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Master Thesis

Effective email marketing: an empirical study of the impact of personalized communication on customer engagement and purchase decisions

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Summary

This study investigates the impact of behavior-based personalization on customer engagement and purchase behavior in the context of email marketing. For this purpose, the author reviews and combines the following research streams in the literature: email marketing, personalization of marketing communication, and customer engagement.

To answer the research question at hand, the author designs a field study in collaboration with Kahoot! AS, a fast-growing Norwegian start-up company operating in the education technology industry. Kahoot!'s game-based learning and trivia platform is used in multiple settings – school and university classrooms, business training and presentations, social, cultural, and other events (retrieved from kahoot.com). By leveraging marketing automation technology, which Kahoot! uses for the email campaigns' creation and management, the author sets up and runs the experiment. Findings of the study provide marketing managers with useful insights on the effectiveness of behavior-based personalization in the email marketing context as well as contribute to the ongoing academic discussion about personalized marketing communication and customer engagement.

The results reveal that email communication has a significant positive effect on customer engagement irrespective of behavior-based personalization. This proves that email is an effective marketing communication channel, and it should, therefore, remain a key part of the digital media mix used by marketers. However, based on the lack of a significant difference in the effectiveness of personalized and non-personalized email campaigns, the author recommends focusing more on high-quality generic content and the design of the email messages. Furthermore, consistent with the viewpoints of researchers in the field, the study confirms that customer engagement is a significant predictor of customer purchases, leading to the conclusion that firms should invest in customer engagement marketing initiatives to ultimately achieve better firm performance.

1.0 Introduction

With an explosion of new digital technologies, consumers have become more empowered than ever before. They are highly demanding and selective in what information they pay attention to (Harvard Business Review, 2018). To create compelling and relevant interactions for their customers, companies are widely using personalization (Chaffey & Ellis-Chadwick, 2016).

Both scholars and practitioners acknowledge the power of personalization. Academic research highlights that the latter ultimately leads to superior value for customers and, as a result, an increase in customer loyalty (Simonson, 2005), long-term profitability and strengthening of companies' competitive positions (Bleier, Keiser, & Verleye, 2018; Kumar & Pansari, 2016). At the same time, 98% of marketing managers acknowledge that personalization advances customer relationships, while 87% specify that personalization campaigns can significantly enhance business results (Researchscope International, 2018).

The role of personalization in the email marketing context deserves special attention. Today, email is viewed as a key part of an effective digital media mix (Hanna, Swain, & Smith, 2015; Chaffey & Ellis-Chadwick, 2016). It remains *"the most pervasive communication tool used by almost everyone, every day, throughout the day"* (Hanna et al., 2015, p.3). According to Statista (2019), there are 3.8 billion email users worldwide, and this number is going to increase up to 4.6 billion users in 2022. Importantly, email marketing plays a significant role in the development of an online marketing communication strategy, which constitutes an integral part of online customer experience management (Chaffey & Ellis-Chadwick, 2016). This being said, marketers can considerably increase the quality of overall online customer experience by building an effective email communication strategy. On the other hand, the acceptance and performance of even desired emails have been recently compromised by the growing amount of spam, i.e., intrusive unsolicited commercial email, which leads to information overload (Hartemo, 2016; Pavlov, Melville, & Plice, 2008). Due to spam, which knowledge workers sift through every day, useful email messages are lost in the "background noise" and, therefore, it is difficult for legitimate marketers to make their email messages stand out in the customers' email inboxes (Pavlov et al., 2008, p.1191). Hence, we consider studying ways to achieve higher email marketing efficiency a particularly relevant research direction. Here, personalization initiatives are of critical importance.

One of the most popular methods used by email marketers to personalize email communication is to add consumer-specific information (e.g., customers' names) to the headline or the content of the email (Sahni, Wheeler, & Chintagunta, 2018; Wattal, Telang, Mukhopadhyay, & Boatwright, 2012). However, such a basic form of personalization is no longer sufficient to engage customers (Chaffey & Ellis-Chadwick, 2016). According to the American Marketing Association, effective personalization relies on behavioral data rather than demographic data (Markelz, 2018). *"It's not about tailoring content. It's about triggering a single e-mail to a single person at a moment in time"* (Markelz, 2018). In other words, effective personalized communication implies the delivery of timely and highly relevant messages to each customer. Today, this is possible due to such technological advances as marketing automation software (Strauss, Frost, & Sinha, 2014; Chaffey & Ellis-Chadwick, 2016; Hanna et al., 2015). By leveraging marketing automation technology, email marketers can automatically trigger relevant messages for every customer based on their behavior, aiming to elicit positive customer responses. For instance, after a shopper abandons a shopping cart, online retailers frequently send a series of follow-up emails to encourage the customer to make the purchase (Osborne, 2017).

As a result of such personalized communication, companies may considerably improve their business results: according to Forbes, 60% of Netflix subscriptions are attributed to personalized messages based on a customer's previous viewing behavior, and 35% of Amazon's sales are possible due to individual suggestions of products based on customers' unique behaviors and purchases (Osborne, 2017). Remarkably, academic research has not previously studied the effectiveness of personalization based on customer behavior in the email marketing context.

The main interest of the following study is to empirically test if behavior-based personalization improves the results of the email communication by examining not only its impact on such outcome variable as customer purchasing behavior but also investigating why personalized email communication may influence customer purchase decisions. Hence, the following study introduces *customer engagement* that we assume is *a mechanism through which marketing communication affects subsequent customer purchasing behavior*. While developing the research framework of the paper, we support our assumptions with the theory on perceived relevance associated with the personalization, and the

theory on perceived value associated with the engagement. To the best of our knowledge, there is no previous research which investigated the relationships between the defined constructs.

1.1 Research question

The current research proposal focuses on the question of the effectiveness of personalized communication based on customer behavior and aims to investigate if such communication has an effect on customer engagement and subsequent customer purchases.

To answer the research question at hand, we decided to conduct a field experiment. For that, we partnered with Kahoot! AS, a fast-growing Norwegian start-up company operating in the education technology industry. Kahoot!'s game-based learning and trivia platform is used in multiple settings – school and university classrooms, business training and presentations, social, cultural, and other events (retrieved from kahoot.com). We leveraged Kahoot! marketing automation technology to set up and run the experiment. Findings of the study provide marketing managers with useful insights on the effectiveness of behavior-based personalization in the email marketing context as well as email marketing effectiveness in general.

2.0 Literature review
2.1 Email marketing and its importance

To date, email remains a cornerstone of the digital media mix (Hanna et al., 2015; Chaffey & Ellis-Chadwick, 2016). It is *"the most pervasive communication tool used by almost everyone, every day, throughout the day"* (Hanna et al., 2015, p.3) with 3.8 billion email users worldwide, predicted to increase up to 4.6 billion users in 2022 (Statista, 2019).

While being substantially less expensive compared to other communication tools (Hanna et al., 2015; Chaffey & Ellis-Chadwick, 2016), email is highly profitable (Hartemo, 2016; Pavlov et al., 2008). According to Direct Marketing Association and Demand Metric, email has a 122% return on investment, which is

more than four times higher than other communication channels like social media, direct mail and paid search (eMarketer, 2016).

