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## Article

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# Personalisation (In)effectiveness in email marketing

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## ABSTRACT

This research explores the effects of personalization in email marketing. Although personalization is expected to positively impact customer experiences through behavioural responses, its effects on consumers' actual behaviour have not been extensively addressed, providing retailers limited guidance on how to develop personalized communication strategies. Two experimental studies were designed to test the effectiveness of personalization. Results show positive effects of personalized messages on retailers' performance while also highlighting instances of reactance. The originality of this paper lies in identifying possible causes of the contrasting effects of personalization on consumer behaviour by investigating them alongside various customers' online shopping decision making phases. It also provides managerial implications by suggesting guidelines on how to implement effective personalization in email marketing.

## 1. Introduction

The ability to personalize an online shopping experience no longer represents a “nice to have” as consumers expect to have personalized interactions with firms. In fact, personalization is a top priority for firms and one of the main areas of technology investment of the coming years (BoF McKinsey & Company, 2022). The interest in personalization is driven by the expected added value it can offer firms (Lynch & Barnes, 2020; Moran, Muzellec, & Johnson, 2020). A recent report shows that firms can expect a 40% revenue increase from personalized marketing tactics (Arora et al., 2021). Indeed, research has identified various positive effects of personalization, such as consumers' positive attitudes towards the brand, increased purchase intention, and willingness to pay (de Groot, 2022; Tomczyk, Buhalis, Fan, & Williams, 2022). However, negative findings have also been identified, such as privacy concerns, feelings of intrusiveness, and reactance (de Groot, 2022; Tran, Muldrow, & Ho, 2021; van Osselaer, Fuchs, Schreier, & Puntino, 2020). These contrasting effects represent the paradox of personalization and have opened an interesting debate on whether personalization represents an effective strategy (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015; de Groot, 2022; Goic, Rojas, & Saavedra, 2021). Such paradox has been explained through the privacy calculus, where the benefits have to outweigh the costs in order for personalization to be effective (Bol et al., 2018; de Groot, 2022). Recent research has started analysing the conditions under which personalization benefits outweigh the costs. The way in which consumers' data is collected (Zeng, Ye, Li, & Yang, 2021),

the level of personalization (Walrave, Poels, Antheunis, Van den Broeck, & van Noort, 2016), the trustworthiness of the platform on which the personalized message appears (van Ooijen, 2022), contextual factors such as the time at which the message is received by the addressee (Salonen & Karjaluoto, 2019), and individuals' characteristics (Schreiner, Rese, & Baier, 2019) have been identified among the factors that impact personalization effectiveness. Due to the many factors affecting personalization, open questions remain on how personalization should be implemented as part of a communication strategy (Goic et al., 2021; Hayes, Brinson, Gregory, & Moeller, 2021; Kalaighnam, Tuli, Kushwaha, Lee, & Gal, 2021). This study aims to address such issue with a focus on email marketing.

Email marketing is selected to study personalization effectiveness as, despite many marketing strategies, it is widely adopted by firms allowing to reach a wide and varied audience at a low cost (Nobile & Cantoni, 2021). Additionally, it offers many opportunities to personalize the interaction between a retailer and a consumer as potentially any aspect can be tailored to the addressee's characteristics and preferences (Goic et al., 2021; Nobile & Cantoni, 2021). Although a message that matches the characteristics of the addressee is expected to increase its elaboration (Petty & Cacioppo, 1986), it could backfire, for example if it provokes privacy concerns (White, Zahay, Thorbjørnsen, & Shavitt, 2008), thus the extent to which a message should be personalized in order to be effective requires further research (Walrave et al., 2016).

Beyond the content, also the time at which newsletters are sent can be personalized. These are called triggered emails, as they are

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automatically sent in accordance to a consumer's action or state, for example after having placed a product in the online basket without concluding the purchase (Goic et al., 2021). Although widely adopted to reach consumers at the right time of their customer journey, their effectiveness has yet to be determined (Goic et al., 2021).

Hence, this study aims to build on the open debate of personalization effectiveness by investigating its effects in email marketing and by studying different levels of personalization as part of consumers' experience.

Effectiveness in this study is measured in terms of the relational performance metrics of open and click-through, and the transactional metric of purchase. As suggested by Hayes et al. (2021), to better understand the effects of personalization, it is necessary to measure actual rather than self-reported behaviour. Thus, two field experiments are conducted in order to measure personalization effectiveness. The first experiment analyses the effects of personalization in an email campaign. The second one extends the findings by identifying the effects of different levels of personalization and its interplay with three customer journey phases in triggered emails.

The subsequent section presents an overview of personalization and email marketing. This is followed by the presentation of the two experiments and their results. The paper concludes with theoretical and managerial implications, study limitations, and future research directions.

