laboratory experiment with two-person groups was conducted[1]. 100 subjects in total aged between 18 and

[1] Collected data and the code used for the predictive analytics can be found here:
https://www.dropbox.com/sh/d3crmew0ww3aeco/AABI3KTnYV_smdrrbT5dFcQIa?dl=0

30 years participated the study (female = 63, male = 37). The majority of the participants (57 %) have a higher-level school leaving certificate, whereas 26 % have a bachelor's degree and 7 % have a master's degree. The average BMI is 22.56.

The Polar H10 HR monitor uses an electrical sensor that is worn across the chest with an elastic band to meaure heart rate. Electrodes embedded in the sensor detect cardiac electrical impulses. The detection of these signals is transmitted via Bluetooth Low Energy to the connected app, which is installed on a Samsung Galaxy S6 edge to measure and store the HR as well as relevant features from Heart Rate Variability (HRV). For this study the Polar monitor was programmed to sample HR values every second. Furthermore, heart rate variability related time-domain features that are frequently used are collected with Polar H10 HR monitor, i.e. SD RR, RMSSD, and pNN50. The HR data as well as HRV related data were stored in the smartphone until it was downloaded for analysis purposes. Polar H10 sensors have been shown to provide scientifically good results in collecting heart rate data and are recommended as the gold standard for heart rate assessments if activities with body movements are investigated (Weaver et al. 2019; Nganou-Gnindjio et al. 2020; Hernández-Ruiz et al. 2018). The AndroSensor app has been installed on the Samsung Galaxy S6 edge for measuring motion data. The participants have put the smartphone into the pocket before starting the shopping scenario. The sample rate was two values per second. AndroSensor has already been used in scientific area such as physics for collecting gyroscope data to generate movement related data, e.g. speed or GPS (Kapucu 2017; Price et al. 2018; Klein et al. 2014). In our study, we calculate the magnitude of acceleration in $\frac{m}{s^2}$ with the help of the x-, y-, and z- acceleration values.

Procedure

In order to be able to produce predictive models for our situation-specific smart retail service, we first conduct a data collection study in a laboratory experiment with two-person groups. The laboratory supermarket was equipped with food products, beverages and drugstore products. Participants were scheduled for an approx. 20 minutes session. Each subject was given one of the following two situations representing different types of shopping situations, i.e. non-stressful shopping situation and stressful shopping situation.

Figure 2. Laboratory Experiment Setup

- Group 1 – non-stressful shopping situation (n = 50): Imagine it is Friday afternoon and you want to enjoy your evening with some food from the supermarket. You have a shopping list but also plan to stroll through the shop to get inspiration for additional products.
  Task description:
  Step 1: Stroll through the laboratory supermarket and pick the items on your shopping list from the shelves. Put the items into the shopping cart.
  Step 2: See whether there is anything else you find interesting.
  Step 3: When you are done, please go to the experimental supervisor with your shopping cart.
- Group 2 - Stressful shopping situation (n = 50): Imagine it is Friday evening. You totally forgot that some friends are going to visit you at 8 pm. You don't have anything to eat at home and plan

to go to the supermarket to buy some food. You already prepared a shopping list before going to the store. When you arrive at the supermarket, you only have 3 minutes left to make your purchase.
Task description:
Step 1: Please go through the laboratory supermarket and pick the items on your shopping list from the shelves. Put the items into the shopping cart.
Step 2: When you are done with the whole shopping list, please go to the experimental supervisor with your shopping cart.
Step 3: For the whole shopping tour, you have 3 minutes.