One of the key advantages of email is that it allows for interactive one-to-one communication with customers (Hanna et al., 2015; Zhang, Kumar, & Cosguner, 2017), which encourages immediate action. For instance, customers can respond to email at the moment they receive it (or later) by clicking through to the sender firm's website (Zhang et al., 2017; Chaffey & Ellis-Chadwick, 2016).

Email marketing captured our academic interest since it plays a significant role in the development of online marketing communication strategy, which constitutes an integral part of online customer experience management. By building up the right email communication, marketers can significantly increase the quality of the online customer experience (Chaffey & Ellis-Chadwick, 2016). In general, creating a strong online customer experience is critical to creating a competitive advantage for businesses (Novak, Hoffman, & Yung, 2000; Lemon & Verhoef, 2016). *"The increasing focus on customer experience arises because customers now interact with firms through a myriad of touch points in multiple channels and media, resulting in more complex customer journeys."* (Lemon & Verhoef, 2016, p. 69).

The "right" email communication strategy primarily means that it must deliver timely and relevant messages to each customer (Chaffey & Ellis-Chadwick, 2016). Today, this is possible due to such technological advances as marketing automation software (Strauss et al., 2014; Chaffey & Ellis-Chadwick, 2016; Hanna et al., 2015). According to Chaffey & Ellis-Chadwick (2016), marketing automation is *"currently used to describe a closely related approach known as one-to-one marketing"* (p.300). With the help of marketing automation technology, marketers can track the behavior of each customer in real time and based on the behavioral data build up communication so that each customer gets highly personalized communication experience with the company. According to the study conducted by HBR Analytic Services (2018) as cited in Harvard Business Review (2018), nine out of ten business executives say their customers now expect them to know and anticipate their needs, and eight out of ten executives state that personalization of customer experiences is an important part of their organization's strategy.

In the following section, we are going to review the literature on the personalization of marketing communication to understand what was done in the previous research and identify the gap in the literature that this research fills.

2.2 Personalization of marketing communication

Contemporary technologies enable companies to collect a variety of individual-level data and then use it to develop personalized online experiences so that they are more aligned with an individual customer's needs, preferences, and interests (Chaffey & Ellis-Chadwick, 2016; Simonson, 2005).

Scholarly research highlights that personalization leads to superior value for customers and, as a result, an increase in customer loyalty (Simonson, 2005), long-term profitability and strengthening of companies' competitive positions (Bleier et al., 2018; Kumar & Pansari, 2016).

Harvard Business Review (2018, p.1) further emphasizes the role of personalization for businesses: *"As the digital age offers new ways to fight for customer mindshare and dollars, consumer-facing organizations are responding with new efforts to personalize the customer experience – and reaping big rewards in the process."* Indeed, 98% of marketing managers acknowledge that personalization advances customer relationships, while 87% specify that personalization campaigns can significantly enhance business results (Researchscope International, 2018).

Overall, personalization is one of the forms of one-to-one marketing, which involves tailoring a firm's marketing mix to the individual customer. The term "personalization" is often used interchangeably with customization; however, these are two different forms of one-to-one marketing (Arora et al., 2008). While customization means customers themselves actively adapt the marketing mix to their needs and preferences, personalization implies that it is the company which determines the optimal marketing mix for each customer (Bleier et al., 2018; Arora et al., 2008).

The following research focuses on personalization of marketing communication based on customer behavior. Bleier et al. (2018) define personalized marketing communication as tailored messages in which content is based on inferred personal interests, experiences, and past customer behaviors. Tam

& Ho (2005) see personalization as the delivery of *"the right content in the right format to the right person at the right time"* (p.271). Taking into account both viewpoints, we define behavior-based personalization of marketing communication as the delivery of the timely messages with tailored content for each customer based on their behavior.

Research to date has widely examined the effectiveness of different forms of personalization of marketing communication with a vast majority of studies conducted in the context of the online banner advertisement.

Scholars, for instance, empirically tested how personalization based on individual browsing history in the online banner ads influences subsequent customer responses (Lambrecht & Tucker, 2013; Bleier & Eisenbeiss, 2015). In particular, Lambrecht & Tucker (2013) investigated how ads retargeting influences customer purchases using field experiment data from an online travel firm; the authors found that brand-level ads (generic retargeting) are overall more effective than personalized ads (dynamic retargeting), i.e., advertisement of the specific products the consumer previously viewed on the firm's website. However, the effectiveness of dynamic retargeting increases when customers are getting highly involved in the advertised category. These findings were reinforced by Bleier & Eisenbeiss (2015), who made a distinction between the low, medium, and high level of ad personalization and tested how those degrees influence advertisement effectiveness. Authors found evidence that a medium degree of personalization increases retargeting effectiveness, while when the advertisement very closely reflects previous customer's preferences, it loses its effectiveness due to the effect of overpersonalization.

Apart from personalization based on the individual browsing history, researchers also tested the effectiveness of banner ads' personalization based on observable consumer characteristics (or customer-related information). For instance, Tucker (2014) investigated whether embedding personal information posted by users on social media (e.g., educational affiliation or preferred celebrity) into advertising content influenced advertisement effectiveness (click-through rates) and found a positive effect. However, Van Doorn & Hoekstra (2013) found that using personal information (e.g., personal identification and information about customers' transactions) in the banner advertisement has a negative influence on customers' purchase intentions.

There have been several studies in the context of online banner advertisement which examined whether matching the ads to the website content leads to better behavioral outcomes. For instance, Goldfarb & Tucker (2011) tested if matching the advertisement content to the website content enhances customer purchase intentions and found a significant positive effect. However, this effect diminishes with the ad's obtrusiveness. Similarly, researchers have found a positive effect of banner ads – website content congruence on attitudes towards the ads (Moore, Stammerjohan, & Coulter, 2005; Shamdasani, Stanaland, & Tan, 2001); however, if the advertised product is low-involvement, the website content has a very low impact (Shamdasani et al., 2001).

In the context of email communication, a few studies showed that the effectiveness of email communication changes with the change of content. For instance, Sudhir, Roy, & Cherian (2016) conducted a field experiment together with a charity organization and found that monthly framing of the donation and inclusion of the story of an in-group member has a positive effect on raised donations.

Several studies looked at the effects of embedding personal information in the email content, and they yielded mixed findings. Sahni et al. (2018) empirically tested how embedding the recipient's name in emails influences sales' leads generation and unsubscription rates and found a significant positive effect, which can be explained by the fact that personal information orients attention, it may serve as a positive cue for the receiver, and may increase elaboration. At the same time, Wattal et al. (2012) studied whether mentioning recipient's name influences such email responses as email opens, unsubscription, click-through, and purchases, and they found that consumers respond negatively to the email when it includes a personal greeting. Such an effect can be explained by an increase in consumers' privacy concerns. However, this effect is moderated by the familiarity of the consumer with the firm. Similarly, White, Zahay, Thorbjørnsen, & Shavitt (2008) studied the effectiveness of the inclusion of personal information in the email content and found that a high level of email personalization may lead to lower click-through intentions due to the effect of personalization reactance, especially when the use of personal information is not justified by the firm.