## 2. Literature review

### 2.1. Personalization (In)effectiveness

Personalization is defined as "a dynamic process in which an object is changed for an individual in order to provide added value for the individual herself/himself. Such process, which takes place in a given context, can be user- or firm-driven. The object, either tangible or intangible, is changed in dimensions at a number of states. The individual either provides information about her/himself, or the information is inferred by the change maker. According to some, personalization and customization are different concepts. Customization is then characterized by an active contribution from an individual, up to her/his involvement in the co- design of a product" (Nobile & Cantoni, 2022 p. 8).

As suggested by such definition, the aim of personalization is to provide added value. Previous research has studied personalization in order to understand whether and to what extent personalized messages exceed general messages' performance (de Groot, 2022; Li, 2016). On one hand, there are compelling arguments in support of its benefits. A message that matches some characteristics of an individual is expected to be more persuasive than a non-matched message and to capture an individual's attention (Petty & Cacioppo, 1986; Tran et al., 2021). Personalization makes individuals feel unique (Vesonen, 2007), it creates strong customer-brand relationships (Goic et al., 2021), it boosts customer brand engagement, which in turn enhances brand equity, brand usage intention, and referral behaviour (Tran et al., 2021). In general, it is suggested to improve the overall customer experience (Tyrvaainen, Karjaluoto, & Saarijarvi, 2020). On the other hand, personalization is not without risks (Villanova et al., 2021). Although limited research has focused on its negative consequences, personalization has been found to backfire by creating sentiments of aversion and increasing privacy concerns (Hayes et al., 2021; Teeny, Siev, Brinol, & Petty, 2020). These conflicting views on the effects of personalization, the so-called paradox of personalization, which is expected to provide positive effects but also provides negative ones, emphasize the need to further research the potential effectiveness of personalization (Riegger, Klein, Merfeld, & Henkel, 2021; de Groot, 2022; Tomczyk et al., 2022).

### 2.2. Email marketing and personalization

Email marketing remains among the most popular direct marketing communication tools utilized by retailers to reach consumers (Goic et al., 2021). An added value of email marketing lies in its potential to contribute to a personalized online shopping experience, while allowing for a wide reach (Nobile & Cantoni, 2021). On one hand, email marketing could positively influence consumers by being perceived as a firm's attempt to build a relationship; on the other, it could be perceived negatively as an attempt to manipulate their choices (Vafainia, Breugelmanns, & Bijmolt, 2019). In order to overcome the latter, retailers are relying on finely grained personalized emails to send relevant content (White et al., 2008). To do so, they need to collect individuals' data, a process which is deemed critical for the (un)success of personalization (Aguirre et al., 2015). Data can be obtained overtly, when the individual is aware that their data is being collected, or covertly, when the individual is not aware (Aguirre et al., 2015).

#### 2.2.1. Overt data collection

A type of overt data collection in permission email marketing is self-disclosure, which involves an individual's proactive act of providing personal information to a retailer, for example through subscribing to a newsletter. This is a useful method to overcome the personalization-privacy paradox as it requires the individual's consent to share personal data (Zeng et al., 2021).

Among the information collected overtly and utilized by firms to personalize the message is the individual's name (Nobile & Cantoni, 2021; Tran et al., 2021). It has been found that when individuals spot their name in an email, they pay more attention to the message (Maslowska, Smit, & van den Putte, 2016) resulting in higher probability of opening rate, which in turn generates higher click-through rates, increases sales, and reduces un-subscriptions (Heerwegh, Vanhove, Matthijs, & Loosveldt, 2005; Munz, Jung, & Alter, 2020; Sahni, Wheeler, & Chintagunta, 2018). However, opposite findings highlight the inability of greetings with personal identifiable information to trigger positive responses due to privacy concerns (Li & Liu, 2017; Watal, Telang, Mukhopadhyay, & Boatwright, 2012).

Thus, the first research question this study aims to answer is:

**RQ1.** Is personalization effective in email marketing?

#### 2.2.2. Covert data collection and triggered emails

Data collected covertly derives from tracking consumers' online behaviour, for example their search and purchase history. Covert data collection implies limited awareness from consumers on how the data collected will be utilized (Grigorios, Magrizos, Kostopoulos, Drossos, & Santos, 2022). Technology advances are enabling new methods to collect data covertly from consumer behaviour by leveraging on information from different channels. This allows retailers to automate the process of sending messages in response to an individual's behaviour (Goic et al., 2021). These messages called "triggered emails" can be considered as a type of personalization as they implicitly respond to a person's action.

To date, there is little evidence on the impact of triggered emails on consumer behaviour. Browse abandonment triggered emails are shown to increase revenue compared to not receiving a message (Goic et al., 2021). Moreover, Zhao, Wang, and Jiang (2020) found that reminding shoppers to clean their basket can provide positive effects such as purchase intent.

