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How Does Personification Impact Ad Performance and Empathy? An Experiment with Online Advertising

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ABSTRACT

This research explores the value of personas for supporting professional advertisers to design adverts for social media. We test if a personified user group (PUG), when provided to online ad designers, results in better ad performance than when using a non-personified user group (NUG) that had no face picture or name. Our experiment has 30 participants that created Facebook ads using both PUG and NUG. We found that using PUG did increase advertising click performance of ads created by people who are more experienced with ads and personas. Moreover, an analysis of the ad texts showed that the use of PUG increased the empathy of the created ads, supporting the foundational empathy benefit cited in HCI literature. However, the use of PUG did not significantly increase purchase intent. The results imply that using PUG for online ad design evokes more empathy and improves click-through performance. More empathetic ads can have a positive impact on social media users, given that they appear to increase relevance.

1. Introduction

The increase of data analytics tools and platforms has led to the availability of “personified big data” on online users (Stevenson & Mattson, 2019), i.e., user statistics and metrics that describe online user behavior. This personified user data enables “*transferring complex market research data into (...) archetype customers.*” (Haas & Kunz, 2009, p. 603). These user archetypes may substantially improve design performance, yet there has been little empirical testing of this possibility.

In the field of Human-Computer Interaction (HCI), the personification of user data – defined as attributing human attributes to the otherwise nameless and faceless data on users or customers (An, Kwak, Salminen et al., 2018) – has traditionally been embodied in the concept of *persona*. A persona refers to a fictitious representation of a known or presumed target group of users or customers (Cooper, 1999; Pruitt & Grudin, 2003). A persona is a user archetype defined by his or her needs, goals, and interests (Nielsen, 2019). Personas have typically been applied in the development and design of computer software, where understanding user behavior is crucial to develop features and functionalities that serve end-users’ needs (Long, 2009). While personas have typically been employed by User Experience (UX) designers, there is considerable research interest to expand the use of personas from software development/design into other fields, such as e-commerce (Al-Qirim, 2006), health informatics (Huh et al., 2016; LeRouge et al., 2013), and marketing (Salminen et al., 2018). This cross-sectionalism of personas is seen beneficial for the widespread adoption of personas as a design technique in

various industry sectors (Duda, 2018) and encourages research in a variety of contexts, including ad design.

Despite this interest, there is scant empirical research demonstrating the value of *personified user groups* (PUG) in real use. While PUGs are applied in industry to some degree (Al-Qirim, 2006; Duda, 2018; Thoma & Williams, 2009), analytics users predominantly use *non-personified user groups* (NUGs), meaning nameless/faceless data about the customers (numbers, tables, charts ...). This format may not be ideal for the decision-makers to empathize with the user group as real people (rather than as numbers). In contrast, personification aims to give “faces to user data” (Salminen et al., 2019, p. 135), thereby facilitating immersion in the needs of the users *in theory*. While this notion of enhancing empathy through a more personified user representation is pervasive in the HCI literature (Cámara et al., 2018; Wright & John, 2008), studies testing the effect of PUGs are scarce and inconclusive.

Moreover, there is increasing criticism in the HCI community and industry toward using PUGs such as personas. On one hand, new analytics tools and platforms (e.g., Google Analytics, Facebook Insights) are providing alternatives for replacing segmented user archetypes (Salminen et al., 2018). The information afforded by these platforms is seen, by some, as more real-time, more personalized, and more useful than aggregated user segments, such as personas (Salminen et al., 2018). On the other hand, some scholars view personas as dangerous and overly limiting, as personas can potentially enhance stereotyping and discrimination (Hill et al., 2017; Marsden & Haag, 2016; Turner & Turner, 2011).

Overall, there is a lack of studies supporting the effectiveness of personified user groups in real use cases (Chapman & Milham, 2006). Some of the qualitative evidence garnered by HCI scholars show that personified user archetypes might be rarely used in real decision making (Friess, 2012), as well as industry members finding them misleading and abstract (Matthews et al., 2012), leading to potentially biased decision making.

On the other hand, there is a strong base of HCI literature “defending” the use of personified user groups, mostly arising from the fact that these can foster a sense of empathy among decision-makers. This advantage is consistently cited in the literature, starting in Cooper’s seminal persona book (Cooper, 1999) and repeated by influential HCI scholars such as Pruitt and Grudin (Pruitt & Adlin, 2006; Pruitt & Grudin, 2003), Nielsen (2019), and others. However, this stream of literature requires empirical verification, as the justification of the empathy benefits has thus far been based on theoretical and conceptual premises.

To address this fundamental question of the *usefulness of personified user groups*, in this research, we carry out an experiment that focuses on evaluating the impact of using a PUG relative to a NUG. The former contains user group information (e.g., age, gender, location, topics of interest) and the name and face of a user group in a personified profile layout. The latter contains the same user group information *without* the name and face, presented in a spreadsheet format. We show both variants to online marketing professionals and ask them to create online advertisements for the user group. We then deploy these ads in a real Facebook Ads campaign and record the results.

Like personas, PUGs provide summarized user information as a ‘bio’ (i.e., profile layout) of a fictive person. For example, if the average user watches YouTube for one hour a day, then the fictive PUG person’s bio will show that they watch YouTube that amount. PUGs have less information than many personas, though, in that PUGs do not contain quotations or goals that are considered typical information in personas (Nielsen et al., 2015). Personas, thus, can be considered a specialized type of PUG.

Our results provide quantitative evidence on the effect of using personified user information for online ad design. More specifically, the results indicate that the use of PUG increases the level of empathy in the created ads, but the effect of PUG on ad performance is mixed. The results suggest that using PUGs can improve online user experiences through more relevant ads. Moreover, the research relates to the increasing automation in online ad design (Chen et al., 2009; Yang et al., 2017), which raises questions about the comparative advantages of humans vs. algorithms for ad design. Platforms such as Google Ads are increasingly introducing features that use machine learning and various optimization algorithms for ad design and targeting. Naturally, this has raised concerns among human ad designers that, in a certain sense, feel threatened by machines (Head, 1960). To address these concerns, it is important to conduct HCI research that tests the effectiveness of human strengths for design tasks, such as ad design.

More precisely, these benefits (i.e., improved user experience, more effective ad, increased empathy) may relate to the ability of

human ad designers to understand their fellow beings (Cooper, 1999; Nielsen, 2019). If so, PUGs can enhance this empathetic ability and provide ways for humans to strengthen their competitiveness against the automatic ad design algorithms.

2. Related literature

Here we present related prior literature concerning the application of personas, most notably in the business domain, and then the benefits of using personified user group information specifically highlight focusing on the user, communication, and empathy.

2.1. Applying personas in the business sector

Thoma & Williams (2009) apply a multi-method process to develop and validate personas for a large e-commerce business. Their use case, however, was interaction *design*, whereas ours is advertising.

Câmara et al. (2018) introduce *Business Affective Personas* as a methodology for enhancing customer relationships with trust and empathy. Their use case is *tourism management and hospitality design*. Caballero et al. (2014) pinpoint the shared goals of HCI and marketing for achieving *human centrality*. However, their research, focused on *software development*, provides no empirical results.

