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The Ability of Personas: An Empirical Evaluation of Altering Incorrect Preconceptions About Users

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Highlights

- personas can alter the incorrect preconceptions of decision makers about users
- personas can increase the accuracy of assessment of users
- personas can increase the confidence of assessment of user attributes
- personas do not change correct preconceptions

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Abstract

False preconceptions about users can result in poor design, product development, and marketing decisions, so rectifying these preconceptions is essential for organizations. This research quantitatively evaluates the ability of data-driven personas to alter decision makers' preconceptions about their online social media users. We conduct a within-participant experiment of 31 professionals carrying out a workplace task scenario. The participants' conceptions of user attributes are recorded both before and after interacting with personas created from real user analytics data. Using statistical analysis to compare the responses, we find that personas had a significant effect on changing preconceptions about the audience segments. After interacting with personas, 81% of the participants changed their preconceptions of the audience, and 94% of the participants maintained or increased the accuracy of their perceptions of the audience after engaging with the personas. Moreover, the confidence of the participants in their responses increased. However, two participants did not change their preconceptions even when faced with contradictory factual information, which highlights the need for accompanying initiatives to align user preconceptions with user data fully.

Keywords

Personas; User understanding; User preconceptions; Social media; Online users; Text analytics

Introduction

Personas "give faces" to people of a user segment from a given population [19, 55], with the intuition being that personas can help guide decisions about system, service, product, or content development [30]. Ideally, personas communicate attributes, behaviors, and objectives of people belonging to a given user segment and help designers understand users [11] in human computing interaction (HCI) and related fields, including system development and design [36, 37, 42, 52, 55], marketing and advertising [57, 71], and content production [64]. The HCI literature claims many benefits of personas compared to other methods such as analytics [66], although several of these claimed benefits [2, 3, 13, 15, 20, 22, 23, 46, 50, 51, 58] have not been empirically verified.

One of the main benefits of personas that is often evoked in the HCI literature is that they can present users' goals that differ from those of decision makers, thereby altering the preconceptions about users [28, 35, 43, 60]. Despite this claimed benefit, there has been little to no quantitative research that would empirically show that personas do shift decision makers' preconceptions about the users [58]. Additionally, there are concerns about whether personas enhance user understanding in the presence of other analytics tools for probing into online users [18, 60, 66]. Therefore, as concepts and tools, personas have come under criticism for being of little actual value for practitioners [15, 16] and for enhancing, rather than reducing, stereotypical thinking [45].

This leads to one of the quintessential questions concerning personas' real value for HCI design: *Do personas impact decision makers' preconceptions about the users, and, if so, do they aid decision makers' ability to create user-friendly products, experiences, and content?* The answers to these questions can advance scientific understanding of personas and also clarify how personas fit into the pedigree of other, perhaps more trending, user insight options, such as Web and social media analytics. The answers can also help businesses and other organizations better identify and meet their users' needs with the most appropriate design tools. Thus, our study advances the field of HCI by testing the effects of personas on shifting preconceptions about users empirically and quantitatively.

We define "preconception about the users" as *descriptive information and insights that a decision maker has internalized about a user segment*. These preconceptions may or may not be factually correct; they simply exist in the decision maker's mind. If personas do enhance user understanding, they *should* change incorrect preconceptions and confirm correct preconceptions, which might lead to an increase in the confidence decision makers have of their user insights.

In this research, we evaluate personas for their ability to change incorrect preconceptions or confirm correct preconceptions, specifically employing data-driven personas (DDPs). These DDPs are based on quantitative data and represent segments of an online population, such as social media users and online audience segments [7, 17]. While personas are traditionally synthesized from interviews or focus groups with users [37, 53, 56], algorithmic methods for creating DDPs are increasingly available and popular [7, 34, 74]. These methods are seen to provide benefits, especially for understanding diverse, large-scale online audiences that typically have a large amount of associated data [38]. Personas have been criticized for lack a real value to enhance user insights, especially in the modern environment where many other analytics tools are available for probing into online users [31]. Conversely, analytics present the cold hard numbers but provide little empathy for the actual users [31]. Using DDPs could provide treatments to enhance the value decision makers [1] get from personas.

In this study, we investigate how users interact with a DDP system. To explore this interaction, we recruit 31 participants and ask them to use the persona system for inferring user insights about their organization's online users. We focus on *Automatic Persona Generation (APG)*— a DDP system that creates personas from online user populations. To explore the ability of personas to change preconceptions, we record participants' responses regarding three important user-centric questions: (a) who the users are (*WHO*), (b) why they are interacting with the company's content (*WHY*), and (c) what can be done to attract more users (*WHAT*). These preconceptions are collected using repeated questionnaires both before (*PRE*) and after (*POST*) participants interact with a set of user personas from the DDP system. This research has direct implications for supporting the value of personas for reducing stereotypical thinking about and increasing the focus on users in a variety of domains, including online content creation, social media marketing, and online advertising; these fields rely on achieving engagement with online users [4].

Literature Review

Personas represent groups of target users with common attributes, needs, characteristics, and goals [19, 55]. This methodological concept was introduced in the late 1990s, in the field of software development [19] and gained popularity as a part of *user-centered design* (UCD) processes in HCI [3, 24, 27, 56, 69]. A variety of benefits are attributed to personas [61], including focused user outcomes, consensus-building among team members, improved user design, and enhanced product positioning [39, 68], although empirical support for these benefits is often lacking [16, 41, 58].

Personas *give faces* to nameless user groups and provide insights to user behavior under different use cases [56]. As personas are presented as 'real' people, they draw from the human ability to form impressions and make inferences about previously encountered people, thus opening a window to biases and stereotyping from the decision makers' social perception [45]. However, at the same time, personas help the decision makers relate with the users, making the decisions more informed [26]. As suggested by Sproull et al. [72], people behave differently when designers introduce more human-like qualities into interfaces, as long as these qualities are relevant and engaging [2]. Therefore, personas can *cognitively engage* the decision makers [55] while making them *empathize* with the users [2, 12, 49]. They also enable decision makers to curb *self-centering bias* (i.e., interpreting happening in a personal way) that may occur during the UCD process [47].