The difference between the relaxed shopping situation (group 1) and the stressful shopping situation (group 2) is that in the stressed shopping situation, participants were given two stressor which were identified by Aylott and Mitchell (1998). First, a time restriction for the shopping was given to group 2. Moreover, to add an additional stressor for group 2, one product from the shopping list was not available on the shelves so that it was not possible for participants of group 2 to find the missing product. Except these two differences, the whole shopping situation and environment was exactly the same. As control variable, we included the shopping behavior mainly responsible for grocery shopping. As an incentive for group 2 to find all products within the time restriction, they got the information to receive and additional reward of 2€ beside the main reward (amazon voucher worth 10€) in case they successfully accomplish the task. After finishing the shopping scenario, the equipment was removed. In a second part, static parameters (i.e. BMI, age, gender) were collected and a paper-and-pencil questionnaire including questions about perceived stress level during the shopping situation was conducted. To assess the participants' perceived stress during the shopping situation, we designed a survey and adopted constructs from distressing quality by Russell & Pratt (1980) and consumer shopping stress (Baker and Wakefield 2012; Miller et al. 2008). An exemplary item of our adopted scale would be "While I was shopping in the store, I felt tense". This adopted scale and all following scales were used as unforced bipolar seven-point Likert scale ranging from "1 = strongly disagree" over "4 = neither agree nor disagree" to "7 = strongly agree". At the end of the study, each participant received an Amazon voucher.

Data Preprocessing

Before we apply ML techniques, we apply a range of pre-processing steps to the data we collected. In particular, records of participants' raw data are represented as vectors of fixed size (feature vector, independent variables) (Hastie et al. 2001). First, we made heart rate curves of both groups comparable by generating 3-min heart rate curves for each participant. Furthermore, in order to reduce the dimensionality due to small data set (n=100) and convert raw heart rate data into feature vectors, we focus on frequently used time-domain features for stress detection, based on literature (see above). Beside maximum HR (max HR), the mean value of the HR (mean HR) was taken into account. Several studies have successfully used 60-second windows for calculating mean HR in order to distinguish between stressed and baseline segments (Sun et al. 2010; Salahuddin 2007). Therefore, we separated the heart rate curve into m=3 segments (each 60-seconds long). Then, we calculated the mean heart rate value for each segment resulting in three mean HR values (see Figure 3). Accordingly, we separated magnitude of acceleration curve into m=3 segments to calculate three average magnitude of acceleration values for capturing physical activity during the shopping scenarios. Additionally, we used SD RR, RMSSD, and pNN50 as heart rate related features in our models. In addition to the mentioned features, we also used a python package called "tsfresh" (Time Series FeatuRe Extraction on basis of Scalable Hypothesis test) for identifying meaningful time series characteristics from heart rate data (Christ et al. 2018). The library by default computes a total of 794 time series features (Christ et al. 2018). After feature selection process, we focused on the seven most relevant features namely number of peaks of support 5 (support 5 = maximum value amongst 5 consecutive HR values), the 0.9 quantile of HR curve meaning the HR value, where 90% of the HR values in the curve are lower, number of appearance of min HR, standard deviation of HR curve, minimum HR, the maximal intercept value after performing linear regression to chunks of 50 heart rate values and mean frequency of Fourier Transform for the HR curve.

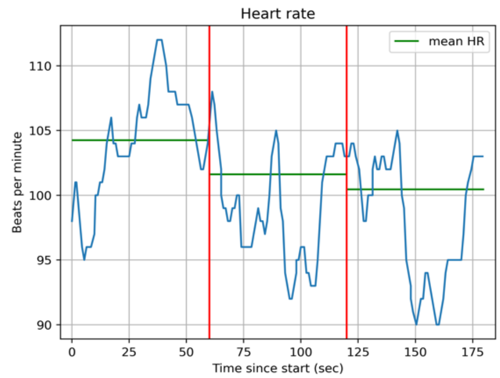

Figure 3. Mean Heart Rate Values from Raw HR Data. Mean Heart Rate Values (Vertical Lines) are Calculated for 60-second Windows

As outputs for our model, we define binary values that represents whether participants felt stressful during shopping or not. These are based on participants' perceived stress level index during the shopping scenario calculated from the answers of the questionnaire. For each participant, the mean value of all answers was calculated to receive a perceived stress level index. The perceived stress level serves as the basis for the output value during the predictive analytics. Due to the fact that we are interested in classifying the participants into "stressed" and "not stressed" to provide situation-specific services, we decided to classify all participants with a perceived stress level index >4 (somewhat agree to strongly agree) as "stressed" and all participants with perceived stress level index ≤ 4 (neither agree or disagree to strongly disagree) as "not stressed".