Onel et al. (2018) used personas to understand consumer behavior regarding *sustainable consumption*, finding three different consumer archetypes with distinct sustainable consumption strategies. Al-Qirim (2006) used personas to investigate e-commerce adoption in small businesses in New Zealand. Thus, their use case was *innovation adoption*. Haas & Kunz (2009) discussed the use of personas for *service mass customization*. Stern (1993) provided a theoretical discussion of using personas for advertising, but they did not actually do that.

Despite being applied to business contexts, we could locate no previous research in the HCI domain about applying personified user group information for online ad design. Ads, in general, have been studied within HCI as a cause for “banner blindness” (Resnick & Albert, 2014) or from the perspective of information saliency and placement (Cao et al., 2019). Some studies have also looked at emotional factors of technology-mediated advertising (Park & Salvendy, 2012) and using technology to adapt advertising for cognitively different users (Sourina & Liu, 2014). The common thread in previous studies is focusing on adverse effects such as interfering with users’ task (Lewandowska & Jankowski, 2017). Even when studies deal with improving ad UX, the focus tends to be on placement and size of ads, rather than their content. Given this, there is a need for experimental studies in HCI that focus on improving *ad content*, not only ad placement.

2.2. Benefits of personified user group information

HCI literature has described several benefits relating to the personification of users, i.e., making nameless/faceless user groups. These include at least the following.

- *Focus on the human.* Personification compresses user data into human representations that include personalized details, such as name and face (Holtzblatt et al., 2005). This humanization can facilitate focusing on the preferred user groups (Miaskiewicz & Kozar, 2011), which is especially beneficial when tailoring product features or communication to users (Cooper, 1999; Jaio & Cindy, 2007; Salminen et al., 2018; Pruitt & Grudin, 2003). Thus, personification can help determine if the right user needs are being addressed (Miaskiewicz & Kozar, 2011).
- *Communication and shared mental models.* Personification summarizes the end-users' attributes in intuitive human representations that are more memorable than tables, numbers, or charts (Cooper, 1999; Nielsen, 2019; Pruitt & Adlin, 2006; Pruitt & Grudin, 2003). These human representations make it “easy for decision makers and employees to understand and to communicate effectively with each other.” (Haas & Kunz, 2009) (p. 603). Often, this involves narratives (Minichiello et al., 2018), e.g., “Mary is a 35-year-old woman who likes ...”. Since humans tend to be receptive to narratives (Polkinghorne, 1988), storytelling facilitates the communication and absorption of attributes of the user group as shared mental models (Madsen & Nielsen, 2010).
- *Empathy toward the users.* Personalized user information enhances identification with the users (Miaskiewicz et al., 2008; Pruitt & Grudin, 2003), enabling decision-makers to obtain an immersive understanding of others. This understanding relies on human beings' ability to empathize with other humans (Krashen, 1984) and is a powerful agent for human-centric design tasks, such as ad design. Consider the difference between writing an ad for a nameless “user group” versus for “a stressed single mom so she can better manage her time.”

Finally, empathy may reduce the self-centering bias of designers, i.e., the tendency to focus on their own experiences instead of those of users (Long, 2009; Matthews et al., 2012). As argued by Hill et al. (2017, p. 6660): “[a decision maker’s] ability to engage and empathize with personas comes in part from the fact that a persona seems like a person – not like a list of facts, a philosophical stance, or an educational document – but an actual person.”

Thus far, quantitative research validating these benefits is scant. There are industry reports and case studies (Forrester Research, 2010; Friess, 2012; Rönkkö et al., 2004; Steenburgh et al., 2009), but there is little empirical work on validating the benefits of PUGs. What is notably missing are experiments or quantitative analyses measuring real performance metrics, such as ad response. In the context of advertisement design, “performance” implies not only the benefit of the advertiser but also the benefit of the audience. If social media platforms expose end-users to “bad” advertising that is irrelevant to them because the ad designers did not truly understand the users, this will hurt the UX of these platforms. In most online platforms, ads are a “necessary evil” as they provide the means to fund the platform and keep its use free for the end-users. In a type of a “social contract” (Salminen, Gach et al., 2018), the

users are willing to accept ads in exchange for the use of the platform. Given this framework, creating more empathetic ads serves the goals of both advertisers and end-users accessing the platforms.

2.3. Research gap

Only a few previous studies consider the impact of PUGs for the design of advertisements or other promotional messages. Vosbergen et al. (2015) used personas to tailor educational messages to the preferences of coronary heart disease patients. However, this study evaluated the messages using self-reported ratings, which is less reliable than observing behavioral data (i.e., if message recipients respond better to the created messages). Chaisuwan et al. (2019) developed personalized user groups to tailor offers and messages to individuals depending upon the user groups' attributes. However, their study did not evaluate the outcome metrics of the messages.

Therefore, there is a lack of research evaluating the communicative and empathy benefits of using PUGs in the design of online advertising. More particular, we could not locate research in HCI concerning the impact of using PUGs to design more empathetic ads. However, the literature does allude to several benefits, often anecdotally backed, of which our primary interest is in the ability of personalized information to *increase communication and empathy toward the user group*.

2.4. Hypotheses

Based on the literature evoking the benefits of personalized user group information in the field of HCI, particularly regarding PUG, we formulate the following hypotheses:

- **H01:** Use of PUG improves ad performance over the use of NUG. Particularly,
 - **H01a:** Use of PUG increases clicking rate of target users (*Communicative aspect*)
 - **H01b:** Use of PUG increases purchase intent of target users (*Communicative aspect*)
 - **H01c:** Use of PUG increase purchase rate of target users (*Communicative aspect*)
- **H02:** Use of PUG increases empathy in the designed ads (*Empathy aspect*)

The first hypothesis deals with the communicative benefits claimed in the HCI literature. It presumes that the use of personification improves communication effectiveness (in this case, ad performance). The reasoning is that ads designed using PUG feel more personal to the consumers than ads designed for nameless/faceless user groups; thus, resulting in an affirmative acceptance.

The second hypothesis deals with the empathy benefit, in that we expect the ads created with PUG to demonstrate more empathetic elements than those created with NUG. Theories of person perception, social facilitation, and self-presentation (Bond, 1982) suggest that adding human characteristics to user interfaces affects individuals' responses to those interfaces. For example, Sproull et al. (1996) found that people

attributed personality traits to a talking-face interface and were more engaged by it than a text-display interface. This heightened immersion, we hypothesize, can also yield different (more empathetic) ad copywriting than using mere spreadsheet information.

3. Methodology

3.1. Performance metrics

To test H01, we choose two metrics that are widely deployed as success metrics for online advertising (see Table 1): clicks and initiated checkouts. Both are important in the industry – click response rates are typically used for assessing advertising appeal (Järvinen & Karjaluoto, 2015), and purchase intent is especially critical for e-commerce companies that want to increase their sales (Clarke & Jansen, 2017; Salminen et al., 2017). We also analyze the actual number of purchases from both PUG and NUG ads.

To test H02, we manually infer “user mentions” from the ad texts to determine their degree of empathy. This approach follows the Cognitive Discourse Analysis (CDA) for accessing cognitive representations and processes through language data (Tenbrink, 2014), specifically employing LIWC (Tausczik & Pennebaker, 2010) to ad texts.