#### 2.2.3. Personalization levels

Both the subject line and the body of an email can be personalized at different levels depending on the number of personal attributes inserted in the message. The "best level" of personalization which adds value without being perceived by the individual as "creepy" and as an attempt to manipulate has yet to be identified (Walrave et al., 2016). On one

hand, higher levels of personalization, identified as including the highest number of personal references, are shown to perform the best (Kalyanaraman & Sundar, 2006; Tam & Ho, 2005; Walrave et al., 2016). On the other hand, White et al. (2008) identify emails with high distinctiveness to be only equal to, not higher than, low distinctiveness messages in terms of click-throughs.

A message with a higher number of personalized attributes might require less processing from the individual and have positive effects. In contrast, it might have negative effects as it could be perceived as too intrusive (Walrave et al., 2016). Arguably, the group of personalized attributes included in the message could partly explain the contrasting results identified in the literature. Thus, it is argued in this study that it is crucial to research not only the type of information but also the group of information that triggers positive responses.

Thus, the second research question of this study:

**RQ2.** Are messages personalized at higher levels more effective than messages personalized at lower levels?

**2.2.4. Personalization and context: Customer journey**

While the content and the design elements are important for the success of an email, other factors such as temporal dynamics, meaning the time at which a message is sent as part of the customer journey, interplay to determine its effectiveness as consumers' preferences change across time (Kumar, 2021; Salonen & Karjaluoto, 2019; Song, Li, Li, & Li, 2021). Hence, it is crucial to understand how personalization strategies can be utilized to influence decision making at different phases of the shopping journey (Lynch & Barnes, 2020; Varnali, 2018).

Online shopping enables retailers to track consumers during their shopping journey. For example, it is possible to track when an individual has searched for a product with no further action or has added it to the cart (Goic et al., 2021). Such information can be utilized by retailers to accompany the individual during the shopping journey through personalized triggered messages. Tam and Ho (2005) show that personalized recommendations are more effective at an early decision-making phase when the decision funnel is more open to new information compared to later ones.

Nonetheless, previous studies have neglected to further research the relationship between personalization and various customer journey phases in triggered email marketing (Goic et al., 2021). As personalization does not occur in silo, studying its effects as part of consumers' shopping journey could help overcome the contrasting effects identified in the literature (Bleier & Eisenbeiss, 2015). Hence, the third research question:

**RQ3.** Is personalization effective during the whole customer journey or does it perform differently at various phases?

**3. Experiments**

Two experiments were conducted in order to measure the effects of personalization on consumer behaviour. This methodology was selected as it enables to measure actual rather than self-reported reactions, which is essential to advance the research on personalization effectiveness (Viglia & Dolnicar, 2020).

**3.1. Experiment 1**

**3.1.1. Study design and procedure**

Experiment 1 was designed with the fashion brand Old Captain Co., interesting for personalization research as it is born as a brand that produces custom-made shirts Made in Switzerland. The aim was to reach a first understanding on the effects of personalization on open and click-through rates in an email campaign by conducting a field experiment in order to measure actual rather than self-reported behaviour. The brand sends monthly newsletters with company updates to its subscribers. For this single factor between-subject experiment, the newsletter of October

2021 was utilized. It involved all the brand's customers who have an online account with the brand and are subscribed to the newsletter. Personalization effects were tested with two types of messages, a personalized and a standard one (control group). Participants were randomly assigned to one of the two experimental conditions in a casual manner.

**3.1.2. Stimuli**

The personalized version greeted the individuals by their first name in the subject line and in the body of the message. Whereas the standard version greeted the individuals with a general "Dear Wanderers", which is used by the brand in its monthly newsletters. The remaining of the message was kept identical for both versions.

**3.1.3. Analysis and results**

A total of 663 messages were sent, of these 330 to the control group and 333 to the treatment group. Table 1 reports the descriptive statistics. While a small positive difference is identified between the number of messages opened in the control and the treatment groups, one-way ANOVA results revealed such difference was not statistically significant ( $p > .05$ ).

**3.1.4. Discussion**

One's name is expected to positively resonate with individuals and provide effective outcomes (Petty & Cacioppo, 1986). Research question 1 asked whether personalization is effective in email marketing. This study shows that greeting an individual by name has a minor, yet not significant, difference on open-rate, suggesting that personalization is not effective. It could be that adding one's name to a message is not sufficient to trigger an individual's response as it affects the cognitive rather than the affective experience, which has a higher effect on behavioural response (Barari, Ross, & Surachartkumtonkun, 2020). Moreover, Old Captain Ltd. is a niche brand based in Lugano (Ticino, Switzerland) formed by a small community that is familiar with the founder, who is also a musician and radio DJ in the area. The high degree of familiarity in Ticino might drive the individual to mostly ignore the presence of the personal greeting as, when receiving the email, the individual already associates it with the company, providing it an intimate tone despite the presence or absence of the name.