Predictive Analytics for Small Dataset

The advantage of Machine Learning (ML) is the ability to learn over time and that also non-linear and complex patterns in datasets can be identified, which makes this methods suitable for our smart retail service approach (Hastie et al., 2001). An important consideration is that the dataset size is relatively small (100 data points), which requires a careful ML approach in order to ensure that no in – sample bias or "overfitting" occurs (Hastie et al. 2001). We describe our approach that caters to this goal below. We use Python package "scikit-learn 0.21.3" (Pedregosa et al. 2011). There are a large number of ML models available in the literature that could be used in our ML pipeline (Hastie et al. 2001). First, we concentrate on models with high empirical performance, as measured by PMLB benchmark (Olson et al. 2017). Second, in order to cover a variety of types of ML models, we look for models from different model classes, such as linear or nonlinear, parametric or nonparametric, black box or white box (Hastie et al. 2001). Our selection resulted in following models: Support Vector Machine (SVM) (Cortes and Vapnik 1995), Decision Trees (Quinlan 1986), K Nearest Neighbors (KNN) (Hastie et al. 2001), Linear Support Vector Machine (Linear SVM), Gradient Tree Boosting (XGBoost) (Friedman 2001), and Gaussian Naïve Bayes (John and Langley 1995). The following analysis was conducted as a classification task to examine whether it is possible to generate a model, which is able to classify the participants into the two groups "stressed" (Y=1) and "not stressed" (Y=0) by using the collected parameters as input variables X and perceived stress level as the output variable Y. For this, the parameters taken as input variables are: heart rate related data (see above) magnitude of acceleration related data (see above), age, gender and BMI. Nested cross validation has been used for training and evaluation of our models. This method has been shown to be more efficient for accurate estimation of true out-of-sample error, compared to simple training/testing partition (Varma and Simon 2006). This approach comprises of outer cross – validation loop and inner cross – validation loop. The outer cross – validation is used to generate numerous training and testing partitions, while the inner cross – validation loop is run separately on every training partition and is used to select hyperparameters of the models. We used different splits of the data in order to test how much of the variance is introduced into estimated error due to various numbers of validation folds (Krstajic et al. 2014). This allows to test whether the generated accuracy of the model is too optimistic as a result of favorably defined numbers of folds.

Results

Empirical Results

In a first part, we conducted a laboratory study by designing two shopping scenarios (non-stressful: group 1; stressful: group 2). Group 1 consisted of 35 female and 15 male participants, whereas group 2 had 27 female and 23 male participants. Concerning these sex distributions Chi²-Tests revealed significant differences from an equal distribution for group 1 and the total sample ($\chi^{2group1}(1) = 8.00$, $p < .01$; $\chi^{2total}(1) = 6.31$, $p < .05$), while only group 2 did not differ significantly from equal distribution ($\chi^{2group2}(1) = 0.51$, $p = .48$) using an alpha level of .05. The BMI of group 1 ($Mdn_{group1} = 21.70$) and 2 ($Mdn_{group2} = 21.74$) also did not differ significantly ($Z = -.43$, $p = .67$). Concerning BMI in terms of categories, 78 % of our total sample had normal weight, while six persons were underweight and 15 overweight, while the distribution of underweight, normal weight and overweight didn't differ between the two groups using a Chi²-Test, $\chi^2(2) = 1.46$, $p = .48$. Using Welch's *t*-tests the two groups did not differ with regard to height ($M_{group1} = 171.37$, $SD_{group1} = 9.76$, skew = .44, kurtosis = -.10; $M_{group2} = 172.38$, $SD_{group2} = 9.75$, skew = -.42, kurtosis = 1.49); neither did they to weight ($M_{group1} = 66.36$, $SD_{group1} = 14.08$, $skew_{group1} = 1.56$, $kurtosis_{group1} = 4.14$; $M_{group2} = 67.55$, $SD_{group2} = 13.58$, $skew_{group2} = 1.07$, $kurtosis_{group2} = 3.46$). Results of the t-test show that average heart rate of participants of group 1 is lower (94 bpm, $SD = 17.71$, skew = .33; kurtosis = .50) compared to group 2 (116 bpm, $SD = 19.15$, skew = -.48; kurtosis = .56). Furthermore, the mean of max HR of group 1 is lower (107 bpm; SD = 17.46; skew = .09; kurtosis = .49) than the one of group 2 (131 bpm; SD = 19.9; skew = -.67; kurtosis = 1.35). In a second part, a paper-and-pencil questionnaire was conducted to analyse the perceived stress of participants' during the shopping scenarios. As manipulation check, Welch's t-test on the perceived stress ratings was applied to give indication on the success of the stress-induced shopping situation. The results show that group 1 – non-stressful shopping scenario significantly perceived the shopping situation less stressful than group 2 (group 1: mean = 2.52, SD=1.07; group 2: mean =4.42, SD=1.20; $t_{SS}(96.78) = -8.36$, $p < .001$). The effect size is $r = .65$ indicating a large effect. The results regarding the construct shopping stress are presented in table 1.