Benefits of personas reportedly also include an increased *focus* on the important user segments and their needs [19, 27, 55] when making key decisions. One way to facilitate such a focus is by having a standard user model [49] for making decisions or evaluating design features. Pruitt and Grudin [56] point out that the personas enable focusing on design aspects. Similarly, Judge et al. [33] present a study of the design and user experience practitioners, reporting that personas led to more group focus and a more complete user discussion. Personas are also supposed to *improve communication* [19, 26] among team members about targeted users with stakeholders of the organization [47]. Purportedly, this communicative ability enables team decision makers to identify backgrounds different from their own and realize that user preferences may deviate from their own inclinations [48, 50].

Understanding the different worldviews of users is tied to personas' ability to *challenge the established preconceptions* about the users within the organization [72]. These preconceptions are the mental representation of users and their behaviors. When personas are created from actual user data [56], the user insights inferred from them can deviate from the existing beliefs about who the users are, why they are users of the company's product, and what can be done to enhance the user experience. Incorrect preconceptions about users within the organization create friction between the perceived and real user segments, resulting in the decisions not being user-centric. A persona that accurately portrays user data can reportedly reduce this conceptual gap by conveying factual information about the users, including their attributes and interests [55].

To reduce this conceptual gap, personas need to successfully change misconceptions about the targeted users. Furthermore, the organizational decision makers should also be open to realigning their preconceptions when they contradict DDPs [37, 54]. This willingness to accept data is required for personas to prevent and rectify false preconceptions [47]. Yet, from our review of prior work, we could not locate any previous study empirically examining whether DDPs or personas, in general, can change preconceptions. Instead, qualitative studies, such as [58], have shown that personas may act instead to justify design rationales 'after the fact'. Still, this criticism also has not been investigated in a quantitative study to the best of our knowledge.

In this research, we address the claimed benefit of personas to enhance user, audience, or customer understanding by specifically focusing on the alleged ability of personas to change/confirm the preconceptions of decision makers about users. This purported ability is a key advantage of the persona design technique, founded in the following aspects:

a) challenging established user preconceptions [72],
b) data in support of deviations from existing preconceptions in the organization about the users [56],
c) reducing the perceptual gap between perceived and real user goals [55],
d) rectifying false perceptions of the users [47], and
e) communicating insights with others [19, 26].

To the best of our knowledge, this ability of personas to alter incorrect preconceptions or confirm correct ones has not been rigorously evaluated. This research gap motivates our current study.

Research Questions and Hypotheses

The research questions (RQs) we address in this study are:

- **RQ01**: Can DDPs change preconceptions about users?
- **RQ02**: If so, what is the effect of DDPs on these preconceptions?
- **RQ03**: If so, what aspects of DDPs are employed in changing those preconceptions?

Addressing these important questions will inform the HCI community on one key aspect of persona benefits. Based on the evidence from the literature review presented above and the research questions, we formulate the following hypotheses:

- **H01:** DDPs change *preconceptions* about users [72] (**RQ01)**.
- **H02:** DDPs improve the *accuracy* of perceptions about users [55] (**RQ02)**.
- **H03:** DDPs improve *confidence* in communication about user attributes [55] (**RQ02)**.
- **H04:** DDPs improve the *empathy* expressed in communication about users [2, 12, 49] (**RQ02)**.

- **H05:** DDPs improve the *detail* (**H05a**) and *precision* (**H05b**) of communication about the users [19, 26] (**RQ02)**.

In summary, the need for addressing these hypotheses is that their rigorous verification/refutation is lacking in the existing HCI literature, even though many claims are made both in favor of and against the impact of personas on understanding users. Relatedly, we investigate what aspect of personas may lead to them being effective for altering preconceptions (RQ03).

Methodology

Research Design

To address the hypotheses, we conduct a within-participant experiment in a professional workplace. We assess the impact of personas on changing the preconceptions of decision makers (i.e., persona end users) concerning the most common audience of the organization's YouTube (YT) channel. This is done by analyzing participant responses before/after using the DDPs. For the study, we selected YT as the platform for analysis as it has the widest adoption across the organizational divisions, and the provision of DDPs using APG and YT data has been established in several prior studies [6, 7, 63]. The experiment design was as follows: (a) we gathered participant preconceptions of the users, (b) participants interacted with personas, (c) we again gathered participant conceptions of the users, and (d) we compared user descriptions before and after interacting with the personas. Our decision for a within-participant design is well suited for the testing of our hypotheses [8], as it reducing the effects associated with individual differences.

Persona Generation for the Experiment

To generate user personas from real YT data of the organization, we use APG, a state-of-the-art data-driven persona creation system [6, 7, 34, 64]. This system was chosen because the personas created using APG accurately portray the underlying user population, including demographics, interests, and other attributes of personas [62]; the underlying algorithm of non-negative matric factorization creates an accurate representation from the actual user interaction data (i.e., base personas) that the system then enriches with name, photo, and other attributes. APG generates personas from online social media user analytics data [10]. An in-depth technical description of the methodology can be found in prior work [6, 7]. For this experiment, APG generated personas from the company's YT channel API using aggregated user statistics. Once the APG system has access to the online accounts, the personas can be generated within a matter of hours, even with thousands of products and hundreds of thousands of users. At the time of the study (April 2019), the organization's YT channel had more than 149K subscribers and 400 videos, with more than 42M content views. The APG system can generate personas from any amount of data; however, the more the better for more effective employment of the algorithmic approach.

Figure 1: The ten personas presented to the participants using the Automatic Persona Generation (APG) system. The three personas in the bold box are the typical YouTube user - Young Male from India / Qatar.

During the experiment, the participants were given access to the APG system, where they could explore the data-driven personas, including selecting a specific persona and viewing the persona profile. By default, APG generates 10 DDPs from the source data, where each persona varies by one or more demographic or behavioral characteristics. The persona profiles contain the following, generally standard, persona information: name, picture, age, gender, location, education level, job, relationship status, topic of interest, viewed video content, social media comments, and the number of people like the persona (Figure 2).