Previous studies suggest that the inability to trigger positive reactions derives from privacy concerns. Whereas positive brand associations (Munz et al., 2020), firm familiarity (Wattal et al., 2012), individual's involvement with the product (Li & Liu, 2017) as well as when the name is voluntarily provided by individual (Sahni et al., 2018) reduce negative responses. In this study, the name was voluntarily provided by the individual, who is also familiar with the brand. This might explain the absence of negative effects.

**3.2. Experiment 2**

**3.2.1. Experiment design and procedure**

Experiment 2 was designed with a company in the sector of products for children and new mothers, which wishes to remain anonymous. Conducting personalization research with this company is considered extremely relevant due to the expected high involvement of the

**Table 1**  
Descriptive statistics experiment 1.

	Standard messages (Control group 330)		Personalized messages (Treatment group 333)	
	Freq.	%	Freq.	%
Bounce rate	2	0.6	3	0.9
Open rate	162	49.4	177	53.6
Click-through rate	29	8.8	30	9.1
Unsubscription	2	0.6	3	0.9

customers (mothers who purchase for their kids) in the shopping experience. This study, conducted in the Italian market, was designed to measure the effects of three levels of personalization on open, click, and purchase. Moreover, the variable of customer shopping phase was observed. Personalization was manipulated on three levels, described as “low”, “medium”, “high”.

To be selected for the study, customers had to:

- (i) be subscribed to the company’s newsletter
- (ii) have an online account with the company
- (iii) log into their account between September 10, 2021 and November 3, 2021 to search for a product on the company’s website

The emails were triggered two hours after the search on the website’s search bar of one of the top 20 keywords from year 2020/21. A typical threshold for an online session is 30 min (Huyng & Miller, 2009). Thus, the cut off is set at two hours as it enables to trigger the emails in a different customer session. Moreover, it is not sent straight after the action as it could result too intrusive and not too long afterwards so the customer still remembers that she/he searched on the company’s website.

Individuals were randomly assigned to one of the three experimental conditions. Furthermore, it was observed in which decision-making phase the customers found themselves. Three phases were identified: phase 1 involved the search of a product on the company website and a “light” product evaluation; phase 2 involved the search of a product and a “thorough” product evaluation; phase 3 involved the search of a product, adding the product to the cart, and not checking out. The transition between phase 1 “light” and phase 2 “thorough” evaluation was determined by the number of seconds an individual spent on the product detail sheet; the cut off was set at 58 s, which is the visitors’ average stay on product pages of the company, thus staying longer than the 58 s was considered as thorough evaluation. When considering the position of an individual, phase 2 ruled over phase 1 and phase 3 ruled over phase 1 and 2.

3.2.2. Stimuli

Three messages (in Italian language) were designed to reflect the three levels of personalization. Messages were “call to action” triggered emails inviting the addressee to go back to the shopping journey from where she/he left off. To manipulate the levels of personalization, previous research was followed, according to which a level can be defined based on the number of personalized placeholders, with lower levels having fewer personalized placeholders and higher levels having more (Walrave et al., 2016). Hence, the three levels should not be considered in absolute terms, but in comparison of each other. Messages with the lower personalization are referred to as “lower personalization” rather than for example “zero personalization” as, even though they do not have any personal placeholder, they are triggered by an individual’s action. The messages personalized at the medium and higher levels added personal placeholders as indicated in Table 2.

3.2.3. Manipulation check

Manipulation checks are essential for experimental design (Viglia & Dolnicar, 2020). To test the stimuli, a pre-test was conducted through an online survey on Qualtrics in order to verify whether the three levels of personalization were perceived and ranked differently by individuals. The participants were asked to imagine three scenarios, which reflected the three customer journey phases previously defined. For each scenario three types of messages were described. Respondents were asked to compare these messages in terms of personalization and position them on a bar from not to highly personalized. Thirty-eight responses were collected.