3.2. PUG/NUG creation

Our goal is to translate user analytics into a format that can be easily used for ad design. For this, we apply a standardized algorithmic approach (An, Kwak, Jung et al., 2018; An, Kwak, Salminen et al., 2018) to generate two PUGs (one male, one female) and then create corresponding NUG spreadsheets using identical user group information from Google Analytics (see Figure 1). Both types, PUG profiles and spreadsheets, are deployed in the industry for customer insights, although the current analytics climate emphasizes the use of numbers (Salminen et al., 2018). We provide the English description of the female PUG (“Veera”) from Figure 1 for convenience:

“Veera is a 26-year-old female living in Finland and works in the Management field. She likes to read about ‘Gift cards’, ‘Best Gift Ideas’, ‘All Experience Gifts’ on her Mobile. Her average page visit time is about 3.4 minutes, and on average she visits 6.1 pages. Most often, she comes through Google.”

The PUGs and NUGs were both created using the Google Analytics data of a Finnish e-commerce company. This company sells “experience gifts,” meaning gift cards that contain an experience (e.g., rally driving, dinner in the dark, tandem jump). This industry sector reflects the trend for immaterial

Table 1. Performance metrics obtained from the Facebook Ads platform.

Metric	Purpose
Number of unique clicks	<i>Click performance:</i> This metric measures the number of times a user group member has clicked the ad.
Number of initiated checkouts	<i>Purchase intent:</i> This metric measures the number of times a user group member has placed items in the shopping cart.

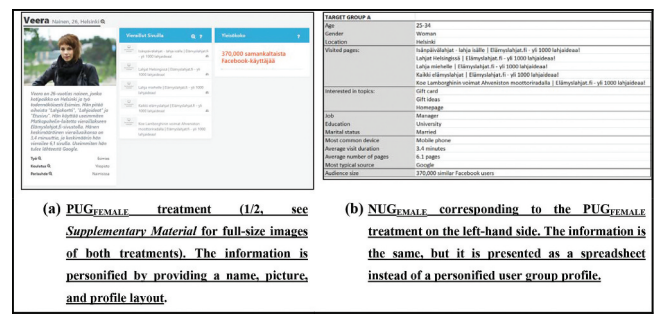


Figure 1. Examples of treatments. Both were created from the real Google Analytics visitor data of the focal organization. PUG_{FEMALE} treatment (1/2, see *Supplementary Material* for full-size images of both treatments). The information is personified by providing a name, picture, and profile layout. NUG_{FEMALE} corresponding to the PUG_{FEMALE} treatment on the left-hand side. The information is the same, but it is presented as a spreadsheet instead of a personified user group profile.

consumption by providing alternatives to material gifts (Clarke, 2008; Clarke, 2006; Salminen et al., 2017).

As the PUG creation methodology has been reported in related work (An, Kwak, Jung et al., 2018; An, Kwak, Salminen et al., 2018; Jung et al., 2018), we omit repetition here. In brief, this approach uses online analytics data to automatically generate personified descriptions of the user segments in the underlying dataset (Salminen, Şengün et al., 2018). This standardization removes human subjectivity from the process of PUG creation, which is a typical concern when creating PUGs (Chapman & Milham, 2006).

Note that we are unable to test “fully rounded” persona profiles (Nielsen, 2019) because of the limitations of the PUG system at the time of conducting the research. The prototype level system did not provide user quotes and goals required for rounded personas. In other words, rather than corresponding with the notion of rounded personas (Nielsen, 2019), the personification we apply corresponds more with the notion of prototype personas (Estell & Reid, 2010) or skeletal personas (Stevenson & Mattson, 2019) from the HCI literature. However, even these less detailed PUGs are worth testing, as they provide the critical personification of *name* and *face*. According to H02, these attributes provide ad writers with enough personified cues to make the designed ads more empathetic.

3.3. Experimental design

The experimental variable is *group*, i.e., use of name and face in a profile layout (PUG) relative to the use of spreadsheet information (NUG). We counterbalanced the sequence of showing the PUGs and NUGs to mitigate potential order effects (Salminen, Nielsen et al., 2018). Thus, each participant uses both a PUG (either male or female) and a NUG (either female or male) in one of the following sequences:

S1: PUG_{MALE} → NUG_{FEMALE} (7 participants)

S2: PUG_{FEMALE} → NUG_{MALE} (7 participants)

S3: NUG_{MALE} → PUG_{FEMALE} (8 participants)

S4: NUG_{FEMALE} → PUG_{MALE} (8 participants)

The 30 participants were randomly assigned to one of these four sequences given the counterbalancing, such that each sequence has a close-to-even number of participants (as shown in the parentheses above). Genders (male/female) were also balanced among the sequences.

3.4. Participants

We recruited the participants from three sources: (a) the focal e-commerce company ($n = 4$), (b) a marketing agency known to the researchers for ($n = 15$), and (c) other marketing professionals known to the researchers ($n = 11$). Out of the 30 participants (see Table 2), 14 (47%) were female. The average age was 30 ($SD = 4.7$), minimum 23, and a maximum of 48 years old. The average experience of participants in online advertising was 3.8 years ($SD = 2.38$) and experience using personas 1.9 years ($SD = 0.47$). Experience using personas was measured because it is a common conceptualization for PUG. Correlation between ad and persona experience was low ($r = 0.098$).

The % for Gender, Ad and persona experience is calculated from the total number of participants.

The participants were grouped in two ways: (a) by their persona experience and (b) by their online ad experience. In both groupings, we labeled participants with more than two years of experience as “more experienced.”

3.5. Task design for Ad design

Each participant (P) was shown a user group with personified information (name, face, and other information) (PUG) and asked to create a Facebook advertisement. Each participant was also shown non-personified information on another user group (i.e., nameless, faceless user group) (NUG), and again asked to create a Facebook ad. Therefore, each participant created two ads.

To facilitate ad design, we provided the participants with a spreadsheet template and instructions that enabled them to write the ads for Facebook. Each Facebook ad consists of text and a picture. Here, the picture was kept constant, and the participants could only design the text part of the ad (see Figure 2).

3.6. Ad campaign creation

After the participants created advertisements, we took the ads and created actual Facebook ad campaigns for the retail company. In Facebook Ads, a campaign contains *ad sets*, and an



Figure 2. Example ad¹ (P17-TG). Each participant created two ads, one using PUG and one using NUG. The image [A], call-to-action button [D], and website URL [E] were constant, while the copytext [B] and ad headline [C] varied by the participant.

ad set contains one or more *ads*. In total, we had 60 ads, two per P (one for PUG, and one for NUG). We divided these into 12 campaigns, each having five identical ad sets with one ad.

For targeting, we created two Facebook target groups whose attributes match the two base target groups (male/female). For example, the female group had the following attributes: Age: 25–34; Gender: Female; Living in: Helsinki; Language: Finnish; Relationship Status: Married; Education Level: College grad. This information corresponded to that shown in the PUGs and NUGs.

The impact of brand familiarity (Campbell & Keller, 2003) was mitigated by excluding Facebook users who may be familiar with the focal company from ad delivery. This exclusion included people that had visited the company’s website in the previous 30 days, and those being on the company’s mailing list. We did this exclusion using the ‘custom audience’ feature of the Facebook Ads platform.