		Group 1					Group 2				
		$n = 50$					$n = 50$				
Questionnaire											
Question	Construct	internal consis-tency	*M*	*SD*	Skew	Kurtosis	internal consis-tency	*M*	*SD*	Skew	Kurtosis
1	Shopping Stress (SS) (Russell and Pratt 1980; Baker and Wakefield 2012; Miller et al. 2008)		2.26	1.29	1.21	.87		3.92	1.83	-.30	-1.39
2			2.72	1.23	.98	.14		4.62	1.52	-.76	-.23
3			2.86	1.41	.80	-.27		4.94	1.74	-.79	-.58
4			2.82	1.55	.83	-.51		5.28	1.39	-1.78	3.05
5		.88	1.62	1.19	2.74	8.69	.85	2.80	1.53	.64	-.41
6			2.84	1.42	.61	-.57		4.98	1.46	-1.10	.65
	SS-Index		2.52	1.07	.83	-.06		4.42	1.20	-.82	.25

Table 1. Mean Values And Standard Deviations Of The Questionnaire Construct Shopping Stress using Welch's t-test. The Likert Scales Ranged from 1 (strongly disagree) to neither (4) to strongly agree (7) for the Items.

As described above, the perceived stress level serves as the output label for our predictive analytics. All participants with a perceived stress level index >4 (somewhat agree to strongly agree) were classified as "stressed" and all participants with perceived stress level index ≤ 4 (neither agree or disagree to strongly disagree) were classified as "not stressed". After classifying the participants, there are 48 participants in group "stressed" and 52 participants in group "not stressed". These two groups were used as target output for the predictive analytics.

Predictive Analytics

We measure accuracy of the model as a percentage of samples where the model estimated correctly the ground truth label. Let the test dataset outputs be denoted as $y^{test} \in \{-1,1\}^n$, where $n \in N$ is the size of the test dataset. Let $y^{pred} \in \{-1,1\}^n$ denote estimations made by the model. Then we calculate accuracy (in %) as

$$\text{Accuracy} = 100\,\frac{1}{n}\left(\sum_{i = \{1, 2, 3, \dots, n\}} I(y_i^{test}, y_i^{pred})\right)$$

where function I is an indicator function, which returns 1.0 if it's two arguments are equal, and 0.0 otherwise. The results of empirical evaluation of different predictive model classes according to methodology discussed above are given in Table 2. For Support Vector Machine, Gaussian Kernel was giving the best results amongst Gaussian, Polynomial and Sigmoid Kernels. We also have seen that the best results were achieved with the mean HR values and mean acceleration values together features extracted with the help of python library “tsfresh”. The parameters age, gender, BMI, max HR, SD RR, RMSSD, and pNN50 didn’t have any further positive impact on the accuracy of the models.

	Accuracy	Sensitivity	Specificity
Linear SVM	**79.5 %**	79.2 %	80.4 %
Gaussian Naïve Bayes	76.5 %	81.2 %	72.5 %
Gaussian Kernel SVM	75.7 %	77.1 %	74.5 %
XGBoost	71.4 %	75.0 %	68.6 %
KNN	70.7 %	70.8 %	70.6 %
Decision Trees	63.6 %	64.6 %	62.7 %
Baseline model	51.6 %	0.0 %	100.0 %

Table 2. Empirical Evaluation of Predictive Models

Figure 4 shows the confusion matrix with True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) for the best performing model (Linear SVM).