Firstly, the messages were analysed to identify whether they ranked differently independently from the customer journey phases. A

**Table 2**  
Personalized placeholders in triggered message.

Customer journey		Medium personalization	Higher personalization
Phase 1: “light” product evaluation	Subject line	a. Name	a. Name b. Address
	Body	a. Name b. Image linked to product searched	a. Name b. Image linked to product searched c. Date last purchase d. Address
Phase 2: “thorough” product evaluation	Subject line	a. Name	a. Name b. Address
	Body	a. Name b. Image(s) linked to product(s) searched	a. Name b. Image(s) linked to product(s) searched c. Date last purchase d. Address
Phase 3: cart abandonment	Subject line	a. Name	a. Name b. Address
	Body	a. Name b. Link to basket	a. Name b. Image(s) linked to product(s) in basket c. Date last purchase d. Address

statistically significant difference was identified between the three levels (low, medium, high) as determined by one-way ANOVA ( $F(2,339) = 290.583, p = .000$ ). Then, it was measured whether the three messages were ranked differently on the scale from not to highly personalized and results show that the messages of each scenario were ranked differently. A statistically significant difference was identified between the messages of scenario 1 as determined by one-way ANOVA ( $F(2,111) = 90.754, p = .000$ ); of scenario 2 ( $F(2,111) = 116.375, p = .000$ ) and of scenario 3 ( $F(2,111) = 89.363, p = .000$ ).

3.2.4. Analysis and results: Descriptive statistics

The company sent 2453 messages to unique customers. Of the messages, 79 were not successfully received and 71 bounced back. Hence, 2303 cases were considered for analysis. The sample is formed by 1974 females, 58 males, and 271 unknown gender. Gender distribution reflects the typical female customer base of the company. Age ranged from 19 to 71 years old ( $M = 35, SD = 6.4$ ).

Table 3 reports the distribution of the messages randomized based on the three personalization levels and the distribution of the number of individuals in the three phases.

Of the 2303 observations, 64% opened the message, of those who opened it, 18% clicked, and of those who clicked 39% purchased. Table 4 provides the open, click, and purchase rates distributed according to personalization levels.

3.2.5. Analysis and results: Logistic regression

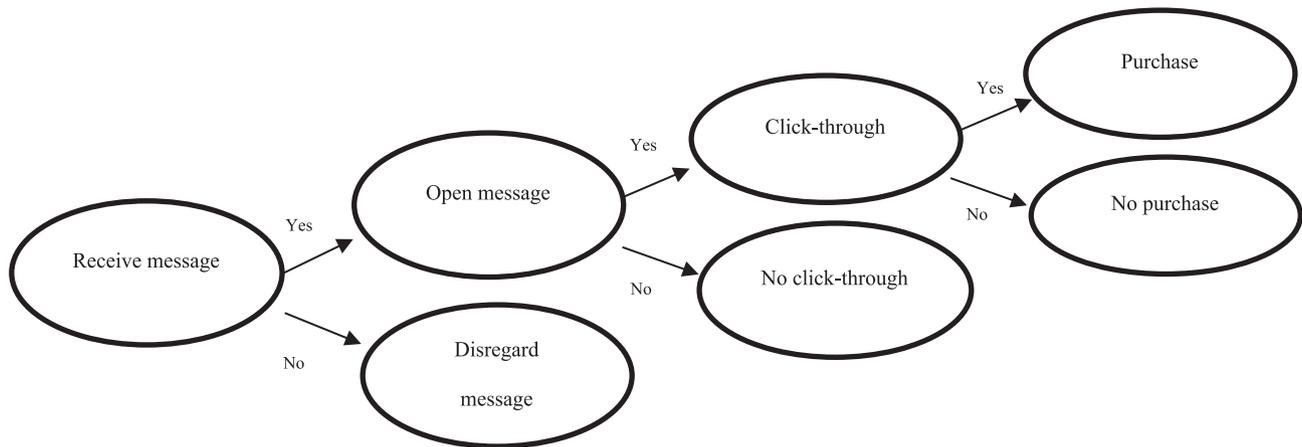
This experiment can be described as a sequence of steps (graph 1). Once the message is received, the addressee can either open or disregard the message. If the message has been opened, the customer can click or not on product links. Then, if the individual clicks, she/he can purchase

**Table 3**  
Distribution: personalization levels and customer phases.

Personalization level	Freq.	%
Low	790	34.3
Medium	752	32.7
High	761	33.0
Customer phase		
Light evaluation	517	22.4
Thorough evaluation	1195	51.9
Abandoned cart	591	25.7

**Table 4**  
KPIs.

	Low personalization (790)		Medium personalization (752)		Higher personalization (761)	
	Observations	%	Observations	%	Observations	%
Open	486	61.5	504	67.0	477	62.7
Click	82	16.9	91	18.0	88	18.4
Purchase	36	43.9	39	42.8	26	29.5



**Graph 1.** Sequential model.

or not a product. Therefore, a sequential logit model was utilized to analyse the data as it enables to estimate the relationship between the explanatory variables of personalization and customer journey phase and the odds of passing each transition, from open to click to purchase.

The sequential logit model was estimated through the robust seqlogit package by [Buis \(2015\)](#) on Stata. Moreover, the effects of age were measured as a continuous variable. To test the model, 66 observations for which the age is unknown were eliminated, resulting in 2237 valid observations. [Table 5](#) provides an overview of the results.