As people in different postal code areas may have different socio-economic characteristics, we used the Finnish postal code system to target people in specific postal codes in the Finnish capital region (Helsinki Metropolitan area). These postal codes were assigned evenly to ensure each ad set had areas from all municipalities in the capital region. Because each ad set had its unique set of postal codes, this also prevented Facebook users from seeing more than one of our ads.

We gave each ad 14 days to run (December 1 to 14, 2018) and a 50 € budget. The campaigns ran in parallel to mitigate temporal effects, such as seasonality (Heien, 2001). The ads ran all the time during the two weeks. The chosen placements were according to each user group’s preferred device on their Facebook feed (desktop or mobile). The ads targeted all operating systems. The Facebook Ads parameters are shown in Table 3.

Table 2. Descriptive statistics for the study sample.

Variable	Summary
Gender	
Male	14 (46.7%)
Female	16 (53.3%)
Ad experience	
Less experienced	11 (36.7%)
More experienced	19 (63.3%)
Persona experience	
Less experienced	20 (66.7%)
More experienced	10 (33.3%)

Table 3. Facebook Ads parameters (C for Campaign, A for Ad set level). All campaigns and ad sets had identical parameters.

Parameter	Explanation
Buying type (C): auction	Participating in competitive bidding with other advertisers.
Campaign objective (C): reach	Facebook's algorithm optimizes for ad exposure.
Budget optimization (C): none	Budget spend is not optimized.
Optimization for ad delivery (A): reach	Facebook's algorithm optimizes for ad exposure.
When you get charged (A): impressions	The advertiser gets charged for each time an ad is shown.
Delivery type (A): standard	The ads can show any time of the day.

After the campaign period, we exported data from Facebook Ads for further analysis. This data included the ads' performance metrics, i.e., *unique clicks* (i.e., each time an ad is clicked), *initiated checkouts*, *impressions* (number of times each ad was shown), *reach* (number of people each ad was shown to), and *frequency* (number of times an ad was shown to a person on average). The three latter were used as control variables (Pedrick & Zufryden, 1991) in the modeling.

3.7. Preprocessing of data

Continuous variables (e.g., number of unique clicks and reach) were summarized using median and *interquartile range* (IQR), as these metrics are more robust when the data is not normal. Categorical data was summarized using counts and percentages. We performed the statistical analysis using the *R* software. We used *principal component analysis* (PCA) to reduce redundancy in the data, as the continuous variables were highly correlated, with Pearson's correlation being above 0.80 across all pairs (see Figure 3a). PCA extracted as much variance as possible from the number of impressions, reach, and frequency. According to standard practice (Jolliffe, 2011), these variables were scaled and centered prior to the analysis. We chose the first principal component (PC1) as a covariate in the analysis since PC1 explained more than 90% of the variance in the three variables. There was a strong positive association between PC1 and the number of unique clicks (see Figure 3b). The distribution of the DV followed a Poisson distribution.

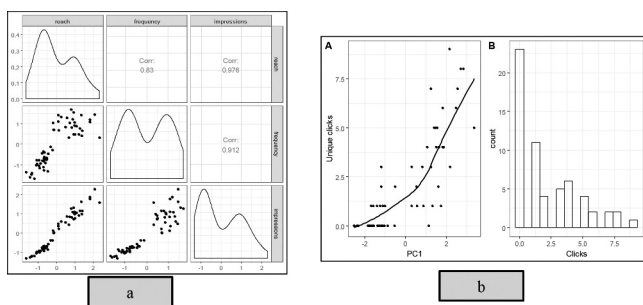


Figure 3. (I) Correlation between ad properties. (II) (a). Association between PC1 and the number of unique clicks. (b). Distribution of the number of unique clicks (a) shows that PC1 is highly correlated with clicks, and thus we needed to include it in the model. (b) shows that the clicks are skewed, which explains why we did not use conventional modeling techniques and why we used median and IQR.

3.8. Number of unique clicks and purchase intention

Generalized Poisson modeling (GPM) was used to model the number of unique clicks and purchase intention. *Generalized Poisson regression* was used since it can model over-dispersion and under-dispersion in count data to a higher degree compared to the conventional Poisson models (Consul & Famoye, 1992). An additional parameter was used to model zero inflation, as the data contained many zeros.

The likelihood ratio test was used to assess whether a random intercept should be used to model the correlation of observations within each participant. PC1 was included as a covariate, as it explains the majority of variance in the three continuous covariates. *Gender*, *group* (PUG vs. NUG), *ad experience* (AE), and *persona experience* (PE) were included as factors in the model. Adding more variables did not result in a better fitting model and would make the model much more complicated. The main effect for these variables was assessed as the following interactions (I):

- **I01:** The interaction between *group* and *AE*
- **I02:** The interaction between *group* and *PE*
- **I03:** The interaction between *AE* and *PE*
- **I04:** The three-way interaction among *group*, *AE*, and *PE*

We used the likelihood ratio test to assess whether these interactions were statistically significant or not. Only significant interactions were included in the model to reduce model complexity. We assessed the model fit using simulated scaled (quantile) residuals for fitted *generalized linear mixed models* (GLMM). The *Quantile-Quantile* (QQ) plot for simulated residuals was examined, as well as the scatter plot for the relationship between the fitted values and standardized residuals.

3.9. Analysis procedure

Regression coefficients were calculated and tested for statistical significance using the Z statistic for GPM (or Wald statistic for binary logistic regression models). Hypothesis testing was performed at the 0.05 level of significance. We exponentiated the model coefficients to obtain the incident rate for the expected count of clicks or checkouts (or odds ratio for completed purchases) since a log link was used when constructing the models.

The final model was used to calculate the estimated marginal counts for GPM at various levels of independent variables, i.e., the expected count of unique clicks at the various levels of factors included in the model. In the presence of statistically significant interactions, the main effects were ignored, and only the interactions were examined to investigate the expected count of unique clicks at various combinations of factors that contribute to these clicks.

4. Results

4.1. Descriptive results

Table 4 communicates the descriptive results of the campaign. The descriptive results indicate that the ads created with PUG

Table 4. Campaign results.

	PUG	NUG	Relative difference*
Number of ad impressions	17,931	14,372	24.8%
Number of people seeing the ads (reach)	3,658	2,817	29.9%
Number of clicks	73	56	30.4%
Click-through-rate**	0.41%	0.39%	5.1%
Number of initiated checkouts	26	20	30.0%
Initiated checkout rate***	35.6%	35.7%	-0.3%
Number of purchases	7	4	75.0%
Conversion rate****	9.6%	7.1%	35.2%

* Calculated as $(PUG - NUG)/NUG$.

** Number of clicks/Number of ad impressions.

*** Number of initiated checkouts/Number of clicks.

**** Number of purchases/Number of clicks.

outperform those created with NUG on all performance metrics. The PUG ads had 30.4% more clicks ($n = 73$ vs. $n = 56$), 30.0% more initiated checkouts ($n = 26$ vs. $n = 20$), and 75.0% more purchases ($n = 7$ vs. $n = 4$). However, the relative differences tend to be small: a 5.1% increase in click-through-rate, a 0.3% decrease in initiated checkout rate, and a 35.2% increase in conversion rate. The reader should not interpret the descriptive results should as proof of PUG outperforming NUG. However, we present this information because it contains basic campaign metrics to inform the reader. The following sections show the results of statistical testing for each hypothesis.