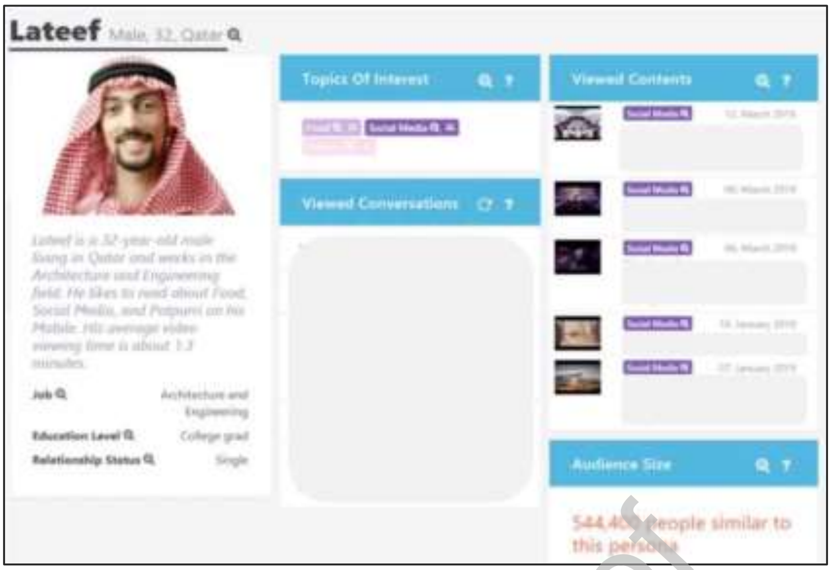

Figure 2: The APG system with the first persona profile displayed. The company identifying content is masked. Each section of the persona profile is titled in the blue bar. Text above the persona image is the Details about the persona. The text below the image is the Details about the persona. The '?' (e.g., About) provides an explanation about that section.

We collected preconception survey responses from the participants before (PRE) and after (POST) interacting with the personas. We asked the participants to provide a user description (i.e., *WHO* is typical YT channel visitor), discussion of the user motivation (i.e., *WHY* does the visitor comes to the channel), and present suggestions to better address user wants and needs (i.e., *WHAT* can be done to serve the visitor better). The WHO, WHY, and WHAT questions correspond to core tasks for the employment of personas for user understanding in large organizations. They also form a basis for evaluating our hypotheses. To analyze the results, we employed both statistical methods and text analytics (i.e., lexical dissimilarity, topic modeling, psycholinguistic analysis).

Research Context and Participants

Our data collection site was a major international airline company with headquarters in the Middle East. The participants were selected from employees of the organization that interact with channels and systems interfacing with social media users. The participants' jobs typically deal with planning and creating content for the targeted users of online platforms. Therefore, the participants are potential end users of personas, with the real needs and actual motivation to learn about their online users.

The study was conducted in the participants' workplace. There were 31 participants (see Table 1). The average age was 35.2 years (SD=5.6). The participants were selected to reflect the various audience-facing staff divisions within the organization and formed a diverse pool of individuals from multiple countries. The participants' average work experience with the organization was 6.3 years with the current company (SD=4.8). The participants' experience with personas and analytics systems varied, with 45% of the participants not that familiar with personas, 32% quite familiar, and the remaining 23% somewhere in the middle. Persona experience did not have an effect on willingness to change, as 88% of participants either changed their perceptions or had the correct persona in the pre-phase, as discussed below. To ensure a foundational level of understanding of personas, we explained the concept of personas to each participant before starting the session and clarifying the personas that they are about to see are 'data-driven', meaning that they are based on the organization's actual YT data.

Gender	**Male**	**Female**
No. (%)	17 (54.8%)	14 (45.2%)
Attributes in years	**Age (yrs.)**	**Experience**
Avg. (±SD)	35.2 (±5.6)	6.3 (±4.8)
Experience	**Analytics**	**Persona**
Avg. scores * *(±SD)*	3.08 (±1.88)	3.00 (±1.71)
Roles / Teams	**No. (%)**	
Customer Relations	8 (25.8%)	
Ecommerce	4 (12.9%)	
Customer Loyalty	8 (25.8%)	
Info. Technology	3 (9.7%)	
Manager	3 (9.7%)	
Marketing	2 (6.5%)	
Resource Management	3 (9.7%)	
	31 (100%)	

Table 1: Detailed information about the 31 participants. All participants identified gender as either Male/Female. * Experience scores are given using a 7 point Likert scale (1 = no experience to 7 = a lot of experience).

Data Collection

We gathered two main types of data from the participants: *Explicit feedback* is gathered via quantitative measures during task completion and from collecting the participants' opinions (as example, statement from of participant concerning gender make-up of persona cast: "*Interesting enough, there are less ladies here. I've only seen two ladies.*"); *implicit feedback* is collected via eye-tracking (and mouse tracking) that records the participants' gaze (and mouse) movements relative to different information elements on the screen. More specifically, the data we collected was:

- **Survey Data:** We collected both the PRE and POST responses about the typical user member via questionnaires. All data was collected online, making it immediately available for analysis. This data was used for addressing RQ01 and RQ02.
- **Think-Aloud Protocol:** In addition to the survey data, we encouraged the participants to speak out loud, explaining what they are doing and why, following the *concurrent think-aloud method* [5]. This data was used for addressing RQ01, RQ02, and RQ03. To avoid interfering with task completion [21, 59], we only spoke to the participants when they stopped voicing their cognitive process to avoid distracting the participants' attention. We could not opt for complete non-obstruction, since we specifically wanted to learn about the thinking taking place when using the personas. The participant utterances were recorded and then professionally transcribed for analysis. We also employed observer notes during the sessions to supplement the voice recordings.
- **Eye-Tracking and Mouse-Tracking**: To conduct the eye-tracking sessions, we use two identical workstations equipped with a laptop (HP Studio G4 laptops with 15" screens), MyGaze eye-tracking device, and associated software[1] for logging the visual engagement of the participants. The eye-tracking device is portable and uses a built-in head movement compensation that is intended for

[1] https://cooltool.com/

improving the measurement accuracy for live systems. The eye-tracking data was used for addressing RQ03.

Given the combination of eye-tracking, mouse-tracking, think aloud, and survey data, we have a rich data set with triangulation along multiple collection avenues for a robust data analysis to address our research questions and hypotheses.