The model is statistically significant (prob > chi2 = 0.0067).

Results (appendix A) reveal that:

- being in phase 3 (cart abandonment) increases the probability of opening the message compared to being in phase 1 and phase 2 (Odds ratio (OR) = 3.77,  $p < .1$ ).
- a medium personalization level increases the probability of open compared to a lower and higher level (OR = 2.93,  $p < .1$ )
- an increase in age increases the probability of opening (OR = 1.04,  $p < .05$ ). Whereas an increase in age decreases the probability of opening when in phase 3 (OR = 0.96,  $p < .1$ ).
- being in phase 2 (thorough evaluation) decreases the probability of clicking compared to being in phase 1 and phase 3 (OR = 0.14,  $p < .05$ ).
- an increase in age increases the probability of clicking when in phase 2 (OR = 1.05,  $p < .05$ ).
- a high personalization level decreases the probability of purchase compared to a lower and medium level (OR = 0.00,  $p < .05$ )

- an increase in age increases the probability of purchase for high personalization (OR = 1.12,  $p < .05$ ).

Subsequently, the model was run a second time by adding the interactions of personalization and phases. The model is statically significant (prob > chi2 = 0.0025). Results (appendix B) show that:

- the interaction of medium personalization with phase 3 (OR = 0.57,  $p < .1$ ) and high personalization with phase 3 (OR = 0.52,  $p < .1$ ) decrease the probability of open
- the interaction of high personalization with phase 2 (odds ratio = 3.31,  $p < .05$ ) and phase 3 (OR = 3.05,  $p < .05$ ) increases the probability of click.

### 3.2.6. Discussion

Experiment 2 provides insightful results regarding the effects of personalization in triggered email marketing performance.

Interestingly, increasing the level of personalization in triggered emails does not increase opening rates. In contrast to the experiment by [Walrave et al. \(2016\)](#) which found that the highest level of personalization performs the best, this study finds that in email marketing a medium level of personalization increases the probability of opening. Adding further personalized placeholders does not have any impact on open. In an information rich environment, individuals scroll through the emails quickly, hence, a subject line that matches some personal attributes captures an individual’s attention ([Petty & Cacioppo, 1986](#)), whereas adding further personalized attributes does not increase

**Table 5**  
Results overview.

	All phases	Phase 1	Phase 2	Phase 3
All personalization	If age increases open rate increases		Click-rate decreases; If age increases click-rate increases	Open-rate increases; If age increases open-rate decreases
Low personalization				
Medium personalization	Open-rate increases			Open-rate decreases
Higher personalization	Purchase rate decreases; If age increases purchase-rate increases		Click-rate increases	Click-rate increases; Open-rate decreases

elaboration. Moreover, individuals might preview only a portion of the message while disregarding the remaining text due to their email interface settings.

Additionally, contrary to expectation, higher levels of personalization decrease the probability of purchasing. Previous studies found that browse abandonment triggered emails influence purchase intent and increase revenue compared to not receiving any message (Goic et al., 2021; Zhao et al., 2020). Arguably, when adding personalized elements to triggered cart abandonment emails, the message is perceived as too pushy or it creates a sense of guilt, resulting in negative effects on purchase probability.

However, with the increase of age, an increase of purchase probability is found for higher personalization. According to the persuasion knowledge model people's experience with persuasion attempts and their ability to cope with persuasion attempts increases throughout life (Friestad & Wright, 1994). Hence, it could be that cart abandonment triggered emails with a higher number of personalized placeholders are perceived as useful as individuals' age increases. Such finding highlights the importance of considering also individuals' characteristics when developing personalization strategies.

*3.2.6.1. Interaction of personalization and customer shopping journey phase.* According to configuration theory, an outcome is rarely explained by single factors and it is usually explained by a combination and interaction of factors (Pallant, Sands, & Karpen, 2020). The interaction of personalization with an individual's customer journey phase provides further elucidations regarding personalization effects.

In accordance with the literature, shopping cart warnings can provide positive effects (Zhao et al., 2020), yet adding personalized placeholders to shopping cart warnings both at medium and higher levels is counterproductive for open as it could be perceived as an excessive persuasion attempt. Moreover, the online basket might be adopted for reasons other than purchase intent (Close & Kukar-Kinney, 2010). As found by Sundström, Lidholm, and Radon (2019) the sole act of browsing and adding products to the basket might provide instant gratification. Hence, in these scenarios personalization might not be a relevant motivator to open the message.