From the above discussion, we can observe that there is no previous research which studied the effectiveness of personalization based on behavior in the context of emailing. Research on email personalization is currently limited to a few studies, which investigated whether the inclusion of customer-related information is an

effective personalization method. In the current research, we aim to investigate if behavior-based personalization is effective in the context of email marketing. In particular, we are going to test if personalized communication significantly affects customer engagement as well as if customer engagement can serve as a mediator between personalized communication and customer purchase behavior.

2.3 Customer engagement

To ensure growth, firms must focus on their customers. However, satisfying customers only with the right product or service is not enough: companies must encourage customer engagement (Kumar & Pansari, 2016).

Acknowledged as one of the top research priorities by Marketing Science Institute (2018), customer engagement is gaining increased attention of academic researchers. Scholars see customer engagement as a new research stream within customer relationship management (Verhoef, Reinartz, & Kraft, 2010; Vivek, Beatty, & Morgan, 2012).

Overall, the notion of engagement has been used in various academic disciplines, such as social and political science, organization behavior, etc. (Brodie, Hollebeek, Jurić, & Ilić, 2011). In marketing, engagement has been recently discussed as an activity of the customer towards the firm (Kumar et al., 2010; Vivek et al., 2012; Brodie et al., 2011).

Scholars discuss the multidimensional nature of customer engagement (Brodie et al.,2011; Patterson, Yu, & De Ruyter, 2006; Hollebeek, 2011). More precisely, research to date sees customer engagement (CE) as a concept which comprises of cognitive, emotional, and behavioral dimensions. Brodie et al. (2011) define CE as the following:

> *A psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g., a brand) in focal service relationships. It occurs under a specific set of context-dependent conditions generating differing CE levels; and exists as a dynamic, iterative process within service relationships that co-create value. CE plays a central role in a nomological network governing service relationships in which other relational concepts (e.g., involvement, loyalty) are antecedents and/or*

consequences in iterative CE processes. It is a multidimensional concept subject to a context- and/or stakeholder-specific expression of relevant cognitive, emotional and/or behavioral dimensions.

The behavioral dimension is of the greatest interest among existing research. For instance, Kumar et al. (2010), Vivek et al. (2012), Van Doorn et al. (2010), Verhoef et al. (2010), Harmeling, Moffett, Arnold, & Carlson (2017), Calder, Malthouse, & Schaedel (2009) view engagement predominantly from a behavioral perspective. According to Kumar et al. (2010), customer engagement implies both transactional (i.e., purchase) and non-transactional interactions between a customer and a firm. At the same time, Vivek et al. (2012), Van Doorn et al. (2010), Verhoef et al. (2010), Harmeling et al. (2017) argue that customer engagement is non-transactional customer behavior.

Vivek et al. (2012) posit that CE is an expanded domain of the relationship marketing and define it as "an intensity of individual participation in and connection with an organization's offerings and/or organizational activities which either the customer or the company initiates" (p. 133). Further, Van Doorn et al. (2010) state that customer engagement is behavior beyond transactions, and it can be defined as "a customer's behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers" (p.253). Similarly, Verhoef et al. (2010) and Harmeling et al. (2017) see customer engagement as non-transactional customer behavior. Conceptualizing customer engagement as a construct capturing the behavior outside the core transaction makes it clearly distinguished from such concepts as behavioral loyalty and other transaction-focused behaviors (Harmeling et al., 2017). Thus, in line with Vivek et al. (2012), Van Doorn et al. (2010), Verhoef et al. (2010), and Harmeling et al. (2017) we will focus on CE as a behavioral manifestation of customers towards the firm beyond the purchase.

Extant literature suggests that higher customer engagement leads to higher customer lifetime value and, as a result, better firm performance (Kumar et al., 2010; Verhoef et al., 2010; Harmeling et al., 2017). Researchers also highlight that ignoring engagement may create lost opportunities for the firm (Verhoef et al., 2010) and/or may lead to the wrong customer valuation (Kumar et al., 2010).

Drawing on a conceptual framework of customer engagement by Van Doorn et al. (2010), customer engagement influences firms on six levels: financial, reputational, regulatory, competitive, employee, and product. With regards to the

consequences of engagement for individual customers, customer engagement leads to cognitive, attitudinal, and behavioral customer responses (Van Doorn et al., 2010). In the following paper, we are focusing on the behavioral outcomes of customer engagement: we will examine whether it has a significant positive effect on customer purchase behavior. We consider purchase behavior the most relevant customer response to focus on since the latter predetermines customer lifetime value (Kumar et al., 2010; Rust, Lemon, & Zeithaml, 2000), customer equity and, hence, overall business performance (Rust et al., 2000).

3.0 Hypotheses

In this section, the hypotheses and the conceptual framework of the paper are developed.

This research focuses on behavior-based personalization of marketing communication that refers to the delivery of the timely messages with tailored content for each customer based on their behaviors (Bleier et al., 2018; Tam & Ho, 2005). In line with Bleier et al. (2018), we assume that personalized marketing communication can foster customer engagement. The reasoning behind this statement is based on the assumption that personalization increases the *relevance* of marketing communication (Sahni et al., 2018; Tam & Ho, 2005; Hawkins, Kreuter, Resnicow, Fishbein, & Dijkstra, 2008), which means that the message at hand is linked to oneself. The linkage to the self increases personal involvement with communication (Sahni et al., 2018). In other words, when the communication is more "for you," the recipient of the message perceives it as more relevant and meaningful (Hawkins et al., 2008). Tam & Ho (2005) use the term "preference matching", defined as the level to which the content generated by personalization agent appeals to users, and state that *"if a personalization agent can generate content that matches the taste and preference of a user, the user is most likely to process the content (e.g., personalized offers) to a larger extent before arriving at a decision (e.g., accept the offers)"* (p. 276). Accordingly, if the marketing communication takes into account customer behavior, it should be perceived as more relevant by the receiver; thus, customers are more likely to respond to personalized than non-personalized communication. Based on written above, we hypothesize:

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Hypothesis 1. Personalized communication based on customer behavior has a direct positive effect on customer engagement.

As discussed earlier, we defined customer engagement as a non-transactional behavioral manifestation of customers towards the firm (Vivek et al., 2012; Van Doorn et al., 2010; Verhoef et al., 2010; Harmeling et al., 2017).

According to Van Doorn et al. (2010), such manifestations towards the firm lead to cognitive, attitudinal, and, most importantly, behavioral outcomes for the engaged customers. Similarly, Lemon & Verhoef (2016) state that customer engagement, which the authors see as *"the extent to which the customer reaches out or initiates contact with the firm either attitudinally or behaviorally"* (p.74), results in various behavioral responses on the part of the customer.

Extant literature acknowledges customer purchases as one of the ultimate behavioral outcomes of customer engagement (Van Doorn et al., 2010; Kumar et al., 2010; Kumar & Pansari, 2016).