Experiment Flow

The specific set-up of the experiment was: (1) gather preconceptions of the participants (PRE) about their users, including their confidence in these preconceptions, (2) have the participants interact with personas developed using actual user data, (3) gather preconceptions of the typical user (POST), including their confidence in these preconceptions, and (4) collect demographic and experience data of the participant, after which we analyze the data. We pre-tested the experiment design using a pilot study with three individuals who did not participate in the actual study, but who have similar positions and backgrounds as the study participants. The pilot study prompted us to make minor wording changes to instructions.

The entire user study took some 40 minutes per participant (P). We instructed all participants in the same way at the beginning of the experiment about the procedure. To begin each trial, we welcomed the participant, introduced ourselves, briefly explained the study, and answered any questions about the study. After completing an institutional review board consent form, each participant was assigned a unique study ID. Then, the participant was shown a series of work scenario tasks (WSTs) [13, 40] to focus communication on the user. The WSTs were also pilot tested on the three individuals mentioned above to ensure that the scenarios were realistic. The WSTs are as follows, presented in succession to the participants:

- The WHO question (WST_1): *Think about the company's YouTube Channel, which has more than 400 videos, more than 149,000 subscribers, and more than 42 million views. The CIO of the company wants to know,* ***"Who is the typical viewer of our YouTube videos?"*** *The work tasking comes to you.*
- The WHY question (WST_2): *You sent your message, but now your boss wants more information, specifically,* ***"Why are these viewers coming to our YouTube channel?"*** *In the space below, type out an email message to your boss describing why these viewers are coming to the YouTube channel (i.e., what attracts them to visit). Be specific. Provide justifications for your answer(s).*
- The WHAT question (WST_3): *The boss likes what you have done so far, but the boss wants still more information, specifically* ***"What can we do to improve the experience for these users coming to our YouTube Channel?"*** *In the space below, type out an email message to your boss describing what you believe the company could do better to support these users coming to the YouTube channel. Be specific. Provide justifications for your answer(s).*

The WSTs are compatible with the organization's user analysis approaches, as the participants frequently communicate about their users via email as a part of their daily work routine. To facilitate comparison, we asked for the typical user of the YT channel. For each WST, we asked the participant to rate how confident they were of the message to their boss on a 7-point Likert scale (Not confident – Extremely confident). We also asked the participant some specific demographic information concerning the viewer described in the WHO question: gender (M/F), age (one of seven US census age groupings), and country (free form). Also, background information concerning participants' expertise with analytics platforms and personas was collected. Concerning genders, the major analytics platforms currently treat gender as binary. We acknowledge this is an unrealistic proxy for the actual gender spectrum, with research being conducted on more nuanced representations [32].

Note that the WSTs were presented identically, so the participant first addressed the three sequential WSTs, then examined the APG personas, and then re-answered the same WSTs (i.e., $WST_{1\text{-}3}$ $\rightarrow$ APG $\rightarrow$ $WST_{1\text{-}3}$). The participants used the APG system to explore the personas for the YT channel.

The participants were not constrained in their interactions with the personas. The moderator answered questions from the participant but otherwise did not guide the interaction with the system. The maximum duration for the APG interaction was 10 minutes, with the typical sessions taking between 9 and 10 minutes. At the end of the session, we thanked each participant and addressed any questions. The participants were rewarded with amble sweets to compensate for their time.

Analysis and Results

H01: DDPs change* preconceptions *about users.

We investigated differences between PRE and POST responses regarding three user attributes: *gender*, *age*, and *location* (i.e., country). We conducted a chi-square test to measure the effect of the change in preconceptions of the typical user by the participants, with the change in preconceptions being significant ($\chi 2$ (1, N = 31) = 14.047, $p < .001$). Our findings show that 25 (80.6%) of the participants changed their preconceptions of the typical user after interaction with the persona system, while 6 (19.4%) of the participants did not change their preconceptions. Of these 6, 4 had accurately identified the user attributes in the PRE responses. So, not only did the persona change the preconceptions of some, it seems to have reinforced the correct preconceptions of others; we discuss this further in the next hypothesis.

Demographics		**PRE**	**POST**	**Change**
Gender	*Male*	77.40%	**90.30%**	+12.90% changed to male
	Female	22.60%	9.70%	
Age	*18-24:*	16%	10%	-6%
	25-34:	52%	**71%**	+19%
	35-44:	29%	19%	-10%
	55+	3%	0	-3%

Table 2: Change in responses for demographic (gender and age) information. '-' sign represents a decrease in value in POST scenarios. Note: three age groups were not specified. The values represent the percentage of participants who correctly identified the persona attributes.

The results in Table 2 show that 12.90% of participants changed their response of user gender to male. The POST treatment gender distribution is in line with the information shown in the APG persona listing, which included eight male and two female personas (as shown in Figure 1), indicating the typical YT users are male. Regarding the age of the user, from Table 2, we observe that PRE and POST responses follow a similar trend, with most participants choosing the age range of 25−34. In POST responses, the age range of 25−34 shows an increase of 19.0%. In POST responses, most of the answers are in the 25−34 range, but some participants were not convinced of the typical user age range based on their selection.

To understand the changes of the participant responses regarding the location of the users, we studied the list of countries that each participant added to their response after using the persona system. For this, we calculated the set difference of the countries (C) for POST for PRE (i.e., $POST_C \setminus PRE_C$). Similarly, we extracted countries that were present in the PRE answers but removed them in the POST responses (i.e., $PRE_C \setminus POST_C$) and countries that the participants kept in both PRE and POST responses (i.e., $POST_C \cap PRE_C$). The results show that 13 participants added *India* in their responses after using the persona system. A similar pattern is seen for *Qatar*; however, unlike *India,* 4 participants also removed *Qatar* from their POST response. Our results show a significant difference between PRE and POST responses in terms of user attributes. Thus, H01 is fully supported. *Personas can change preconceptions of who the online users are.*

H02: DDPs improve the* accuracy *of perceptions about users.

To address H02, we conducted a Wilcoxon signed-rank test to compare the number of correct user attributes recognized by the participants in the PRE and POST responses. For this, we calculated the accuracy of user attributes by comparing the participants' responses — regarding the three attributes: *gender, age, and location* with each attribute weighting 1 point when correct — with the gold standard typical user presented in the persona system (i.e., Male from India and/or Qatar of age 25-34, as shown in Figure 1). If a participant mentioned an attribute that was not listed in the persona profile, it was not counted as a correct response. We conducted this PRE and POST. From the analysis, we observed a significant difference in the accuracy of the user assessment by participants for PRE (Mdn=2) and POST (Mdn=3) responses ($t=18$, $z=3.39$, $p<0.01$).