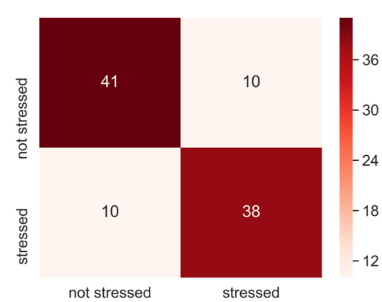

Figure 4. Confusion Matrix for Linear SVM

Table 3 shows the weights of the parameters used for the best performing model namely linear SVM model (rounded to 2 decimal places): the three mean HR values (HRmean_x, with x representing the mean value for the specific minute), the three mean acceleration values (ACCmean_x, with x representing the mean value for the specific minute), the maximal intercept value after performing linear regression to chunks of 50 heart rate values (HR_linReg50), number of appearance of min HR (HR_#appearanceHRmin), mean frequency of Fourier Transform for the HR curve (HR_FT_meanfreq), number of peaks of support 5 (HR_#peaks5) (support 5 = maximum value amongst 5 consecutive HR values), minimum HR (min HR), the 0.9 quantile of HR curve meaning the HR value, where 90% of the HR values in the curve are lower (HR_90_q) and standard deviation of HR curve (HR_curve_SD). Higher score of the linear model indicates higher probability of a person perceiving stress.

HRmean_1	HRmean_2	HRmean_3	ACCmean_1	ACCmean_2	ACCmean_3	HR_LinReg50	HR_#appea-ranceHRmin	HR_FT_meanfreq	HR_min	HR_#peaks5	HR_90_q	HR_curve_SD
0.28	0.07	0.05	0.02	0.01	-0.14	-0.50	-0.06	-0.57	0.50	1.0	0.49	-0.03

Table 3. Weights Of The Parameters for Linear SVM.

Discussion

The goal of this paper was to show how insights about a shopper's perceived stress level in a retail environment can be obtained by dynamic as well as static parameters (RQ1) and how these insights can be used for our designed situation-specific smart retail service (RQ2). To do so, we first applied a laboratory experiment where we designed two shopping scenarios – stressful and non-stressful – collecting dynamic sensory data (heart rate and magnitude of acceleration related data) and static parameters (age, gender, BMI). Then, the participants of the experiment had to complete a paper-and-pencil questionnaire so that the perceived stress level of the participants during the shopping scenarios could be assessed. Second, we analysed to which extend perceived stress during shopping can be predicted with the help of the collected static as well as dynamic parameters. The results of the analysis of the laboratory study and the questionnaire has shown that mean perceived stress level was significantly ($p < .001$) higher for participants of group 2 with a left-skewed distribution compared to group 1 having a right-skewed distribution (group 1: M = 2.52, SD=1.07, skew = .83, kurtosis = -.06; group 2: M =4.42, SD=1.20, skew = -.82, kurtosis = .25). The t-test of the questionnaire has shown the success of the stress-induced shopping situation, meaning that the two stressors in shopping scenario 2 have caused stress. Moreover, the average heart rate of participants of group 1 was lower (94 bpm) compared to group 2 (116 bpm). Furthermore, the mean of max HR of group 1 is lower (107.22 bpm) than the one of group 2 (131.28 bpm). This result follows literature showing that average HR and max HR increases when individuals are exposed to stressors (Taelman et al. 2009; Draper and Marschall 2014; McGuire and Beerman 2011). Interestingly, 9 out of 50 participants of group 1 felt stressful during shopping (perceived stress level index >4), although they were not having time restriction or missing products. The reason for this could be that they were not able to find the products from the list and felt (slightly) overwhelmed by the product portfolio or the store layout. This shows that in a normal shopping situation, customers feel stressed due to various stressors, which makes each shopping event individual. Furthermore, 11 out of 50 participants of group 2 did not feel stressed (perceived stress level ≤4). This might be due to the fact that participants could cope with the time restriction, were not aware of the fact that one product from the list was not available in the shelves or didn't care too much about the missing product. This indicates that the constructed shopping situation was not stressful enough for these participants. Thus, additional or other stressors might have been useful. Another explanation could be that participants gave biased answers, although we mentioned in the questionnaire that there are no false or correct answers.