The connection between customer engagement and customer purchase behavior can be explained as follows. As a consequence of being more engaged, customers derive more *value* from their experience with a firm or a brand. According to Zeithaml (1988), the value can be defined as the quality one gets for the price paid. The value is shown as a direct consequence of customer engagement in the conceptual framework of CE by Vivek et al. (2012). The author states that *"greater engagement is positively associated with perceptions of greater value received"* (p. 134). At the same time, when customers have higher value perceptions of the product or brand, they are more willing to purchase from the company (Zeithaml, 1988; Dodds, Monroe, & Grewal, 1991; Patterson & Spreng, 1997). The above discussion leads us to the following hypothesis:

Hypothesis 2. Customer engagement has a direct positive effect on customer purchase behavior.

Consequently, we assume that highly relevant communications make customers more willing to engage with a firm or a brand; the more they are engaged, the stronger value perceptions they form and, as a result, the higher is their willingness to purchase. Based on written above, we hypothesize that customer

engagement can serve as a mediator between personalized communication based on customer behavior and customer purchase behavior.

Hypothesis 3. Customer engagement mediates the relationship between personalized communication based on customer behavior and customer purchase behavior.

Figure 1 summarizes the conceptual framework of the paper. The independent variable is personalized communication based on customer behavior, and the outcome variable is customer purchase behavior. We assume that behavior-based personalized communication will have a significant positive effect on customer engagement. At the same time, customer engagement is expected to positively influence customer purchase behavior. As a result, customer engagement can serve as a mediator between personalized communication based on customer behavior and customer purchase behavior. To the best of our knowledge, no previous research examined the relationship between the defined constructs.
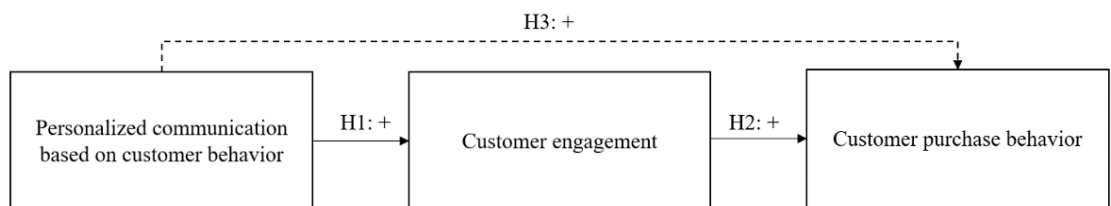
Figure 1. Conceptual framework

4.0 Methodology

In the following part of the paper, we will provide an understanding of the chosen methodology, in particular, study setting, experimental design, sampling, measurement, data collection process, and statistical analysis strategy.

4.1 Study setting

To test the identified hypotheses, we conducted a between-subjects field experiment in line with Sahni et al. (2018). Importantly, the field experiment allows

testing the hypotheses in a real-life setup. Despite a relatively low level of control in comparison with a laboratory setting (Malhotra, 2010), the results of the field study reflect actual consumer behavior. By conducting a field experiment, we also ensured a high level of ecological validity, which means that the results of the study are generalizable.

To perform the experiment, we partnered with Kahoot! AS. Kahoot!'s platform enables users to create, share, and play different types of quizzes. The audience can join the game on the presentation screen using their mobile devices (retrieved from kahoot.com). As of the end of 2018, Kahoot! reached 13 million unique users with registered accounts (Kahoot! Press Kit, 2019). Kahoot! games have been played in all countries in the world. Over 60 million games were created on the platform and played by 2 billion non-unique players cumulatively since its launch in 2013 with 1 billion users in 2018 alone (Kahoot! Press Kit, 2019). Most of Kahoot! customers (60%) are based in the United States (retrieved from kahoot.com).

While signing up, each user chooses whether they want to use Kahoot! as a teacher, as a student, socially, or at work (for business purposes). Based on that information, Kahoot! segments their users into four groups: educators (school and university teachers, administration of educational institutions), students, social users (i.e., those who use Kahoot! during various cultural and social events), and business users. The main segments are teachers and students. With that said, 50% of teachers in the US use Kahoot! during a school year, and more than 50% of K-12 students play Kahoot! every month (Kahoot! Press Kit, 2019).

From a marketing perspective, one of the critical managerial goals for Kahoot! is to create a compelling customer experience for its users. Although the greatest attention is given to the development of new product features, Kahoot! extensively focuses on the delivery of customer experience through effective email communication. For that, the company is adopting marketing automation technology. With the use of marketing automation Kahoot! can track the user behavior on the platform in real time and based on the behavioral data create highly personalized email campaigns to best address the needs and preferences of each customer. We leveraged Kahoot! marketing automation technology to run the experiment. The design of the experiment is described in the next section.

4.2 Experimental design

The aim of this study is to test the effectiveness of behavior-based personalized communication in the context of email marketing. For that, we are working with the "Onboarding" email campaign, designed for the main Kahoot! user segment – teachers. This email campaign represents a series of welcoming or "onboarding" emails, and it is aiming to familiarize new users with Kahoot! as a service, its features, benefits and, as a result, activate users on Kahoot! platform. The campaign starts being sent to newcomers immediately after they sign up. It includes a welcoming email, emails with tips on how to create Kahoot! game, host (play) Kahoot! game in the classroom and assign it as homework, an email with an invitation to join Kahoot! Certified, which is a free personal development program for teachers.

In order to check the effect of the behavior-based personalization on engagement and purchase behavior, *we introduced three experimental groups*. The treatment group (1) received the "Onboarding" email campaign, which was personalized based on customer behavior (see appendix 1). All the emails received by users from the treatment group were trigger-based, which means that *each email was sent based on specific user activities on the Kahoot! platform*. In one minute after a user created an account, marketing automation software checks if the user gave consent to receive emails from the company (as only those who gave the consent can receive emails). Immediately after that, the user gets the first email – "Welcome to Kahoot!". In two days after the previous email, marketing automation software checks if the user played and/or created the game. If the user created the game but did not host it, they receive an email with the tips on how to host the game ("Play Kahoot!"). If the user hosted an existing game but did not create their own, they receive an email with the tips on how to create the game ("Create Kahoot!"). If the user neither created nor hosted (played) the game, they receive an email with the tips on how to create and host (play) the game ("Create & Play Kahoot!"). If the user created and hosted the game, they do not receive any emails regarding game creation or hosting. In five days after the previous query, the software checks if the user assigned Kahoot! game as a homework (challenge). If no, then the user gets an email with the tips on how to use Kahoot! for homework ("Kahoot! Challenge"). In three days after the last query, the software checks if the user participated in Kahoot! Certified. If no, they get an invitation and, later, a reminder in case the user

did not participate in Kahoot! Certified before the query. Otherwise, the invitation is not sent. As a result, each user in the treatment group receives *timely emails with only relevant information* about Kahoot! offerings.