Our analysis shows 4 participants (12.9%) had accurate descriptions of the typical user in their PRE responses. Of the 31 participants, 19 (61.3%) provided more accurate descriptions of the typical user, while 10 (32.3%) had the same level of accuracy in POST responses. Interestingly, 2 participants (6.5%) who had inaccurate preconceptions of the users had even less accurate descriptions of the typical user after examining the personas.

The personas seemed to have the most positive effect on changing preconceptions of location, followed by age, and then gender. In the POST responses, 28 (90.3%) participants correctly identified the location of the typical user (an increase of 21 participants, 67.7% of total), showing a 300% increased accuracy. Concerning age, in the POST responses, 22 (71.0%) accurately identified the correct age category of the typical user.

Interestingly, personas had a mixed effect on changing accuracy preconceptions of the gender of the typical user. In total, 28 (90.3%) participants correctly identified the typical user as male (see Table 2); however, there were 3 participants who still classified the typical user as female. We return to this phenomenon in the discussion of findings. However, one aspect may be the lack of female personas, which was mentioned by some participants (e.g., "*Why hasn't she come out though when I picked my personas. I only got one.*"). Overall, H02 is fully supported: *The use of personas increases the accuracy of user descriptions*.

H03: DDPs improve* confidence *in communication about user attributes.

We conducted a paired-sample t-test to compare average confidence in PRE and POST responses (see Table 3). There was a significant increase in the confidence scores for POST (M=5.73, SD=0.41) compared to PRE (M=5.16, SD=0.48) conditions (t (30) = 4.43, p<0.01).

Surveys	t (30)	*p*	PRE: Mean (±std)	POST: Mean (±std)
Who	4.509	0.0001	4.97 (±0.48)	5.74 (±0.43)
Why	2.802	0.0088	5.29 (±0.57)	5.77 (±0.56)
What	2.447	0.0205	5.23 (±0.39)	5.68 (±0.55)
Overall	4.432	0.0001	5.16 (±0.48)	5.73 (±0.41)

Table 3: Paired t-tests for WHO, WHAT, and WHY of confidence of answers concerning the typical user attributes from participants.

To understand this increase in confidence of the participants in-depth, we analyzed shifts in confidence per participant. For this, we calculated the $\Delta Conf$ by subtracting the PRE response confidence from POST response confidence (see Equation 1), where P_i *represents* the i^{th} participant.

$$\Delta Conf\ (P_i)\ =\ Conf\ _{POST}\ (P_i)\ -\ Conf\ _{PRE}\ (P_i) \quad (1)$$

We observed that in the WHO survey, most participants (N=19, 61%) increase their confidence after using personas, while for 9 (29%) participants' confidence remains unchanged. A similar pattern is observed for the WHAT question. In total, 16 (51.6%) of participants had higher confidence scores in POST responses, and only 5 (16%) participants decreased their confidence. However, 14 (45%) of participants increased their confidence in the WHY question.

Our analysis shows a significant increase in confidence after using personas; in particular, the results indicate that a higher number of users increased their confidence while communicating about WHO the user is and WHAT can be done to increase online traffic (e.g. participant statement: "*It would be very good if we have this kind of rich information, which is really, really good.*"). There was less increase concerning the effect concerning WHY they are visiting, although the difference is still significant. Therefore, findings from our investigation fully support H03, indicating: *The use of personas* *increases the perceived self-confidence in communications about users.*

H04: DDPs improve the* empathy *expressed in communication about users.

Motivated by the use of psycholinguistic information to model empathy in conversation [70], we investigated the change in psycholinguistic information in PRE and POST responses, including the change of *adjective, negation*, and *personal pronoun* usage, along with other features representing *personal concerns* while writing the responses. To extract these features, we use the *Linguistic Inquiry Word Count* (LIWC) [73] system that is used for studying human interaction behavior in multiple contexts.

Generalized linear mixed modeling was used to investigate the effects of PRE and POST responses on the psycholinguistic characteristics. Question type (Who, What, and Why) and time (before and after) were included as fixed within-subjects effects. The interaction between time and question was also included in the model. The main interest for the analysis was the main effect of time. For testing the significance of the fixed effects, we used ANOVA (Type II Wald-Chi-square statistic). Statistical analysis showed that there was no statistically significant main effect for time ($X2 = 0.587$, $P > 0.05$). We now report the overall effect (i.e., PRE and POST) along with a post hoc analysis for the contrast between PRE and POST responses for each WST, using incident ratio (IR), standard error (SE), and adjusted p-values (p) for false discovery rate.

Our findings suggest that there was a weak statistically significant main effect (PRE vs POST) at the 0.1 level: $\chi2\ (1, N = 31) = 2.77$, $p < 0.10$, for adjective usage. In post-hoc analysis, we observed an overall 50.3% (IR=1.503, SE=0.278, $p = 0.029$) increase in POST-treatment adjective usage compared to the PRE-treatment responses for WHY.

However, we observed no significant difference in other psycholinguistic variables, such as the use of pronouns, negation, or social words. Therefore, results indicate no change in the use of these psycholinguistic markers reflecting increases in empathy for the user after using personas. Thus, we reject H04, implying the need for further investigation, as this deviates from findings reported in prior literature, as discussed in the review section [2, 12, 49]. It may be that empathy is demonstrated in other ways than via user descriptions.

H05: DDPs improve the* detail *(H05a) and* precision *(H05b) of communication about the users.

To investigate if personas enhance participants' communication, we analyzed the changes in lexical keywords that describe the motivation of the users for visiting the channel (Topic 1) and offering ways to attract an increased audience (Topic 2), as well as the responses of who the users are. For detail, we defined as communicating individual persona features, items, facts, or attributes. For precision, we defined as the total number of persona details mentioned that accurate.