Predictive analytics has shown positive results regarding predicting perceived stress level ("stressed" vs. "not stressed") of participants during the shopping scenarios. Linear SVM, which is the core model for our situation-specific smart retail service, performs best with an accuracy of 79.5% and is better than the baseline model, meaning random guessing by always giving the most represented label as output, i.e. "not stressed" (accuracy = 51.6%). The input parameters leading to best results were the mean HR values and mean acceleration values together with the static parameters age, gender and BMI as well as features extracted with the help of python library "tsfresh". The result follows literature showing that mean HR values are indicators of stress (Taelman et al. 2009). Moreover, physical activity, represented by the acceleration, also seems to have an impact on the perceived stress level, which is supported by literature (Sun et al. 2010). Interestingly, tsfresh has extracted relevant features from the heart rate curves that were able to increase the accuracy of our models. This shows that there might be relevant information hidden in the heart rate time series data that might help to detect perceived stress. The parameters age, gender, BMI, max HR, SD RR, RMSSD, and pNN50 did not have any further positive impact on the accuracy of the models and thus, were discarded. This might be due to the fact that these features are more suitable for medical laboratory settings than for our laboratory experiment, more specifically for the two shopping scenarios we constructed.

Theoretical and Practical Implications

The analysis results show that the usage of vital signs help to predict stress level in a shopping environment. As discussed above, higher mean heart rate values as well as acceleration and static parameters are indicators of perceived stress in our laboratory experiment. According to table 3, heart rate related values have the highest influence on the detection of stress during shopping highlighting the importance of objectively measured vital signs. Additionally, ML algorithms might be able to further detect previously unknown or unclear relationships in the data that has been collected in the scope of the experiment. This is supported by the relevant characteristics of heart rate time series data that python library tsfresh was able to extract. We show that paradigms such as predictive analytics used in IS research provide a useful lens for the analysis of environments, in particular customers' perceived stress level in stationary retail environment, characterized by a high degree of uncertainty, and provide promising solutions for challenges embedded in such environments. In this paper, sensory data, i.e. heart rate and acceleration, were collected and analysed with the help of ML methods to predict customer's stress level and act accordingly. Predicting an event is especially important if there is a substantial cost associated with that event, such as stressed customers leaving the store without buying less or even nothing. By classifying customers regarding stress level and thus, consider the individual shopping situation of each customer, retailers have the potential to create an interactive shopping experience, improve customer loyalty. More specifically, suitable product recommendations or coupons for discounts can be offered to raise the attention in case that customer is classified as being "not stressed". Furthermore, more cognitively demanding activities, e.g. advertisement on new product launches, can be provided (via smartphone) when the system classifies the customer being "not stressed". In contrast, customers experiencing stress could be provided with help such as navigation to products or sending additional staff for help. Furthermore, customers have the advantage to shop stress-free and experience the advantages of shopping in-store. Compared to e-commerce, stationary shoppers have the ability to physically inspect or try on the items being considered for purchase or ask a service staff when problems arise. All this can help to survive the increased competition due to the booming e-commerce.

Conclusion and Future Work

In order to recognize customers' perceived stress and enhance shopping experience, retailers have to take countermeasures in-store. This can be realized by understanding the customer's individual perceived stress and thus, improve customer experience. Our work presents a potential methodological basis and proves that stress signals can be identified through machine learning methods. As our results have shown that machine learning is a valuable tool to predict perceived stress with an accuracy of 79.5 %, it can be used to classify the customers into stressed and not stressed (see Table 2). The results show that heart rate related data have the highest impact on the classification task, demonstrating the importance of objectively measured vital signs during shopping. The results of the analysis serve as insights that serves as the basis for future research focusing on an envisioned situation-specific smart retail service, which generates different services based on the customers' perceived stress level. The envisioned situation-specific smart retail service could enable applications such as: (a) targeted and customized advertisement: e.g. new product launch; (b) proactive retail help: a shop assistant directed to help customers finding products or recommendations for additional products suitable for purchases in the shopping list; providing help for carrying the shopping bags (c) crowdsourced store profiling: In combination with tracking data, crowdsourced data from a pool of shoppers using the service can be used to build typical "experience profiles" associated with the store areas, for use in decision-making regarding product placement, promotion, store arrangement, cashier management and staffing. Despite the fact that the service provides multiple advantages not only for retailers but also for customers, they need to be motivated to use the smart retail service (downloading the app and sign in, wearing the wearable during shopping). For instance, retailers could provide incentives (vouchers, discounts or small gifts) for the initial sign in. Moreover, the fact that the smart retail service is privacy-friendly could be an argument for customers to join. In this context, taking adequate measures to ensure data privacy but also data security is crucial. Due to the exploratory nature of this work, several limitations need to overcome by future research.