H01: Use of PUG improves ad performance over NUG

4.1.1. GPM results for number of clicks (H01a)

We first examine the clicks.

4.1.1.1. Likelihood ratio test for comparing models.

Likelihood test results showed that including random effects for participants did not significantly improve model fit ($X^2 = 0$, $P > .05$). Thus, we used a GPM with no random effects. Results also showed that including a polynomial (quadratic) term for PC1 did not improve model fit ($X^2(3) = 4$, $P > .05$). The three-way interaction between *group*, *AE*, and *PE* was not statistically significant ($X^2(2) = 3.43$, $P > .05$). Also, the two-way interaction between *AE* and *PE* was not statistically significant ($X^2 = 3.4$, $P > .05$). Thus, we included only the two-way interactions between *group* and *PE* and between *group* and *AE* in the model.

4.1.1.2. Model fit. We conducted two tests to determine if the model was a good fit. First, comparing the distribution of expected zeros in the data against the observed zeros showed that the expected count is not significantly different from the observed count ($P > .05$). Second, comparing the dispersion of simulated residuals to the observed residuals using non-parametric testing showed that the dispersion of simulated residuals is not significantly different from the dispersion of observed residuals ($P > .05$). These results show that the proposed model has a good fit for the data.

4.1.1.3. Model results. The group shows (see Table 4) a statistically significant negative association with the number of unique clicks ($IR = 0.417$, $P < .05$). This result indicates that the expected count of unique clicks among ads written by participants with low *AE* and *PE* when using a PUG is 58.3% lower compared to when using a NUG. Thus, the effect of a PUG is lower compared to the effect of the NUG among ads by participants with low *AE* and *PE*.

Also, *PE* ($IR = 0.665$, $P > .05$) and *AE* ($IR = 0.916$, $P > .05$) do not show a statistically significant association with the unique number of clicks (see Table 5). This result indicates that the main effects of *AE* and *PE* do not affect the number of clicks among ads by participants when using a NUG. However, PC1 shows a significant association with the number of unique clicks ($IR = 1.93$, $P < .001$), indicating that the linear combination of *impressions*, *reach*, and *frequency* is positively associated with the *number of unique clicks*.

Two interesting aspects of the model are the two-way interaction between the *group* and *PE* ($IR = 2.08$, $P < .05$) and the two-way interaction between the *group* and *AE* ($IR = 2.82$, $P < .05$). The two-way interaction between *group* and *AE* indicates that the expected count of unique clicks among ads by participants with more *AE* who are using a PUG is 2.82 times the expected count for ads by participants that have more *AE* and are using a NUG. These results indicate that participants with more *AE* are more likely to benefit from using a PUG.

Similarly, the statistically significant two-way interaction between the *group* and *PE* indicates that the expected count of unique clicks among ads by participants with more *PE* who are using a PUG is 2.08 times the expected count of ads by participants with more *PE* who are using a NUG. This result suggests that participants with more *PE* are more likely to benefit from being shown a PUG.

The expected count of unique clicks among ads written by participants with low *AE* and *PE* who are using a PUG is 58.3% lower compared to those who are using a NUG. This result indicates that the effect of a PUG is lower compared to the effect of the NUG among ads by participants with low *AE* and *PE*. So, participants with less *AE* and *PE* are more likely to benefit from using a NUG compared to a PUG. In contrast, participants who either have more *AE* or *PE* are more likely to benefit from using a PUG. Moreover, the benefit is higher for participants who have both more *AE* and more *PE* since the effects are multiplicative ($IR = 2.08 \times 2.82 = 5.69$). The result

Table 5. The GPM for the count of unique clicks. IRR = Incident rate. The intercept ($IR = 1.23$, $P = .29$) represents the expected number of unique clicks for the ads written by a female participant with less *AE* and *PE*.

Predictors	IR	CI	p
Intercept	1.23	0.835–1.81	0.29
Group (NUG)	Ref		
Group (PUG)	0.417	0.237–0.733	0.002*
Persona experience (Less)	Ref		
Persona experience (More)	0.665	0.363–1.22	0.187
Gender (Female)	Ref		
Gender (Male)	1.18	0.791–1.75	0.42
Ad experience (Less)	Ref		
Ad experience (More)	0.916	0.545–1.54	0.739
PC1	1.93	1.69–2.19	< 0.001*
Group (PUG) × Persona experience (More)	2.08	1.03–4.2	0.04*
Group (PUG) × Ad experience (More)	2.82	1.4–5.7	0.004*

indicates that the participants more experienced with both personas and ads are more likely to benefit from using a PUG compared to the other participants.

4.1.1.4. Estimated marginal count of unique clicks. The counts of unique clicks were estimated at various combinations of *AE*, *PE*, and group (see Figure 4). The counts for these various combinations were estimated at various levels of PC1 to consider such covariate since reach, impressions, and frequency affect the final number of clicks regardless of the factors included in the model.

Based on model results, participants with less *AE* and *PE* are more likely to benefit from the NUG compared to PUG. The participants more experienced with ads and personas are the ones who are most likely to benefit from a PUG.

Based on these results, H01a is partially supported: *At high levels of ad and persona experience, using personified user groups increases the ad clicks.*

4.1.2. GPM results for purchase intent (H01b)

We next examine purchase intent.

4.1.2.1. Model fit. As before, we use GPM to model purchase intent (i.e., the number of initiated checkouts). Model residuals indicate that the model was a good fit for the data. The three-way interaction was not statistically significant, so we did not include it in the model. All two-way interactions were statistically significant ($X^2 = 1.97$, $P > .05$). Including a random intercept also did not improve the model fit ($X^2 = 0$, $P > .05$).

4.1.2.2. Model results. The intercept (IR = 0.016, $P < .05$) represents the expected number of initiated checkouts for ads written by a female participant with less *AE* and *PE* (see Table 6). The group did not show a significant association with the expected number of checkouts (IR = 5.35, $P > .05$).

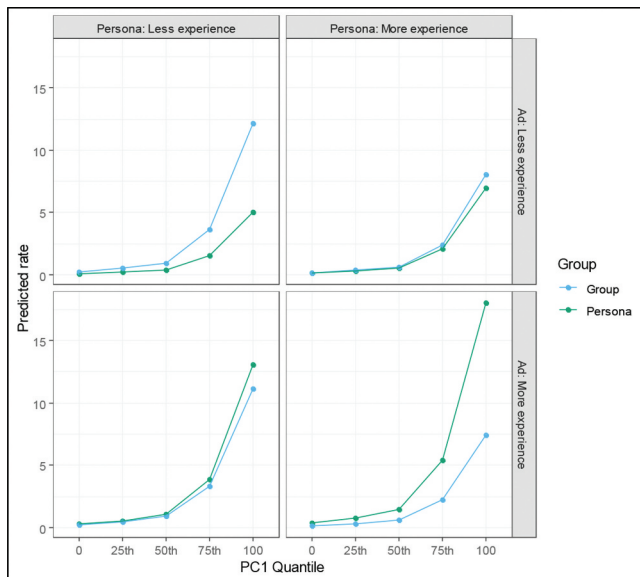


Figure 4. Estimated counts at various combinations of factors. The figure on the top left shows that NUG is more beneficial than PUG (low *AE* and *PE*), while the bottom right shows that PUG is more beneficial in those with high *AE* and *PE*.

