

Personas and Analytics: A Comparative User Study of Efficiency and Effectiveness for a User Identification Task

Joni Salminen^{a,b}, Soon-Gyo Jung^a, Shammur Chowdhury^a, Sercan Şengün^c, Bernard J. Jansen^a

^a Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha, Qatar

^b University of Turku, Turku, Finland

^c Wonsook Kim College of Fine Arts, Illinois State University, Normal IL., USA

sjung, jsalminen, shchowdhury{@hbku.edu.qa}, ssengun@ilstu.edu, jjansen@acm.org

ABSTRACT

Personas are a well-known technique in human computer interaction. However, there is a lack of rigorous empirical research evaluating personas relative to other methods. In this 34-participant experiment, we compare a persona system and an analytics system, both using identical user data, for efficiency and effectiveness for a user identification task. Results show that personas afford faster task completion than the analytics system, as well as outperforming analytics with significantly higher user identification accuracy. Qualitative analysis of think-aloud transcripts shows that personas have other benefits regarding learnability and consistency. However, the analytics system affords insights and capabilities that personas cannot due to inherent design differences. Findings support the use of personas to learn about users, empirically confirming some of the stated benefits in the literature, while also highlighting the limitations of personas that may necessitate the use of accompanying methods.

Author Keywords

Personas; analytics systems; mixed methods

CSS Concepts

• Human-centered computing~Human computer interaction (HCI)

INTRODUCTION

A persona is a personified segment of users, customers, or audiences [18]. Personas are used in many industries, such as system design [18, 55], marketing [16, 57, 64], product design [20, 28, 31], and content creation [4].

In many cases, personas are synthesized from user data collected via interviews, focus groups, or surveys [21, 50], although there are also algorithmic approaches for generating personas [4, 37, 70]. Personas are typically presented in a profile of 1-2 pages showing a photo,

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

CHI '20, April 25–30, 2020, Honolulu, HI, USA
© 2020 Copyright is held by the owner/author(s).
ACM ISBN 978-1-4503-6708-0/20/04.
<https://doi.org/10.1145/3313831.3376770>

attributes, behavior patterns, goals, or skills, with the intent of making the persona a realistic character [50]. The purpose of personas is to provide insights about the needs, desires, and goals of the targeted segment for guiding decisions about the features of a system, service, or product. In sum, personas are assumed to be cognitively compelling by putting a human face to user data.

There has been much prior research concerning personas [18], with many stated benefits [1, 8, 19, 21, 24, 26, 28, 30, 44, 48, 56, 58] primarily highlighting keeping the focus on and emphasizing communication about users, audiences, or customers in order to improve design and development. Among others, benefits include a common understanding of the user, avoiding stereotypes, and focused communication.

Despite the claimed benefits in the human computer interaction (HCI) literature [1, 19, 21] and some qualitative research into how personas are used [1, 28, 29, 36, 49, 50, 55], there is little quantitative research that would empirically show *whether personas are actually beneficial* [14, 15]; and if so, *whether they are more beneficial than other methods for inferring insights about users?* Such research is needed, as personas, both as concepts and tools, have also been criticized for being of little value [14, 15] and not being a valid scientific method, even calling into question whether their use could be validated at all [15].

The issue is also pressing because, since personas were first proposed, a plethora of alternative online analytics tools, services, and measures have emerged [11, 17, 35] (e.g., Google Analytics, Facebook Insights, IBM Analytics) that organizations can employ to understand user, audience, or customer segments. Organizations have gained access to individual user data – “personified big data” [65] – challenging the value of using personas or other segment-based user representations instead of just using individualized data [62] for user insights.

On the practical side, many organizations operate online and wish to understand their audiences and users, including the foundational task of *identifying* those audiences and users. If personas are not competitive for inferring user insights, they would simply be discarded as a *passé* method. Thus, there are valid concerns about personas providing real value compared to other available analytics tools [16]

Benefits of personas (3Cs)		References	Criticism of personas (3Es)		References
Communication	Personas facilitate user-oriented communication within and between teams providing a common reference point.	[28, 33, 45, 68]	Envision	Personas lack credibility, are not accurate or verifiable; the information in personas is not relevant for decision makers, and personas are inconsistent.	[10, 15, 45]
Consideration	Personas enhance the immersion required for designing for a person instead of nameless segments. They create empathy for the user.	[40, 46, 56]	Execution	Persona creation takes a long time and is expensive; can be biased by their creators' motives and misbeliefs, and personas are based on non-representative data.	[13, 15, 33, 56, 58, 59, 61, 66]
Concentration	Personas challenge existing assumptions and help keep the focus on the user when there are conflicting design needs.	[18, 43, 45-47, 55, 56]	Evaluation	Personas are not useful or are used for politics. There is little empirical support that personas provide actual user benefits.	[10, 14, 15, 44, 45, 58]

Table 1: Benefits (3Cs of persona benefits) and criticism (3Es of persona criticisms) of personas in the HCI literature.

for understanding online users [62]. Therefore, the quintessential question is: *do personas have inherent usefulness (i.e., value) to their end users?*

Addressing this question can inform efforts to determine the value of personas for better understanding users, audiences, or customers. As such, the research has important implications in HCI and related fields. We could locate no prior research that rigorously evaluates the benefits of using personas versus some other method for a user-centric task. The existing literature concerning the benefits of personas is mainly anecdotal, containing case and qualitative studies, with few to no empirical comparisons to other methods.

REVIEW OF LITERATURE

Personas were introduced in the field of software design, and the concept gained popularity in the late 1990s [1]. The techniques and best practices were expanded by Pruitt and Adlin [55] and others [49-53, 56, 57, 63]. Since the introduction of personas, HCI researchers have both highlighted benefits and offered criticisms of personas. We first present the benefits and criticisms of personas and then the underlying assumptions that each of these benefits and criticisms has in common. Our research then specifically evaluates these underlying assumptions.