The next group (2) of customers received "Onboarding for teachers" email campaign, which was not personalized based on customer behavior (see appendix 2). With that said, users received the following flow of emails regardless of their activity on the Kahoot! platform: "Welcome to Kahoot" in one minute after registration, "Create Kahoot!" in two days after the previous email, "Play Kahoot" in five days after the last email, "Create Challenge" in three days after the last email, "Join Kahoot! Certified" in nine days after the last email. The number and the content of emails are the same for every user in this group.

In order to eliminate procedural confound the design and description of the offerings (e.g., description of creation functionality or challenge functionality) used in emails, which the treatment group and the first control group of customers received, were the same. For both personalized and non-personalized campaign, the copy was created by a professional copywriter and the visual components of the emails – by a professional designer.

The last group (0) of customers did not receive the "Onboarding for teachers" email campaign. This control group was introduced with the purpose of testing if email communication irrespective of personalization affects customer engagement and purchase behavior.

The experiment ran for 3 months, starting from December 2018 until February 2019. This way, we avoided a threat to internal validity, which could have occurred due to seasonality issue (e.g., Kahoot! users are considerably less engaged during holidays). Importantly, we tracked the behavior of each customer over the same time period; mainly, the observation period for each user was restricted to 30 days after the sign-up date.

4.3 Sample design and sample size

As previously stated, the experiment was based on the "Onboarding" email campaign created for school and university teachers, who use Kahoot! service for formative assessment and homework. The majority of users (60%) are located in the U.S. (retrieved from kahoot.com). Throughout the field experiment, we

collected the data on 4350 users, 1450 subjects in each group. To avoid experimental confounds, we assigned subjects randomly to each of the experimental conditions.

4.4 Measurement of the outcome variables

Within academia, there is no one established way of measuring customer engagement, primarily because the methodology highly depends on the context of the study, availability of the resources and whether the researchers investigate cognitive, emotional, or behavioral dimension of engagement. With that said, Lehmann, Lalmas, Yom-Tov, & Dupret (2012) suggest that the measurement of engagement can be conducted in three ways: self-reported engagement, for which questionnaires and interviews are used; cognitive engagement, for which task-based methods and physiological measures are used; and online behavior metrics that accesses the depth of customer engagement with the help of web analytics. In the following study, we used online behavior metrics since the focus of the author is on the behavioral dimension of customer engagement.

In their study on user engagement, Lehmann et al. (2012) state that *"we should not speak of one main approach to measure user engagement – e.g., through one fixed set of metrics – because engagement depends on the online services at hand"* (p.1) and further highlight that engagement consists of different characteristics depending on the web platform of interest. Engagement metrics includes but is not limited to click-through rates, number of page views, time spend on a site, return rate, number of users. Importantly, the engagement metrics should reflect the following: the higher and the more frequent is the usage, the more engaged the user is (Lehmann et al., 2012).

Taking into account the nature of Kahoot! service, we decided to focus on such engagement metrics as the number of created Kahoot! games, the number of hosted (played) Kahoot! games, and the number of assigned Kahoot! challenges. We decided not to take into consideration participation in Kahoot! Certified since the participants of Kahoot! Certified are initially much more active with regard to game creation and hosting, so participation in Kahoot! Certified reflects the behavior of just a small fraction of the users.

Drawing on the business model of Kahoot!, which implies that customers can either use the service for free or upgrade to the paid plan to get additional

features, we were able to capture purchase behavior of each customer with the dummy variable (purchase or non-purchase).

4.5 Data collection

In order to form the dataset with all identified engagement variables and purchase behavior variable, first, we retrieved three lists of unique user IDs for each experimental group after the experiment was finished. We also obtained the dates when each user signed up. With regards to the treatment and first control group, the date of sign-up was the date when the users started to get personalized and non-personalized "Onboarding" email campaigns, respectively.

With the help of the list of unique user IDs, we were able to obtain information on the number of created games, number of hosted games, number of assigned challenges, and purchase behavior of each subject. Importantly, we made sure that the observation period was restricted to 30 days after the sign-up date so that the behavior of each subject was tracked over the same time period. This way, we were able to eliminate procedural confound.

4.6 Statistical analysis

To analyze the data, we used SPSS or Statistical Package for Social Science. To test the first hypothesis about the positive effect of behavior-based personalized communication on customer engagement, we used *ANOVA, "a statistical technique for examining the differences among means for two or more populations"* (Malhotra, 2010, p. 531). In particular, we compared the means of the number of created Kahoot! games, the number of hosted Kahoot! games, and the number of assigned Kahoot! challenges across three experimental conditions described in the experimental design section: personalized communication vs. non-personalized communication vs. no communication. This method was the most appropriate statistical technique to test the first hypothesis since we wanted to establish the relationship between the categorical independent variable and metric dependent variables (Malhotra, 2010). Although ANOVA is overall robust to violations of its underlying assumptions, after we found non-normality of residuals of the DVs (based on Kolmogorov-Smirnov test), we also decided to perform *Kruskal-Wallis*

test, which is a non-parametric equivalent of ANOVA that does not require normality of residuals.

To test the second hypothesis about the positive effect of engagement on customer purchase behavior, we used *binary logit model or binomial logistic regression*, which estimates the probability of an observation belonging to a specific group (Malhotra, 2010). Binomial logistic regression analysis was the most appropriate method for investigation of the relationships between engagement variables and purchase behavior since we wanted to explain a binary dependent variable (purchase/non-purchase) in terms of several metric independent variables.

For the test of the third hypothesis about the mediation effect of customer engagement, we followed a widely used methodology suggested by Judd & Kenny (1981) and Baron & Kenny (1986).

Researchers state that in order to establish mediation, the following conditions must hold: the treatment must significantly affect the outcome variable, the treatment must also significantly affect the mediator and the mediator must affect the outcome variable. If these conditions hold, further mediation analysis should be performed. Authors recommend running a series of regression models: regressing the mediator upon the independent variable, then regressing the dependent variable upon the independent variable, and lastly, regressing the dependent variable upon both the independent variable and upon the mediator (Baron & Kenny, 1986). In the following research, the outcome variable is a dummy variable (purchase/non-purchase); thus, we performed logistic regression analysis following the next steps:

- First, the relationship between the treatment and the outcome variable should be checked by running simple logistic regression:

$$Purchase = \beta_0 + \beta_1' * type\ of\ communication + \varepsilon$$

- In case a significant relationship between the treatment and the outcome variable is established, mediating variables should be added to the regression (multiple logistic regression):

$$Purchase = \beta_0 + \beta_1 * type\ of\ communication + \beta_2 \\ * number\ of\ hosted\ games + \beta_3 \\ * number\ of\ created\ games + \beta_4 \\ * number\ of\ assigned\ challenges + \varepsilon$$

- then, mediation should be controlled by calculating the difference between regression coefficients $(\beta_1' - \beta_1)$.

5.0 Results
5.1 Descriptive statistics

Overall, the number of subjects in the study is 4350. The average number of created games is .84 (SD = 1.79). The range is 51 with the minimum 0 and maxim 51 created games. 55.00% of subjects created 0 games, 29.30% created 1 game, 8.20% of subjects created 2 games, 3.20% created 3 games, and 4.4% created 4 or more games.