Table 6. GPM for the count of initiated checkouts.

Predictors	IR	CI	p
Intercept	0.016	0.001–0.223	0.002*
Group (NUG)	Ref		
Group (PUG)	5.35	0.388–73.82	0.21
Persona experience (Less)	Ref		
Persona experience (More)	84.597	6.72–1064.55	< 0.001*
Gender (Female)	Ref		
Gender (Male)	0.99	0.317–3.09	0.986
Ad experience (Less)	Ref		
Ad experience (More)	13.489	1.347–160.354	0.04*
PC1	3.177	1.699–5.94	< 0.001*
Persona experience (More) × Ad experience (More)	0.062	0.005–0.752	0.03*
Group (PUG) × Persona experience (More)	0.015	0.001–0.197	0.001*
Group (PUG) × Ad experience (More)	0.844	0.072–9.848	0.892

The result indicates that the expected count of initiated checkouts by participants with low *AE* and *PE* when using a PUG is not significantly different from the count when using a NUG.

Higher *AE* (IR = 13.489, $P < .05$) and *PE* (IR = 84.597, $P < .05$) were significantly associated with the expected count of initiated checkouts. The result indicates that the main effects of ad and persona experience affect the number of checkouts. PC1 showed a statistically significant association with the number of unique clicks (IR = 3.177, $P < .001$), indicating that the linear combination of impressions, reach, and frequency is positively associated with the number of initiated checkouts (see Figure 5).

The estimated marginal counts show that the effect of *PE* is significant among participants with low *AE*. Among participants with high *AE*, the expected count was similar among participants irrespective of *PE*. However, the expected count was significantly different among participants with low *AE*. The estimated marginal count of initiated checkouts in ads by participants with low *PE* was 91.3% lower compared to participants with high *PE* ($P < .05$). The difference was not statistically significant within participants with high *AE* ($P > .05$).

The two-way interaction between *PE* and *group* was statistically significant (IR = 0.015, $P < .05$). The result indicates that the expected count of initiated checkouts in ads by participants with high *PE* when using a PUG is 98.5% lower compared to the expected count among those with high *PE* when using a NUG, meaning that NUG is more helpful for participants with high *PE*.

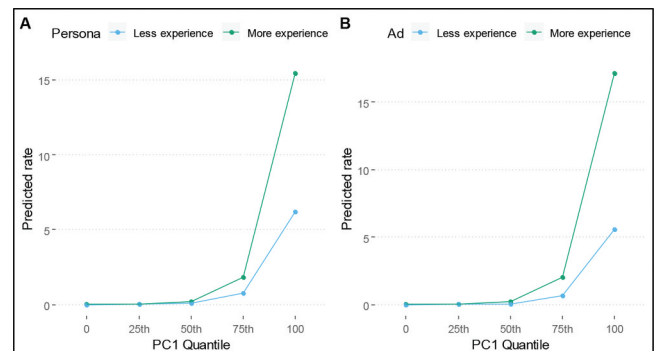


Figure 5. The expected count of checkouts based on ad and persona experience.

Thus, there is not enough evidence to support H01b: *The use of a personified user group did not improve the purchase intent of the target users.*

4.1.3. GPM results for purchase rate (H01c)

Results showed that none of the interactions was statistically significant ($P > .05$). Thus, we included only the main effects in the model. The analysis also shows that a random intercept is not needed for participants. The model explained 28.7% of the variance in the DV (completing a purchase).

Results in Table 7 show that only the linear combination of impressions, reach, and frequency was significantly associated with the odds of obtaining a purchase ($OR = 10.6$, $P < .05$). The results indicate that the odds of completing a purchase increases with increasing reach, frequency, and impressions. *Group*, *AE*, or *PE* were not significantly associated with the odds of completing a purchase. Thus, there is not enough evidence to support H01c: *The use of a personified user group did not improve the purchase rate of the target users.*

H02: Use of PUG Increases Empathy in the Designed Ads

Addressing the second hypothesis, we used two main approaches: (1) an Empathy dictionary developed based on manual analysis of the ad texts, and (2) Linguistic Inquiry and Word Count (LIWC) dictionary with predefined vocabularies for psychological processes. We carried out multiple analyses to increase the robustness of the findings. The following sections report the results.

4.1.4. Empathy dictionary

For building a dictionary that reflects the observed empathy in the designed ads, we used CDA (Tenbrink, 2014), a technique that aims to extract meanings from text. The number of user group mentions determined the level of empathy in ad texts created by the participants.

In this process, we divided all ad texts created by the participants into two text corpora, CORPUS_{PUG} and CORPUS_{NUG}, according to whether they were created using a PUG or a NUG. These text corpora were processed by an algorithm that computed word frequency, i.e., the number of times each unique word was mentioned. Two researchers then manually coded the Top-400 words for each corpus to extract *if the word referred to a specific user group* (i.e., binary classification of ‘yes’ or ‘no’), such

as “her,” “him,” “husband,” “wife,” “your family,” and so on. If a word contained a user group mention, we coded it as ‘1’; if not, we coded it as ‘0’. The reasoning is that the user group mentions are considered to be a sign of empathy. That is, an ad mentioning a person or people demonstrates more empathy toward the user group than an ad not talking about people.

Because the coding process involves some degree of subjectivity, i.e., two people may disagree if a particular word refers to a user group, two researchers independently coded the ad texts. We did not deem the inter-rater agreement score after the first iteration (Cohen’s $k = 0.788$) satisfactory. This prompted the researchers to work collaboratively toward an understanding of what empathy means in the ad design context (see Table 8). For example, “for husband” is a user group mention displaying empathy because it reflects the user group information given to the participants (Veera’s marital status = married → buys a gift for husband), while “gift recipient” is not because it does not specify a user group. Other non-empathetic words included “experience” (i.e., mentions a *product*, not people), “Christmas” (mentions a *gift-giving occasion*, not people), “unforgettable” (mentions a *product benefit*, not people).

Through this collaborative coding process, we established a shared agreement of which words reflected empathy in the ad texts and which not. Examples of the former, dubbed ‘empathy vocabulary,’ are shown in Table 9. We provide the full list in the *Supplementary Material* in both English and Finnish.

After coding the empathy mentions, we tallied the number of total mentions displaying empathy for CORPUS_{PUG} and CORPUS_{NUG}. We did this by multiplying each word that was labeled as empathetic with the frequency of that word in the corpus. The results show that ad texts designed using a PUG yield 56.4% more user group mentions ($n = 61$) than those designed using a NUG ($n = 39$).

We also conducted a paired samples t-test to compare the number of empathy words in PUG and NUG conditions. There was a significant difference in the scores for the PUG ($M = 1.24$, $SD = 1.29$) and NUG ($M = 0.80$, $SD = 0.86$) conditions; $t(48) = -1.95$, $P = .056$. These results indicate that when ad designers use PUG to design ads for a user group, the number of user group mentions in the ad text increases.