First, we only measured heart rate and acceleration of the participants as dynamic parameters and several static parameters (age, gender and BMI). Additional dynamic parameters regarding the participants' shopping behavior, such as shopping path might provide important information with direct impact on stress and cognitive attention. This information could have given further insights into the heart rate development of customers and the parameters influencing the customers' heart rate during shopping, making the predictive analytics and thus the smart service more accurate in its decision. Accordingly, future research should focus on this aspect by e.g. tracking the shopping path of the customers and mapping them to specific sections in the (laboratory) store. Furthermore, in a more expensive study, skin conductance giving insights about stress could be measured to replace the subjective label, namely perceived stress, and focus more on objectively measured parameters to increase the model accuracy.

Second, the observation was conducted in a laboratory setting with products of daily use (food, beverage and drugstore items). Thus, the results apply to customers who buy products of daily use. Therefore, it requires further research whether results translate into other shopping environments such as an electronic store or a store for luxury clothes and jewelry. By doing so, drawing comparisons between customers' heart rate developments in different shopping environments or situations would be possible and could give interesting insights for situation-specific smart retail services. Furthermore, we focused on a laboratory study to have control over depended and independent variables. In contrast, a field study with a more natural environment could give further insights into perceived stress and heart rate as well as acceleration development under natural conditions. Moreover, the study would need to be re-conducted with smartwatch sensors, which become more and more precise with time, to see whether their results still hold true. Additionally, using more accurate and expensive heart rate measuring methods such as Electrocardiogram might have lead to higher model accuracy. Furthermore, since HR can also increase by just moving arms and not making a step, another study should be conducted using the accelerometer from a smartwatch or attach the smartphone to the arm. Doing this study with customers of different age groups might also lead to different results. Third, the laboratory study focused on two stressors during shopping identified by Aylott and Mitchell (1998), namely product out of stock and time pressure. However, further research should focus on additional possible stressors at the point of sale. The results could give valuable insights and might increase the accuracy of the machine learning model.

Fourth, for further research, additional physiological control variables such as resting HR and „walking" HR of each participant to assess the normal HR increase for each individual due to normal walking should be considered. This can both help to better interpret the higher values of group 2, and probably also increase the accuracy of the ML approach.

Fifth, this paper focused on specific research questions and thus, unveils certain results regarding heart rate development in retail environment. For this purpose, various analysis methods have been applied. Conducting other relevant analysis methods could help to discover further interesting insights. Future work should also focus on additional shopping scenarios and having a multiclass instead of a binary classification tasks. For this, additional experiments have to be conducted. Conducting a technology acceptance study to analyse how customers would adopt such a service is a topic of further research. Some participants of the experiment even mentioned that a system helping to find products, especially when they are under time pressure, would be very useful. However, doing such an analysis would have gone beyond the scope of this paper. Data security and the ethical aspect of such a situation-specific smart retail service are important aspects and should be taken seriously. Thus, retailers have to ensure data security by newest security technologies (see above). Furthermore, future research should specifically focus on ethical aspects regarding such situation-specific smart retail services where sensory data is collected and analysed, such as user acceptance studies or theory based research. How to design a suitable architecture ensuring highest data security standards is a topic of further research. The literature review has shown that there is no research on heart rate development in the context of retail environment. Furthermore there are no services considering customers' stress, although it is an important factor influencing customer behavior in-store. Therefore, this paper serves as a first step in designing a situation-specific smart retail service based on vital signs and getting a deeper understanding of the role of vital signs in the context of retailing. Additionally, our analysis results serves as insights for an approach to generate a situation-specific smart retail service, which reacts according the customers' level of perceived stress. Moreover, to provide more value to individual customers, we need to better understand how customer behavior is affected by such new digital technologies, how customer preferences change and how smart retail services need to be adapted in response. The growing interest in sensor technologies and their ramifications, like data volume and acceleration or information processing capabilities, moves the process of predictive analytics to the front burner of current IS research.

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