The average number of hosted games is 3.06 (SD = 5.83). The range is 93 with the minimum 0 and maximum 93 hosted games. 40.60% of subjects hosted 0 games, 15.60% hosted 1 game, 10.60% hosted 2 games, 7.40% hosted 3 games, 5.20% hosted 4 games, 4.20% hosted 5 games, and 16.40% hosted 6 and more games.

The average number of assigned challenges is .19 (SD = 1.05). The range is 31 with the minimum 0 and maximum 31 challenges. 91.70% of subjects assigned 0 challenges, 4.6% assigned 1 challenge, 1.70% assigned 2 challenges, and 1.90% assigned 3 or more challenges.

As we can see from Figures 2-4, the distributions of all three variables are skewed to the right. The main reason is that the majority of Kahoot! users, who register on the platform, are completely inactive after registration.

Figure 2.

Frequency distribution: number of created games

Figure 3.

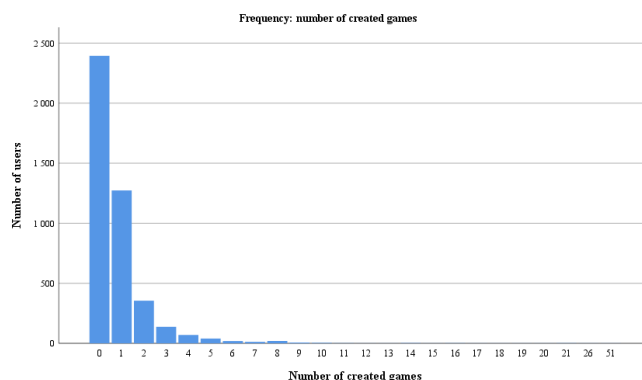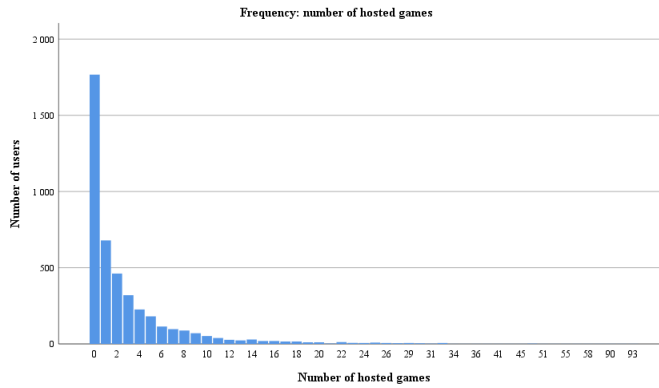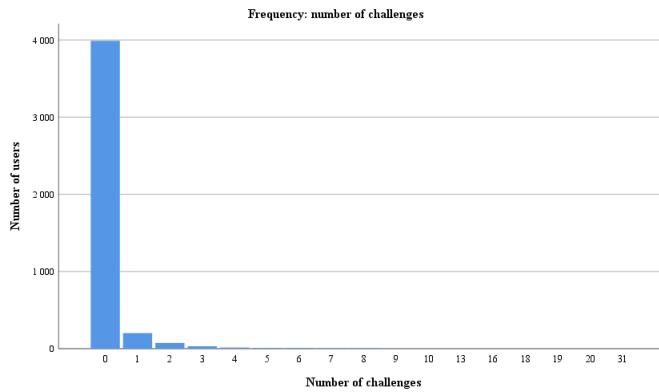*Frequency distribution: number of hosted games*
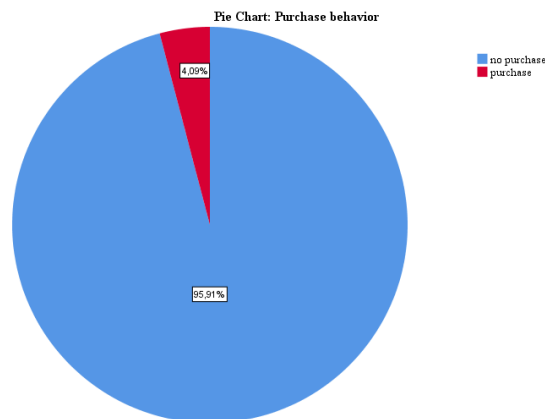

Figure 4.

Frequency distribution: number of challenges

The number of subjects who made a purchase is 178, which is 4.09% of the sample (see figure 5).

Figure 5.

Pie chart: purchase behavior

5.2 ANOVA and Kruskal-Wallis test for hypothesis 1

In order to test whether behavior-based personalized communication positively affects customer engagement (Hypothesis 1), we first used the ANOVA test. We preferred univariate ANOVA tests to MANOVA since we wanted to see the group differences for each dependent variable separately rather than differences between the variable combinations (results) which are created by the chosen dependent variables (Janssens, De Pelsmacker, Wijnen, & Van Kenhove, 2008). The results of the ANOVA tests are shown in table 1 below.

Table 1.

ANOVA results

		Sum of Squares	df	Mean Square	F	Significance
Number of created games	Between Groups	78.263	2	39.131	12.311	.000*
	Within Groups	13817.499	4347	3.179		
	Total	13895.761	4349			
Number of hosted games	Between Groups	819.999	2	409.999	12.141	.000*
	Within Groups	146798.05	4347	33.770		
	Total	147618.05	4349			
Number of challenges	Between Groups	.812	2	.406	.367	.693
	Within Groups	4807.137	4347	1.106		
	Total	4807.950	4349			

the level of significance is .05

According to the results of one-way ANOVA for the number of created games, $F (2, 4347) = 12.311$, $p = .000$. Since $p < .05$, we can conclude that there are significant differences in the means of the number of created games across three experimental conditions.

According to the results of one-way ANOVA for the number of hosted games, $F (2, 4347) = 12.141$, $p = .000$. Since $p < .05$, we can conclude that there are significant differences in the means of the number of hosted games across three experimental conditions.

According to the results of one-way ANOVA for number of assigned challenges, $F (2, 4347) = .367$, $p = .693$. Since $p > .05$, we can conclude that there are no significant differences in the means of the number of assigned challenges across three experimental conditions.

Although two of the above described ANOVA tests show significant differences across means, these results do not indicate which pairs of means have a significant difference. To identify the pairs, we ran the ANOVA Post Hoc tests. The results of the tests are shown in table 2 below.

Table 2.

ANOVA Post-Hoc test (Bonferroni)

Dependent Variable			Mean Difference	Std. Error	Significance	95% Confidence Interval Lower Bound	Upper Bound
Number of created games	0	1	-.317*	.066	.000	-.48	-.16
		2	-.234*	.066	.001	-.39	-.08
	1	0	.317*	.066	.000	.16	.48
		2	.082	.066	.646	-.08	.24
	2	0	.234*	.066	.001	.08	.39
		1	-.082	.066	.646	-.24	.08
Number of hosted games	0	1	-.963*	.216	.000	-1.48	-.45
		2	-.872*	.216	.000	-1.39	-.35
	1	0	.963*	.216	.000	.45	1.48
		2	.092	.216	1.000	-.43	.61
	2	0	.872*	.216	.000	0.35	1.39
		1	-.092	.216	1.000	-0.61	.43
Number of challenges	0	1	.028	.039	1.000	-.07	.12
		2	.030	.039	1.000	-.06	.12
	1	0	-.028	.039	1.000	-.12	.07
		2	.001	.039	1.000	-.09	.09
	2	0	-.030	.039	1.000	-.12	.06
		1	-.001	.039	1.000	-.09	.09

the mean difference is significant at the 0.05 level.