Furthermore, if personalization alone had no effect on click-through rates, the interaction of higher levels of personalization with phases two and three provide significant results. Due to the high cost of collecting information consumers often "satisfy", thus receiving personalized information helps reduce the cost of searching for other information and simplifies information processing (Kumar, 2021). Additionally, according to the persuasion knowledge model, when individuals perceive the topic to be relevant and the agent from which they receive the persuasion attempt to be trustworthy they are more likely to ignore their persuasion knowledge and accept the personalized message (Brinson & Eastin, 2016), such as in this case where the individual has opened the message. Hence, the individual uses simple rules to make inferences such as "if the company addresses me personally, the message is relevant for me" (Tam & Ho, 2005). In the case of a higher personalization level, the individual easily has access to information to make various inferences, triggering positive outcomes such as click-through. Whereas this is not sufficient to trigger a purchase response. Individuals are not always able to evaluate all the options available and many online purchases are made impulsively (Ampadu et al., 2022; Song et al., 2021), thus, personalization is expected to have positive effects on consumer behaviour. However, the company selected for this experiment offers mainly products for children and new mothers. Therefore, when shopping with this company, it could be that shoppers act as rational individuals, who consider aspects such as product quality and price, valuing the cognitive component of the shopping experience more than the affective one (Barari, Ross, & Surachartkumtonkun, 2020).

To summarize, the results suggest that focusing solely on personalization provides a narrow view of its effects, rather the interplay of

various factors is necessary to measure its effectiveness.

#### 4. Theoretical and managerial implications

Hereafter, theoretical and managerial implications of both experiments are discussed.

##### 4.1. Theoretical contributions

This study contributes in several ways to personalization literature. It responds to the need to further understand the effectiveness of personalization (RQ1) by investigating contextual factors (RQ 2 and 3). Although the results show that personalization can enhance message effectiveness, both experiments demonstrate that personalization does not always improve the effectiveness of a message performance.

This study reveals that the interplay of a consumer's shopping phase with personalization should be considered when analysing its effectiveness as empirical results show that under certain shopping circumstances it can even negatively impact message effectiveness. While previous research has highlighted contrasting results of personalization (Goic et al., 2021; Hayes et al., 2021; Kalaignanam et al., 2021; Tyrvainen et al., 2020), this study suggests a new dimension, the one of customer shopping phase, in order to partly explain the different effects.

As stated by Riegger et al. (2021), the studies that emphasize personalization ineffectiveness focus mainly on privacy concerns and utilize theories related to perceived risk in order to justify such results, suggesting overt data collection to overcome the personalization-privacy paradox (Zeng et al., 2021). In this research, individuals have engaged in an act of self-disclosure by subscribing to the newsletter and creating an account. Yet, findings show that it is not sufficient to overcome negative effects of personalization.

According to social exchange theory, consumers in the data exchange process with retailers weight the benefits and the risks and might be willing to provide their personal information for relatively small rewards, such as a discount (Pallant et al., 2020). Hence, despite being subscribed, they might not be interested in all kinds of personalized messages.

Second, this study builds on self-referencing theory and the need to identify the information and group of information that activate self-referencing (Maslowska et al., 2016) by testing different levels of personalization. Findings suggest that adding a higher number of personalized information does not always increase message effectiveness. Finally, although personalization is expected to attract attention of all consumers, this study highlights age as one of individuals' characteristics that might partly explain the contrasting results of personalization.

##### 4.2. Managerial implications

There is a clear need of research that can support managers in implementing personalized communication strategies. In this direction, the study provides discerning suggestions for managers.

Generally, retailers should desist from adding too many personalized attributes in their email campaigns as it could result in counterproductive effects. Managers should consider including only attributes that could benefit the consumer. For example, in the subject line adding the name could be beneficial for big retailers to provide a "human tone" to the email. Whereas adding other personal information in the subject line could be perceived as too intrusive; similarly for the body of the message as it could negatively affect purchases by resulting too pushy.

The findings also highlight the relevance of contextual factors when sending personalization emails. Consequently, managers, to optimize personalization effectiveness, should take into consideration the decision-making stage of the customer. Managers should leverage on personalization when customers are further on in their shopping journey, as it improves click-through rates, suggesting that it can help

their decision-making process.

Furthermore, retailers should actively collect information from their customers. For example, this research shows that age could be an interesting variable to take into consideration when developing personalized messages; thus, rather than relying on mass personalized strategies, managers should identify the characteristics of their consumers who are more likely to react favourably to personalization and develop their communications accordingly. Indeed, consumers' privacy and willingness to share their data should be a priority in the data collection process.

### 5. Conclusion, limitations and future research

This study provides valuable insights into personalization effectiveness. Notwithstanding the contributions of this research, there are some limitations that provide fruitful avenues for future research.

First, this research is limited to the Italian and Swiss-Italian markets. Future studies should consider expanding the research to identify any salient cultural differences.

Second, it measures only one individual characteristic, age. Studying other individuals' characteristics could provide interesting findings. For example, individuals in geographical regions with different income levels could have distinctive behaviour.