Moreover, the PUG corpus includes 40% more unique empathy words than the NUG corpus (see Figure 6), indicating a wider variety of empathy mentions.

Overall, these results support the second hypothesis: *Use of PUG increases the level of empathy in the designed ads.*

Table 7. Binary logistic regression model results for the probability of completing a purchase.

Predictors	OR (Odds ratio)	CI	p
Intercept	0.022		0.002*
Group (NUG)	Ref		
Group (PUG)	5.16	0.29–6.65	0.68
Persona experience (Less)	Ref		
Persona experience (More)	12.9	0.5–13.31	0.26
Gender (Female)	Ref		
Gender (Male)	1.14	0.14–8.05	0.96
Ad experience (Less)	Ref		
Ad experience (More)	0.596	0.067–4.36	0.57
PC1	10.6	1.68–45.75	0.01*

Table 8. Examples of an empathetic and non-empathetic ad.

Empathetic ad (P25) that mentions specific user groups (in yellow)	(B) Non-empathetic ad (P02) that mentions product benefits and the company’s offering (in yellow)
<i>Gift card from [company name] provides an easy and quick way to delight your spouse on a special day. Delight your husband with a memory that lasts for a lifetime!</i>	<i>Give a gift that doesn’t collect dust in the corner! One gift card – more than 1300 choices. Check out the constantly expanding selection: [link to website]</i>

Table 9. Examples from Empathy vocabulary with the number of times mentioned in ad texts created using PUG and NUG. The most common user group mention is ‘he/she’ (n = 6).

Empathy word	LIWC category**	PUG	NUG
Man/husband*	SP	10	2
Loved one	AP, SP	2	3
Your spouse	PP, SP	7	3
He/she* (or him/her)	PP	8	4
Dad/father	SP	4	7
Mom/mother	SP	0	1
Wife	SP	1	4
Family	SP	5	2
Boyfriend	SP	2	0
Girlfriend	SP	1	0
In-laws	SP	1	0
...
Total	...	57	37

* ‘He’ and ‘she’ are the same word in Finnish. ‘Man’ and ‘husband,’ too.

** Definitions below:

- SP = Social Processes.
- AP = Affective Processes.
- PP = Personal Pronouns.

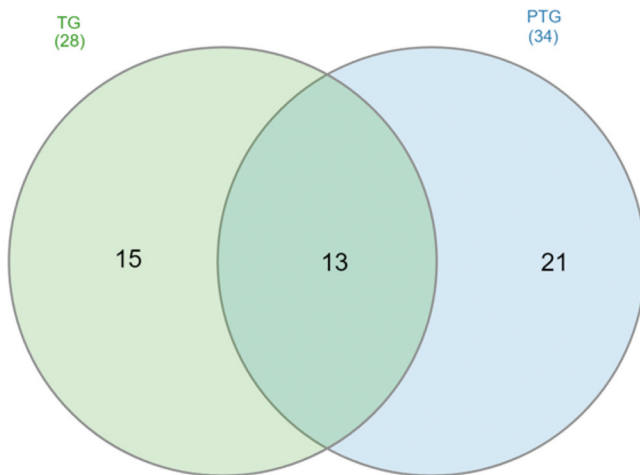


Figure 6. Empathy words appearing in PUG and NUG ad texts. Twenty-one words appear only in PUG, 15 only in NUG, and 13 appear in both.

4.1.5. LIWC analysis

We used the LIWC dictionary (Tausczik & Pennebaker, 2010) to analyze the ad texts further. While the previous step of using an empathy dictionary represents an *inductive* approach where we derived the words from the data, the use of LIWC represents a *deductive* approach, in which we use an established word-level coding scheme. In other words, the methods provide methodological triangulation.²

LIWC represents an established word-level coding scheme that has “been linked in hundreds of studies to interesting psychological processes” (Tausczik & Pennebaker, 2010, p. 30). LIWC has also been deployed for the lexical analysis of empathy in previous research. Alam et al. (2016) use the full categories for an automatic machine learning analysis. Marina Litvak et al. (2016), in turn, focus on specific categories for hypothesis testing. The latter approach seems more appropriate for our use of LIWC, as we are interested in addressing a specific hypothesis of there being more empathy in PUG ad texts.

The LIWC taxonomy contains 80 categories with a varying number of words reflecting that category (e.g., sentiment).

While these categories do not directly contain words labeled for ‘empathy,’ we identified several categories that are relevant for our research purpose and match our operational definition of empathy. These include (1) *Personal pronouns* (subcategories: i, we, you, she or he, they), (2) *Affective processes* (positive emotions, negative emotions, anxiety, anger, sadness), and (3) *Social processes* (family, friends, female, male). Because LIWC dictionaries are not available in Finnish, the ads were first translated to English and then passed to the LIWC 2015 software (the latest version in January 2020).

Descriptive statistics were performed using counts and percentages. The differences in scores between PUG ads and NUG ads were statistically tested. More specifically, we used multivariate logistic regression analysis to assess whether the odds of using the selected categories were significantly different between the PUG and NUG ads. The odds ratio (OR) was calculated for each of the categories and tested for statistical significance, i.e., whether the OR significantly differs from 1. Hypothesis testing was performed at the 5% level of significance.

The results (Table 10) showed an overall increase of 3.1% in the use of personal pronouns in PUG ad texts (87.5%, n = 28) relative to NUG ad texts (84.4%, n = 27). The difference in their use was not statistically significant ($P = .26$). However, the analysis of individual categories revealed some interesting findings. The increase in ‘he’ and ‘she’ pronouns (+12.5%) in PUG ad texts (21.9%, n = 7) compared to NUG (9.38%, n = 3) was statistically significant (OR = 6.5, $P = .04$). Moreover, there was a statistically significant increase (OR = 7.72, $P = .04$) in the use of “We” in the PUG ads (43.8%, n = 14) compared to the NUG ads (21.9%, n = 7).

Furthermore, we observed a 12.5% decrease in the use of negative emotions in ads created using PUGs (21.9%, n = 7) relative to those created using NUGs (34.4%, n = 11). This difference is not statistically significant ($P = .71$). The use of positive emotions decreased slightly in the PUG group (84.4%, n = 27) compared to the NUG group (87.5%, n = 28). There was also an increase (+6.25%) in the ‘friend’

Table 10. LIWC categories and results. Relative differences in LIWC use between PUG and NUG (PUG % – NUG %) in square brackets. Significant differences bolded.

LIWC category	Correspondence to empathy
Personal pronouns (PPs) [+3.1%]	Using PPs in ads indicates empathy because PPs refer to people (thus, PUG ads are expected to have more PPs)
● she or he [+12.5%]*	
● we [+21.9%]*	
● you [–6.25%]	
● they [0%]	
Affective processes (APs) [–9.38%]	Stronger expressions of affection indicate empathy because empathy evokes other emotional states (thus, PUG ads are expected to have more APs)
● positive emotions [–3.12%]	
● negative emotions [–12.5%]	
● anxiety [0%]	
● anger [0%]	
Social processes (SPs) [+3.12%]	Expressions of social processes indicate empathy because these terms relate to an individual’s roles in society (thus, PUG ads expected to have more SPs)
● family [0%]	
● friend [+6.25%]	
● female [+12.5%]	
● male [+9.38%]	

*significant at $\alpha = 0.05$.

category when comparing PUG (21.9%, $n = 7$) and NUG ads (15.6%, $n = 5$). The difference was not statistically significant ($P = .19$).