0 refers to no communication, 1 refers to personalized communication, 2 refers to non-personalized communication

As we can see from the table, there is a significant difference in the number of created games between group 0 and group 1 (p = .000), group 0 and group 2 (p = .001), but there is no significant difference (p = .646) between groups 1 and 2. The average number of created games is .66 for group 0, .98 for group 1, and .89 for group 2. Hence, we can conclude that making marketing communication personalized based on customer behavior does not affect the number of created games. However, drawing on the significant difference in means between groups 0 and 1, 0 and 2, we can conclude that email communication itself has a significant positive effect on the number of created games regardless of behavior-based personalization.

Similarly, there is a significant difference in the number of hosted games between group 0 and group 1 (p = .000), group 0 and group 2 (p = .000), but there is no significant difference (p = 1.000) between groups 1 and 2. The average number of hosted games is 2.45 for group 0, 3.41 for group 1 and 3.32 for group 2. Therefore, we can conclude that personalized communication based on customer

behavior does not affect the number of hosted games. At the same time, based on the significant difference in means between group 0 and 1, 0 and 2, we can conclude that email communication itself irrespective of behavior-based personalization has a significant positive effect on the number of hosted games.

The results of ANOVA were also supported by the results of the Kruskal-Wallis test (see table 3 below). The Kruskal-Wallis (KW) test is a non-parametric equivalent of ANOVA (Kruskal & Wallis, 1952). Since KW test is non-parametric, it does not assume a normal distribution of residuals. Based on Kolmogorov-Smirnov test results, the distributions of residuals of all dependent variables are non-normal ($p < .05$). Although ANOVA is overall robust to violations of the assumptions, the KW test should be performed.

Table 3.

Kruskal-Wallis test summary

	Number of hosted games	Number of created games	Number of challenges
Kruskal-Wallis H	9.412	20.407	3.085
df	2	2	2
Asymptotic Significance	.009*	.000*	.214

*the significance level is .05

Similar to ANOVA, the results of the KW test show that there is a significant difference in the number of hosted games and the number of created games across groups. Based on pairwise comparisons, the number of hosted games is significantly higher for the group which received non-personalized email campaign ($p = .006$) and the number of created games is significantly higher for both the group which received non-personalized email campaign ($p = .002$) and personalized email campaign ($p = .000$) compared to the group which did not receive any campaign.

5.3 Logistic regression analysis for hypothesis 2

To explain purchase behavior with the engagement variables, we applied bivariate logistic regression after controlling for multicollinearity.

To ensure there is no multicollinearity, we first calculated Pearson correlation coefficients and found no indication of a possible problem as there were no correlation coefficients greater than .6 (Janssens et al., 2008): the maximum correlation coefficient was .462. Tolerance coefficients also indicated no

multicollinearity issue as all the tolerance values were greater than .5 (Janssens et al., 2008): minimum tolerance value was .787.

Since it is impossible to calculate an R² for logistic regression, we need to use approximations such as Cox & Snell R² and Nagelkerke pseudo-R². The Model Summary resulted in *Cox & Snell R² = .007* and *Nagelkerke R² = .024*. Drawing on Nagelkerke R², which is preferred over Cox & Snell R² since Nagelkerke R² ranges from 0 to 1, the full model has a reasonable model fit since pseudo-R² is typically very low.

At the same time, based on the results of the Chi-Square test ($\chi^2 = 29.960(3)$, $p = .000$), we concluded that it makes sense to include explanatory variables to the model.

The results of the model obtained is described in table 4 below.

Table 4.

Full model estimates

	B	S.E.	Wald	df	Sig.	Exp(B)
Number of hosted games	.030	.010	9.227	1	.002*	1.031
Number of created games	.063	.030	4.366	1	.037*	1.065
Number of challenges	.057	.047	1.484	1	.223	1.059
Constant	-3.354	.088	1468.776	1	.000*	0.035

*significance level is .05

We can see that the number of hosted games and the number of created games has a significant effect on purchase behavior ($p < .05$), while the number of challenges is not a significant predictor of purchase behavior ($p > .05$).

First, β-coefficients gave us the possibility to define the direction in a change of "log odds." As we can see from table 4, all the independent variables have a positive effect on the dependent variable. Second, exp(β) gave us a possibility to assess the magnitude of change in odds ratio:

- With the increase of the number of hosted games by 1 the odds ratio $\frac{p(y=1)}{p(y=0)}$ purchase increases by 3.1%.

- With the increase of the number of created games by 1 the odds ratio the odds ratio $\frac{p(y=1)}{p(y=0)}$ increases by 6.5%.

The probability to purchase could be then calculated using the following equation:

Logit (Purchase) = -3.354 + .030 × number of hosted games + .063 × number of created games + .057 × number of challenges (1)

5.4 Logistic regression analysis for hypothesis 3

To demonstrate mediation, we first must prove that the treatment significantly affects the outcome variable. If this condition does not hold, then the subsequent analysis of mediation makes little sense (Judd & Kenny, 1981).

According to the results of the logistic regression analysis with the purchase behavior as a dependent variable and experimental group as an independent variable, the model indicated zero fit since both *Cox & Snell R² = .000* and *Nagelkerke R² = .000*.

Also, based on the *Chi-Square test* ($\chi^2 = .079(1)$, *p = .806*), we concluded that the model did not adequately explain the outcome variable. According to the results of logistic regression (see table 5), none of the levels of the treatment variable had a significant effect on the outcome variable ($p > .05$).

Table 5.

Full model estimates

	B	S.E.	Wald	df	Sig.	Exp(B)
Communication type			.433	2	.805	
Communication type1	-.068	.185	.137	1	.711	.934
Communication type 2	-.123	.188	.429	1	.513	.884
Constant	-3.092	.129	576.052	1	.000*	.045

*significance level is .05
Personalized communication was chosen to be a base category; communication type 1 refers to no communication, communication type 2 refers to non-personalized communication

Since the treatment variable does not have a significant effect on the outcome variable, there is no need to conduct a further regression analysis, and after this step, we can conclude that the hypothesis about the mediation effect of engagement was not supported.

6.0 Discussion and conclusions

This study investigated how consumers respond to email marketing communication personalized based on customer behavior. Limited prior research studied the effects of behavior-based personalization in the context of email marketing. Rather, scholars to date have put their efforts into the investigation of the effects of email personalization based on customer-related information (Sahni et al., 2018; Wattal et al., 2012; White et al., 2008). Particularly in this study, we investigated the relationships between personalized communication based on customer behavior, customer engagement, and customer purchase behavior.