This involved several text preprocessing steps: first, we manually reviewed the responses to fix spelling errors and remove repeated words. Then, for the lexical analysis, we tokenized the input responses and removed stop words (i.e., common words that add no information). We then generated bi- and tri-grams and selected the tokens that are either a 'Noun', 'Adjective', 'Verb' or an 'Adverb'. For the topic modeling, we added an extra processing layer, where we removed tokens composed of three or fewer characters. To study the lexical *dissimilarity* between the PRE and POST responses, we used Jaccard distance (see Equation 2), where $0 \leq \partial J_{P_i} \leq 1$, with 0 representing no dissimilarity between the PRE and POST responses and *vice versa*.

$$\partial J_{P_i} = 1 - \frac{|PRE \cap POST|}{|PRE| + |POST| - |PRE \cap POST|} \quad (2)$$

The observed means (±SD) of lexical dissimilarities between the PRE and POST responses per participant are as follows: WHO = 0.87 (±0.094), WHY = 0.89 (±0.090), and WHAT = 0.88 (±0.097). The results indicate that the responses changed in terms of lexical token usage. To investigate if these lexical changes resulted in a change of information, we studied shifts in response topic by participants.

For finding shifts in topics in the responses, we first designed a statistical model to describe abstract topics for each set of WST responses (WHO, WHY, and WHAT). As a reminder, we asked participants for a user description (i.e., *WHO* is the typical visitor, *WHY* does the visitor come, and *WHAT* can be done to serve the visitor better. The WHO, WHY, and WHAT questions correspond to core tasks for the employment of personas for user understanding in large organizations. For the task, we used *Latent Dirichlet Allocation* (LDA) [9], a topic modeling technique that is widely used for text analysis. Using LDA, we generated topic models for each WST survey and extracted the topics (two topics and their top ten associated key-phrases) at the 2000th iteration of the Gibbs sampler [14].

Each topic (see Table 4) is shown with the ten words or phrases ordered by the weight of the phrase conditioned on that topic. Looking into the topics extracted from the WHY question, the PRE list includes entries *offer*, *destination*, whereas the POST list includes more specific motivation for the user to visit the organizations' channel – i.e., motivation to learn about *cabin*, *opportunity*, *aircraft*, among others. Similarly, POST responses to the WHO question show a clear shift in preconceptions in terms of gender and age. The PRE list includes both *male* and *female*; however, in the POST list, only *male* is present (in line with our observations for H01 and H02). In the POST responses, the participants were able to describe the user in detail using words such as *young*, *single*, *frequent*, *flyer*, *aspires*.

These results are aligned with the findings of H04, implying that in POST scenarios, the participants used more adjectives (50.3% increase in WHY questions), thus providing further descriptive information about the users. Similarly, our findings from H01 and H02 support the notion that the participants also describe user segments in greater detail in terms of WHO the users are.

	PRE-Treatment		**POST-Treatment**	
	Topic 1	**Topic 2**	**Topic 1**	**Topic 2**
WHO	Travel	video	video	people
	Video	people	viewer	**aspire**
	View	group	brand	believe
	Base	follow	demographic	youtube_viewer
	watch	<O>	**young**	**promoter**

	PRE-Treatment		POST-Treatment	
	Topic 1	**Topic 2**	**Topic 1**	**Topic 2**
	User	airline	**single**	join
	Male	believe	type	**frequent**
	female	promote	travel	**flyer**
	viewer	share	follow	employee
WHY	holiday	service	airways_youtube	male
	<O>	link	travel	provide
	information	customer	aircraft	customer
	destination	youtube_channel	destination	information
	Offer	view	viewer	benefit
	Brand	directly	youtube_channel	convenience
	Video	article	interested	view
	customer	chance	**cabin**	<O>
	airline	click	**experience**	brand
	product	timeline	**social_media**	video
WHAT	service	newsletter	expect	**opportunity**
	content	video	video	customer
	Offer	user	destination	content
	channel	feature	information	promote
	customer	information	**persona**	bring
	promotional	destination	travel	value
	benefit	provide	**aircraft**	long
	describe	view	**food**	destination
	convenience	specific	specific	video
	Gceo	product	airway	viewer
	support	youtube_channel	**user_experience**	channel

Table 4: Top 10 words per topic for PRE- and POST-treatment for WHO, WHY and WHAT. The *bold* words represent the new addition POST-treatment with very specific descriptions of the criterion asked in the survey. <O> represents the name of the organization, masked for anonymity.

As an example of WHY perceptions PRE and POST, P1 stated (PRE), "*We do many online campaigns as well as we have good control on social media platforms. Also, [company name] is big brand and people wants to see all new updates.*" P1's POST comment for WHY was "*To know updates on the football world cup, any new things happen with [company name], to appreciate and to provide any feedback.*" As an example of WHAT perceptions PRE and POST, P18 stated (PRE), "*We can provide more gamification features in the YouTube channel such as featured videos for select destinations and games.*" P18's POST comment for WHAT was "*We could share videos that encourages more engagement with the viewer instead of only one-way communication about new* *product or destinations as it is important to ensure the viewers are motivated to share out the video or stay engage in the conversation.*"

Drawing from all these observations, our results indicate that after exploring the personas, the participants gain a deeper understanding of the user's identity and motivation, and the participants can communicate that understanding within the team using more detailed information. Thus, providing support for H05, such that *personas improve both the detail and precision of communication about users*.

RQ03: What aspects of DDPs are employed in changing preconceptions?

To analyze the participant's behavior during the system use, we studied the screen recordings of the eye tracking and mouse tracking. We divided the system interface into *Areas of Interest* (AOI) based on the information it provides to study and studied how often and how much time the participants spend glancing (gaze) and pointing the mouse to the particular area. From the analysis, we observed the *participants spend the majority of their time exploring the list of personas and their profiles*. Although the APG system offers a variety of reports and other features, 38.7% of the participants only explored the persona lists (see Figure 1) and the profiles (Average treatment session of ~9.60 min with SD=0.94 min), with time about equally split between the two. We are particularly interested in the duration participants interacted with the persona profiles and sections of the person profile (see Figure 2), with results presented in Table 5. The APG interaction duration of all participants is provided as supplementary material.