Also, for experiment 2, it could be that consumers searched for

products online yet purchased offline. Hence, when measuring transactional metrics, consumers' omnichannel shopping journey could be considered.

Furthermore, personality variables are not taken into consideration in the experiments. For instance, for high involved consumers, who desire to find a connection with the brand (Lynch & Barnes, 2020), the effects of personalization might be different compared to less involved shoppers. Future research should strive to identify different types of consumers, who would appreciate personalization in their communications.

Finally, it examined only some of the many personalization types and levels in email marketing, hence it would be compelling to examine different possibilities in order to identify their effectiveness.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

The data that has been used is confidential.

### Appendix A. Model 1

Outcome Non-open vs Open	Odds ratio	Robust Std. Err.	z
Phase			
Phase 2	1.764	1.110	0.90
Phase 3	3.767	2.796	1.79*
Pers_level			
Medium	2.929	1.787	1.76*
High	1.079	0.655	0.13
Age	1.041	0.018	2.21**
Pers_level#Age			
Medium	0.974	0.016	-1.46
High	0.997	0.017	-0.12
Phase#Age			
Phase 2	0.976	0.017	-1.34
Phase 3	0.964	0.020	-1.75*
Outcome Non-click vs Click			
Phase			
Phase 2	0.141	0.131	-2.11**
Phase 3	0.454	0.455	-0.79
Pers_level			
Medium	1.529	1.395	0.47
High	0.847	0.776	-0.18
Age	0.998	0.025	-0.07
Pers_level#Age			
Medium	0.989	0.025	-0.41
High	1.006	0.025	0.25
Phase#Age			
Phase 2	1.054	0.26	2.06**
Phase 3	1.038	0.028	1.38
Outcome Non-purchase vs Purchase			
Phase			
Phase 2	1.363	2.709	0.16
Phase 3	1.544	3.308	0.20
Pers_level			
Medium	0.572	0.936	-0.34
High	0.005	0.011	-2.56**
Age	0.988	0.055	-0.21
Pers_level#Age			
Medium	1.016	0.045	0.36
High	1.129	0.061	2.23**
Phase#Age			

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Outcome Non-open vs Open	Odds ratio	Robust Std. Err.	z
Phase 2	0.995	0.055	-0.07
Phase 3	1.005	0.059	0.10

Note. Pers\_level = Personalization level; \*p < .1 \*\*p < .05.

**Appendix B. Model 2**

Outcome Non-open vs Open	Odds ratio	Robust Std. Err.	z
Phase			
Phase 2	1.851	1.218	0.94
Phase 3	5.239	4.015	2.16**
Pers_level			
Medium	2.876	1.847	1.64
High	1.525	0.982	0.65
Phase#Pers_level			
Phase2#Medium	1.103	0.305	0.36
Phase2#High	0.688	0.186	-1.37
Phase3#Medium	0.568	0.185	-1.73*
Phase3#High	0.518	0.167	-2.04**
Age	1.039	0.018	2.13**
Pers_level#Age			
Medium	0.977	0.017	-1.30
High	0.997	0.017	-0.12
Phase#Age			
Phase 2	0.977	0.017	-1.26
Phase 3	0.966	0.020	-1.61
Outcome Non-click vs Click			
Phase			
Phase 2	0.095	0.094	-2.38**
Phase 3	0.470	0.496	-0.71
Pers_level			
Medium	1.413	1.342	0.36
High	0.361	0.355	-1.03
Phase#Pers_level			
Phase2#Medium	1.630	0.715	1.11
Phase2#High	3.313	1.606	2.47**
Phase3#Medium	0.784	0.361	-0.53
Phase3#High	3.047	1.478	2.30**
Age	1.005	0.024	0.22
Pers_level#Age			
Medium	0.988	0.024	-0.46
High	1.004	0.025	0.17
Phase#Age			
Phase 2	1.049	0.027	1.88*
Phase 3	1.029	0.029	1.03
Outcome Non-purchase vs Purchase			
Phase			
Phase 2	3.503	7.670	0.57
Phase 3	2.820	6.680	0.44
Pers_level			
Medium	0.689	1.156	-0.22
High	0.001	0.005	-2.37**
Phase#Pers_level			
Phase2#Medium	0.562	0.472	-0.69
Phase2#High	1.662	2.164	0.39
Phase3#Medium	0.838	0.716	-0.21
Phase3#High	3.810	4.851	1.05
Age	1.006	0.059	0.11
Pers_level#Age			
Medium	1.019	0.045	0.43
High	1.135	0.065	2.21**
Phase#Age			
Phase 2	0.975	0.056	-0.42
Phase 3	0.983	0.062	-0.27

Note. Pers\_level = Personalization level; \*p < .1 \*\*p < .05.

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