In conclusion, the LIWC analysis shows that some dimensions of personal pronouns are higher in the PUG ad texts. Most notably, the use of 'We' and 'She/He' was higher in PUGs compared to NUGs. Therefore, H01 is partially supported: *Use of personified user groups increases personal pronouns in the created ads (particularly the dimensions of 'We' and 'She/He')*.

5. Discussion

This research tested if a (PUG) results in better ad performance relative to a (NUG) in a 30-participants experiment of creating Facebook ads. Findings show that using PUG increased the number of clicks for ads created by people more experienced with both ads and personas. An ad text analysis showed that using PUG increased the empathy expressed in the ads. However, PUG use did not significantly increase purchase intent.

5.1. Main contribution for HCI

Our research makes three main contributions:

- First, we report behavioral data from a real-world experiment testing PUGs to complement case studies (Friess, 2012; Matthews et al., 2012) and self-reported metrics (Vosbergen et al., 2015) reported in previous studies. Running the ads in a real advertising channel affords insights into how the members of the user group respond to the ads created with PUG vs. NUG.
- Second, we apply PUGs, of which personas are a type, on a quickly growing industry. Competition in online advertising is fierce, and the results can yield performance gain, especially for gaining clicks, for organizations applying PUGs. The raw counts of our experiment show that ads created with PUG as well as those created with NUG on all critical metrics, with PUG ads receiving more clicks, more initiated checkouts, and more purchases. However, only the click results are statistically significant, and only for a subset of participants (those more experienced with both ads and personas).
- Third, we empirically investigate empathy that is widely proposed in HCI theory as a foundational benefit of personified user information (Cooper, 1999; Hill et al., 2017; Jansen et al., 2017; Nielsen, 2019) but lacking empirical verification – specifically, we show evidence of its existence in the ad design context. Based on our analysis, the empathy benefits of PUG claimed in the HCI literature appear real.

Overall, our results show that PUGs are especially powerful for people with previous experience in online advertising and HCI methodologies. We speculate the reason being that these people are able to leverage both the human-centricity of PUGs as well as the best practices of advertising, thus achieving better advertising results.

5.2. Implications for dialogue between marketing and HCI

Duda (2018) asks (p. 173): *who owns personas?* Personas are sometimes developed by the UX department in organizations, sometimes by the marketing department. Regardless of who creates PUGs, for both domains, the purpose remains the same – shift decisions toward user-centered thinking. By enhancing empathy, PUGs can become a vehicle for a higher degree of market orientation and thus support both commercial objectives and UX.

Recognizing this shared goal can bridge some of the research findings in these two fields. Calls for increasing interdisciplinarity have previously been made concerning management information systems and HCI (Zhang & Dillon, 2003), for example. We suggest that marketing and HCI should exchange theories and concepts, as well. In particular, marketing concepts that could benefit HCI scholars include *market orientation* (Kohli & Jaworski, 1990; Narver & Slater, 1990) and *customer-dominant logic* (Stauss et al., 2010), as these concepts are similar to the concept of *user-centricity*.

For HCI, our findings provide empirical support for the claimed empathy benefits of personification. While in the past personas have primarily been studied in the perspective of UX designers (i.e., “design personas” (Matthews et al., 2012; Nielsen et al., 2015)), it is important to explore persona applications in other domains, such as marketing, to build bridges within the different disciplines that can employ PUGs as decision-making tools.

5.3. Practical implications for online Ad writers and end users

We are safe to recommend the use of human-centric approaches in online ad design, as doing so actually improved the click performance for the participants who were more experienced with online ads and personas. The fact that persona experience increases ad performance relative to only advertising experience suggests that online advertisers should be trained in the use of PUG and personas, as this leads to performance increases over having higher advertising experience only.

Given that showing a PUG increases empathy in the ads, is the use of a persona necessary? Or, should we just tell advertisers to incorporate language about a specific type of person (e.g., he/she, husband/wife) in their advertisements? While this is an interesting interpretation of the results, the real question may be: *how* to make ads more empathetic? From the advertising theory of segmentation, targeting, and re-targeting (Jenkinson, 1994; Lambrecht & Tucker, 2013; Matz et al., 2017), it seems apparent that empathetic messages improve performance. This appears to be one of the *core* tenets in advertising. If the principle of making ads personalized is so well known, why do the ad writers not apply this principle in *all* of the ads? From our findings, we can see they are not doing this. Instead, the numbers-oriented information about the user group seemingly sets a mental frame of writing less empathetic ads, whereas showing the information in the form of real people

seems to frame the participant's mind-set to focus on the individual, which appears to be a benefit of PUG usage.

While this can be considered as a “trivial” rationalization for HCI theory (long arguing in favor of empathy), the fact is that the effect of PUGs on the empathy in ads has not been empirically shown in previous research, addressing a need in the literature (Kuhn, 1970). The fact that our study provides evidence to back the usefulness of PUGs, especially in the design task of creating advertisements, provides fuel for the dialogue of theory and empiry within the HCI discipline.

Regarding the end-users exposed to online advertising on social media platforms, we argue that more empathetic ads can also be considered as more user-friendly. The relevance of the shown advertisements is relevant for UX on social media platforms. Although we do not directly measure the impact of better ads on UX, metrics such as click-through-rate *approximate* improvement of UX, as users indicate by clicking that the ad is perceived as relevant by them (Jansen, 2011; Kathuria et al., 2010). Making more empathetic, more relevant ads can, therefore, be well aligned with the core values of the HCI community.

5.4. Limitations and future research

The rarity of initiated checkouts (<30 for both PUG and NUG) can hinder the detection of real effects. Higher ad exposure could yield significant differences. Moreover, we omitted the reporting of completed purchases from this study due to their small number. More widespread and longer campaigns may be needed to test completed purchases because they are relatively rare occurrences (less than 0.05% of people who saw an ad completed a purchase).

Another limitation is that we were not testing real personas but PUGs with limited personified information. Nevertheless, the advantage of this approach is that the system generating the PUGs from Google Analytics data is readily deployable. We also show that including only name and face as personified information can be enough to add the level of empathy in PUG users' creative outputs. Future studies should explore NUG vs. PUG vs. fully rounded personas.

Future research could also inspect several aspects of ad texts, such as lexical diversity, gender differences in empathy mentions, as well as operationalizing empathy as a dummy variable for the performance analysis.

6. Conclusion

Using PUG increased click performance of ads created by people who are more experienced with ads and personas. Moreover, the use of PUG increased the empathy of the created ad texts. However, the use of PUG did not significantly increase purchase intent or actual purchases. The results imply that using PUG for online ad design evokes more empathy and improves some aspects of advertising performance. Benefits are the highest for users that are experienced with both personas and online advertising.

Notes

1. Translation in English (original in Finnish): Ad text: “*Getting a meaningful gift for a male loved one can cause headache, but through [company name] you can find ideas also for the difficult cases!*” Ad title: “*When scent candle is not enough*”.
2. Note that this analysis involves some overlap between the empathy dictionary – we have highlighted the overlapping terms in Table 9 where applicable.

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