The first question addressed in this study was related to the effect of behavior-based personalization on customer engagement. Results suggest that email campaigns personalized based on customer behavior compared to non-personalized email campaigns do not lead to significantly higher engagement. First, the reason for the absence of the significant effect might be related to the choice of engagement metrics. While such widely used metrics as a number of visits or number of clicks also reflect the intensity of customer engagement online (Lehmann et al., 2012), we focused on the engagement behaviors that require more effort on the part of a customer. Visiting a webpage or clicking through the link is not as time-consuming and does not demand as much involvement as game creation and game hosting. Second, another possible reason for the absence of a significant difference in the effectiveness of personalized and non-personalized email campaigns might be related to the overall low intrusiveness of the email content used in this study. All the content was more of educational (according to Content Marketing Matrix suggested by Chaffey & Ellis-Chadwick, 2016, p. 450) than promotional nature. Hence, even though the users in the non-personalized condition received emails with information about Kahoot! that was not always relevant to them (e.g., received an email about how to create Kahoot! game after they created it or email about how to host Kahoot! game after they hosted the game), still they did not perceive the emails as highly intrusive and, thus, responded positively. Important to mention, these research findings do not contradict the existing research on behavior-based personalization. In fact, the results of our study are supported by previous studies on personalization in the online banner advertisement context. Scholars concluded that personalized ads based on individual customer browsing

behavior do not lead to better customer responses than generic ads (Lambrecht & Tucker, 2013; Bleier & Eisenbeiss, 2015).

What is particularly interesting, after comparing customers who received email campaigns with those who did not receive any email campaign, we found that the email communication itself irrespective of personalization had a significant positive effect on customer engagement. This proves that email is an efficient digital media channel. Considering the massive popularity of email as a communication tool for both personal and professional usage, one can argue that being regularly present in the email inbox of customers helps brands to increase their visibility substantially and, thus, make their audience more engaged.

Another question addressed in our research was related to the influence of customer engagement on customer purchase behavior. Findings show the significant positive effect of customer engagement on the probability of making a purchase. This being said, the more engaged are customers, the more value they derive from the experience with the company or a brand and are, therefore, more likely to buy. This result is consistent with the viewpoints of other researchers in the field (Kumar et al., 2010; Verhoef et al., 2010, Harmeling et al., 2017, Van Doorn et al., 2010).

We also find it important to elaborate more on the reason why one of the engagement variables, mainly the number of Kahoot! challenges (i.e., assigned homework), did not significantly differ across any of the experimental conditions. This variable also did not significantly affect customer purchase behavior. For students to play Kahoot! game as homework, they need a mobile phone or a tablet with installed Kahoot! mobile application (retrieved from kahoot.com). Taking into account that not every student has a smartphone (Versel, 2018), we argue that this creates a barrier for the active usage of challenges functionality. Thus, teachers overall do not use this Kahoot! feature much (as confirmed by Lifecycle marketing director at Kahoot!, Arnbjørn Marklund). Since the user can create and host Kahoot! games using any device and they do not need to install any special application or software, we drew our conclusions regarding engagement based on the following engagement metrics: number of Kahoot! games created and number of Kahoot! games hosted.

Lastly, we addressed the question of possible mediation effect of engagement between the type of email communication customers receive and their subsequent purchase behavior. The hypothesis about the mediation effect of

customer engagement was not supported because there was no significant main effect found. Therefore, we can conclude that for the customers to make a decision to buy, they primarily need to engage with the company to gain the perception of value about a product or a brand.

6.1 Managerial implications

First, our study empirically confirms the importance of customer engagement since the latter was found to have a significant positive effect on customer purchase behavior. Although customer engagement can occur organically, in order to achieve better firm performance, companies are recommended to invest in customer engagement marketing initiatives, meaning that they should make an effort to motivate, empower and measure customers' contribution to the firm beyond purchase (Harmeling et al., 2017).

We suggest that one of such engagement initiatives should be email marketing. Customers who get emails from the company are overall more willing to engage with a brand than those who do not. Since email communication was found to have a significant positive effect on engagement, managers are recommended to invest both in talent and in technology for the creation of email marketing campaigns. At the same time, based on the insignificant effect of behavior-based personalization, we suggest email marketers put more focus on high-quality generic content and responsive design rather than personalization of the emails.

7.0 Limitations and future research

Most of the concerns related to our study originate from the chosen study setting. Our partner company, Kahoot!, offers a highly technological product, thus, the profile of Kahoot! customer might differ from the average consumer using email. Consumers embracing technology have an optimistic view of its benefits and are overall more innovative (Parasuraman, 2000). Thus, the subjects in this study can be characterized by a high level of technological readiness. Technological readiness is *"people's propensity to embrace and use new technologies for accomplishing goals in home life and at work"* (Parasuraman, 2000, p. 308). One

can argue that the high level of technological readiness, which Kahoot! users possess, might bring a thread to the external validity of the study results. Therefore, we suggest replicating the study in different, more traditional, setting. For instance, future research might be performed in collaboration with online retailers, online magazines, or service providers, who also use email marketing as a part of their digital media mix.

Another limitation is related to the lack of data available for this research. Since we did not have full access to the profiles of Kahoot! users, we could not implement some control variables in the study (although the time users started getting email campaigns and the observation period were strictly controlled, we could not control from which device they open emails, for instance). Also, due to the limited access, we could not provide an extensive description of subjects (i.e., demographics). In the future research, more data about the subjects should be collected.

Although current study closed the gap in the research on behavior-based personalization in the context of email marketing, more empirical effort is needed to investigate if there are any moderators affecting the relationship between personalized communication, customer engagement, and purchase behavior. Future research may, for instance, investigate the interplay of behavior-based personalization and personalization based on customer-related information. By running a field experiment with the two-factor design (where the first factor would be personalization based on customer-related information and the second factor would be behavior-based personalization), researchers might find interaction effects between two variables. This would bring a more detailed view of the effectiveness of both types of personalization in the email marketing context.

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9.0 Appendices

Appendix 1: Email campaign personalized based on customer behavior

User triggers an event "Create account"

1 min

Query: user type is "Teacher"

No → Path End

Yes → Immediately

Query: user gave consent to the email marketing

No → Path End

Yes → Immediately

"Welcome to Kahoot!"

2 days

Query: user hosted a game

No → Query: user created a game

Yes → Query: user created a game

No → "Create&Play kahoot"

Yes → "Play kahoot"

No → "Create kahoot"

Yes → No email

5 days

Query: user assigned a challenge

No → "Kahoot! Challenge"

Yes → No email

3 days

Query: user participated in Kahoot! Certified

No → "Join Kahoot! Certified"

Yes → No email

9 days

Query: user stated Kahoot! Certified

No → "Reminder: participate in Kahoot! Certified"

Yes → No email

Appendix 2: Non-personalized email campaign

User triggers an event "Create account"

1 min

No — Query: user type is "Teacher" — Yes

Path End

Immediately

No — Query: user gave consent to the email marketing — Yes

Path End

Immediately

"Welcome to Kahoot!"

2 days

"Play kahoot"

5 days

"Create kahoot"

3 days

"Kahoot! Challenge"

9 days

"Join Kahoot! Certified"