Element	Minutes	Percentage
Profile	132.81	100.0%
Profile Section		
Conversation	40.37	30.4%
Scanning of Profile	35.99	27.1%
Viewed Contents	22.96	17.3%
About	20.33	15.3%

Element	Minutes	Percentage
Details	4.14	3.1%
Audience	3.26	2.5%
Topics of Interest	2.71	2.0%
Demographic	2.74	2.1%
Filter of Listing	0.31	0.2%
	132.82	100%

Table 5: Overall durations of participants' interactions with the persona profiles and sections of the persona profiles (see Figure 2).

From Table 5, interestingly, the sections of the persona profile that participants most interacted with were the Conversations, following by scanning of the complete profile, and then Viewed Contents, and the use of the About feature (see Figure 2). While not definitively being a causal factor of the changes in preconceptions, the influence of this information in shifting those preconceptions makes sense. The Conversations and Content would be most insightful concerning WHY and WHAT is driving the users to come to the site. The overall persona profile itself would address the WHO the users of the site are.

Qualitative Analysis of Think Aloud

Based on the empirical results, we observe that personas can both change preconceptions regarding the user and make the preconception more accurate. However, for two participants, personas were not compelling enough to change their false preconceptions. To understand these variances of behavior in-depth, we studied the transcripts of the think-aloud data obtained during the experiment for all participants.

Dialog Excerpts
Example 1: **P:** A lot of Indians. It was ***right, pretty right***. It looks at Southeast Asia as well. This gives you a profile, more interested in mostly food social media. **P:** Okay, yeah. Seeing some topics of Interest, mostly it's the…a lot of people on the food, social media, potpourri. There is less interest on cabins, adventure travel, the brand, aircraft, education. ***I am surprised of the aircraft***. **P:** I can see the biggest market share is India, followed by the potential market size. ***Again, it says India*** and Indonesia. **P:** Age group is 25-34, the biggest one, okay. Again, ***that's slightly off what I expected***, and gender, it is the male, ***so pretty right***. **P:** Personas, country I could say in Asia, but I had India in mind as the highest, ***so it's more or less the same***.

Example 2:
M: Right. Okay. I'm just curious because there were no teenagers in the list whatsoever but you still ....
P: There is no group like ***that but you can say*** that falls in the 18-24 group.
M: Okay. Alright. So, 18-24.
P: Yes.
M: Okay. And where did the Netherlands and Germany thing come from?
P: Germany and the Netherlands...
M: ... because the only European country was the UK.
P: Yeah. In the list, I found only UK ***but actually***, the response was given ***from my personal view basically*** because what happened when I traveled to some destinations was, ***I found out*** that there are a lot of people from those regions especially.

Table 6: Examples from think-aloud transcriptions. P stands for Participants, and M stands for facilitator/moderator. Bolded terms are key text used in the discussion of these exchanges.

From Example 1 in Table , we can observe the participant expressing positive emotion (or signs of satisfaction) when s/he found out some of the pre-existing preconception s/he had were correct using phrases like *"right, pretty right"*, *"more or less the same",* among others. In contrast, when the PRE responses of the participant did not match the information shown in the system, the participants showed signs of surprise ("*that's slightly off what I expected"*), but at the same time accepted the information. Moreover, Example 2 in Table 6 shows a POST conversation between the participant and the moderator (i.e., discussion at the end of the session), where the participant refused to accept the information displayed during the treatment and alter his/her preconceptions. While doing so, the participant used several phrases to reflect the intention of not altering his/her views, like "*but actually"*, "*basically"*, among others indicating a reluctance to change preconceptions.

Discussion and Implications

Key Contributions and Core Propositions

We investigated the effect of using personas to change preconceptions about users and improve the accuracy of perceptions by professionals in marketing and related professions.

Although Nielsen [53] and others [47, 55] have iterated that personas have several benefits, there has been a lack of empirical studies quantifying these benefits and supporting the use of personas in real organizations and use cases. This research represents a step in addressing the challenge of quantitatively evaluating personas. Quantitative findings reported in this research both support and contrast with those reported in some prior work, especially the criticism toward personas' lack of benefits.

The main findings, summarized as core propositions (CP), are: first, *DDPs change preconceptions about online audiences* (CP1). Second, DDPs *increase the accuracy of these user preconceptions for decision makers* (CP2). Third, *after using DDPs, the professionals' descriptions of the user segments tend to be more specific* (CP3).

Fourth, there is a notable increase in the confidence of the participants' user understanding after interacting with the personas for the WHO and WHAT aspects. This positive shift in self-reported confidence indicates that *the use of the personas solidifies user understanding* (CP4), with the exposure to personas making the participants more certain about their own descriptions of the online audience segments.

The empirical analysis yields further findings and implications for the broader HCI community. To complement Rönkkö's [58] proposition that personas often function as an internal concept to justify design rationales 'after the fact' to other team members, our findings suggest that *personas can serve a useful function in altering preconceptions before decisions are made and while still in the communication phase* (CP5). Certainly, user understanding formation is the result of a 'messy' cognitive process and cannot be tracked perfectly, as there are possible confounding factors, such as unknown data sources, problems with recall, organizational politics [45], personal experiences [45] about different people, and so on.

Some of these issues may be related to questions in the minds of decision makers about the underlying data or methods of how personas are created – meaning, trust towards the shown personas [65]. APG and other DDP approaches address this concern by generating the personas from quantitative data. As stated in CP2, the analysis suggests that personas crafted from actual data can alter preconceptions in a manner to improve accuracy. Regarding this, we observed an interesting behavior of the participants when responding to the country they consider the users from. In POST responses, 42% of the participants added India to the list of the countries for the typical user segment. However, this was not the case for the country of Qatar. Even though Qatar is presented as one of the major locations for the YT user in the persona listing, 13% of the participants removed Qatar from their responses. This is potentially explainable through information saliency theory postulating that the most visible or frequent information (in this case, "India" as the personas' country) is given the most consideration in information processing [67, 67]. Applying this principle to personas, we suggest that *the most salient persona characteristics among a set of personas take precedence when decision makers form their preconceptions of users based on personas* (CP6).

One of the stated benefits of personas is that they are cognitively compelling for designers [55]. Our findings propose that *personas are compelling for presenting specific user attributes in a manner that alters preconceptions of professional decision makers* (CP7). Goodman et al. [25] have proposed that user information should be quick and easy to both find and use, visual and stimulating, flexible and open-ended, and related clearly and concretely to design issues, implying that information presentation can affect its frequency of use. Our analysis of participant interaction suggests that, DDPs, and possibly personas in general, present the user information in a manner that matches the information needs of participants.

This leads to another important aspect. Matthews et al. [47] noted that practitioners used personas almost exclusively for communication and stated that personas could not replace immersion in actual user data. Our findings suggest otherwise — *DDPs are a viable method for conveying specific user information in an actionable manner that alters the cognitive perspective* (CP8). Specifically, we find that the use of DDPs resulted in more precise communication about the user, including more fine-grained descriptions, while being more accurate. However, perhaps user data could result in even better results; this would need to be evaluated. However, our findings show that personas can be effective as a representation of the user data.

Matthews et al. [47] further suggest that if the organization and its decision makers are open to realigning their preconceptions, personas could rectify false preconceptions about the users. We observed some variation in this regard, with not all participants willing to realign their user understanding to match the information shown in the personas. The findings indicate that for some participants, personas were not compelling enough to change preconceptions. Specifically, two participants did not change their preconceptions, even after viewing personas that were at odds with their perceptions of who is the typical user. This suggests *there can be "resistance to change" in terms of using personas for realigning entrenched stereotyping* (CP9). While previous research has offered qualitative support for this effect [54], our findings provide quantitative evidence. In post-session discussions and from qualitative analysis of the think-aloud transcripts of these two participants (and some of the other participants), there were two motivations at play, which we dub as (a) data resistance and (b) attitude stubbornness.

In terms of **data resistance**, one participant refused to alter his/her view, even after seeing the personas and noting during the session that his/her preconceptions were incorrect. In a post-session interview, the participant stated: "*the response was given from my personal view basically because what happened when I traveled to some destinations was, I found out that there are a lot of people from those regions especially*". At first, we considered that the participant did not understand the WST, but this was not the case based on further discussion. For this participant, personas by themselves did not alter his/her preconceptions.

The issue of **attitude stubbornness** was related to the participant selecting the incorrect gender because, as the participant stated: "*I believe that we should be focusing more on the female audience members*". In this case, the participant altered the actual work task, knowingly providing incorrect information, in pursuit of a different, and perhaps worthwhile, goal of producing more content for a female user segment. This supports the position of Rönkkö [58] that personas can be used to advance specific political agendas, as well as being associated with gendered stereotyping [45].

In summary, our findings indicate that, for most professionals, DDPs change existing preconceptions, which is at the core of the persona methodology, as explained by Cooper [19]. Our findings also show that DDPs also increases the accuracy of user understanding, which has been proposed as one of the primary benefits of personas [26], but it has not been, to our knowledge, empirically validated until now.

Limitations and Future Work

One limitation of our research is that it focuses on online user personas and not design personas, marketing personas, advertising personas, ad hoc personas, and other persona types deployed in HCI and related fields. There may be domain-specific or organizational aspects concerning other personas types that may impact the generalizability of our findings. However, there are similarities in the use of nearly all personas; moreover, our research focused on preconceptions and personas' ability to affect these preconceptions, so one would expect these human preconceptions to be similar across domains. However, this would need to be validated in repeated experiments in other domains and other organizations.

The responses of the participants changed in terms of the psycholinguistic variables, such as the use of adjectives, personal pronouns, and other categories revealed no significant changes for the use of most of the psycholinguistic features, apart from adjective usage, which implies that further studies are needed to test the effect of personas on the participants' empathetic attitudes towards online users. The often stated benefit of personas to increase empathy [2, 3, 29, 44] for the users was not supported by our findings, although we found weak signals that personas could increase empathy toward users' needs and motivations. Quantifying empathy from creative text outputs is an open research question that calls for further research.

Finally, our research evaluated the effect of personas and did not compare personas to other design methods that may be as or more effective in altering preconceptions. This comparison of alternative methods with personas in changing decision makers' perspectives is outside the scope of our present study, as we were interested in examining the effect of personas. Also, outside the study's scope were other persona profile structure methods, such as excluding gender or replacing the picture with non-human images. However, replication studies comparing the ability of personas to other types of analytics platforms (e.g., Facebook, Google Analytics) or methods (e.g., use cases, scenarios) to alter preconceptions are possible future research.

Practical Implications

The central implication is that personas can help professionals relate to and characterize their actual social media audiences (and presumably users, customers, etc. in other domains) by providing more accurate insights about user segments, including *who* the user is, *why* they are visiting, and *what* can be done to enhance the user experience. This is supported by the findings showing that the personas had the positive effect of altering the participant's perceptions of the users, and these perceptions were more accurate after interacting with the personas.

We used realistic WSTs of communicating with others in the company, asking the participants to respond to three essential questions: *WHO are the users*, *WHY are they visiting*, and *WHAT can be done to attract more users*. These are key questions for the development and nurturing of online user segments and are also applicable to the use of other persona types, such as design personas, marketing personas, and prototype personas.

For organizations, our findings provide two major implications:

(1) Personas work: if personas are data-driven, accurate, and precise in reflecting the underlying user (and presumably customer) data, they can both shift and improve the accuracy of preconceptions This is directly clear from both the statistical testing and textual analysis results.

(2) Education may be needed concerning (a) the use of personas and (b) how personas were created to increase the positive impact of personas among the widest range of decision makers.

The latter is based on a few participants being resistant to changing their preconceptions, indicating that personas, by themselves, might not be enough. Using personas in conjunction with additional training and other user-focused methods may help alleviate the preconception persistence of some end users [54]. Finally, with DDPs, the relatively high degree of understanding issues implies there is a need for system-specific training. For optimal usability, self-explanatory features would be the ideal design goal; however, interactive persona UIs can become complex, prompting the use of various educational means, such as explainer videos, video tutorials, and collaborative workshops. For adoption in the target organization, these measures are needed.

Conclusion

Our research is a step toward quantifying the impact of personas for organizations wanting to increase their user orientation. Findings show empirical evidence on decision makers changing their preconceptions of their users after using data-driven personas. Interacting with the personas increased both the accuracy of user descriptions and the self-reported confidence in these descriptions. Thus, personas can change and increase the accuracy of preconceptions about users. However, interacting with personas does not alter the preconceptions of all decision makers, indicating the need for accompanying methods.

Author Statements

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Declaration of interests

☒ 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.

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