Reported Benefits of Personas

The proposed benefits of personas can be summarized into the categories of *Communication*, *Consideration*, and *Concentration* (we dub these the '3Cs of persona benefits'), as shown in Table 1 and discussed below.

Communication: The reported collaboration benefits are supposedly derived from the ability of personas to summarize user information into an intuitive format of representation (i.e., a real person) that can be readily communicated [68] to stakeholders within teams and organizations [45] and that is more memorable than numbers [28, 33]. At their best, personas become *shared mental models* that professionals rely upon when making

choices [49] concerning the specific user type [18] and enabling decision makers to communicate about user preferences that may deviate from their own [46].

Consideration: The claimed psychological benefits are rooted in emotional identification with the personas [46], which helps professionals to draw from predicted user behavior in different contexts [56]. This mental modeling relies on human beings' innate ability to show *empathy* and *immersion* [40]. Personas are also said to challenge the established preconceptions about the users within the organization [47], conveying factual information of users' needs/wants [55], and rectifying false preconceptions [45].

Concentration: Personas reportedly can facilitate focusing on the most important user segments [46] by pinpointing a default user for developing products and services. This concentration helps decision makers to define appropriate product features [18, 43] while curbing the self-centering bias that may occur during the design process [45].

Reported Criticisms of Personas

There are also substantial criticisms of personas in the HCI literature. We categorize these arguments into *Envision*, *Execution*, and *Evaluation* (we dub these the '3Es of persona criticisms') as shown in Table 1 and discussed below.

Envision: Chapman and Milham [14] argue that personas have no direct relationship to real user data, represent few real people [14], and cannot be considered scientifically valid [13], raising the question of personas' falsifiability [54]. Vincent and Blandford [66] state that persona creation varies depending on what people want to accomplish. Thus, personas often deviate from the actual user segments [15], and, with no definitive information to include in the profile [10, 15, 63], there is a lack of trust of the personas.

Execution: Hill et al. [33] point out that creating high-quality personas takes considerable time and effort.

Consequently, as Rönkkö [58] found, the amount of effort may lead to questioning the return on investment of persona creation. Moreover, the high cost of persona creation tends to exclude them from the reach of small businesses and startups [63]. Personas are also said to be inconsistent in that they are created by combining information from unrelated sources [10] without ensuring that the pieces of information are commensurable [45] or up-to-date [38].

Evaluation: The reported research on evaluation, until now, has generally offered criticism of the persona methodology or used soft metrics for the success of personas, such as anecdotal feedback from stakeholders. Also, Rönkkö describes how organizational issues led to use limitations [58]. Ma and LeRouge [42] state that user profiles are preferred to personas. Analytically oriented decision makers may consider personas as ‘nice narratives’ resulting in resistance for their use [44]. Matthews et al. [45] report personas were found abstract and not a replacement for the underlying user data.

Summary and Research Motivation

The literature is lacking in empirical research that either supports the claimed benefits or justifies the stated criticisms of personas. Concerning benefits, we could locate no prior work comparing the personas technique to another technique for inferring insights about users, with the possible exception of Long [41] that used students employing personas for decision making in their course work. The researcher reported that the use of personas resulted in slightly more user-friendly solutions than a user-centered method. Conversely, with the possible exception of Chapman et al. [14], who conducted a probabilistic evaluation of persona representation, we also find no quantitative investigation of the criticisms of personas or a comparison of personas to an alternate approach.

As such, there is a *critical need for a rigorous quantitative evaluation of personas as a tool for understanding user segments*, which is the motivation for our research. The lack of rigorous evaluation leaves many open questions concerning both the reported benefits and challenges of employing personas.

There are foundational assumptions for the claimed benefits and criticisms that facilitate an overarching evaluation. For the benefits, the assumption is that personas are beneficial for *user identification* (i.e., isolating a targeted user group and identifying user attributes). Without proper user identification, the 3Cs of communication, consideration, and concentration concerning the user are not possible. In his seminal work, Cooper [18] discussed this exact point of identifying the users to design for, which personas are the archetype, or which personas not to target.

Similarly, the criticisms also have an implied assumption, which is that *there is something better than personas*. The criticisms suggest that there is some approach superior for accomplishing the aim of identifying and understanding

users, that is easier to apply than personas, and has benefits that have been validated (the 3Es). To our knowledge, no prior work evaluates an alternative approach to personas in the HCI or related literature, even though there are a plethora of techniques for learning about a user.

Therefore, this research examines personas relative to the method of analytics for the task of *user identification* – which we define as *the act of identifying a specific user segment and inferring insights about this user segment*. This is a central task at the core of the persona concept and for practically all user understanding methodologies.

RESEARCH QUESTIONS AND HYPOTHESES

Analytical tools (i.e., ‘analytics’) are widely used approaches in organizations for retrieving information about specific targeted users or customers. Inferring insights about users utilizing analytics is a crucial use case for many professionals, including designers, content creators, marketers, and advertisers who are frequently asked to clarify details and infer insights about specific user segments. Given that analytics is a widely used and industry-standard approach for understanding users, we deem it worthy to compare an analytics method with personas. We specifically focus on one analytics platform, *YouTube Analytics* (YTA), a de facto industry standard for video audience analytics that is similar in design and scope to other analytics platforms (i.e., Adobe Analytics, Google Analytics, Facebook Analytics, IBM Analytics, etc.).

Although personas have traditionally been presented in static media (i.e., paper or PDF), the use of such a medium would confound the comparison with an online analytics platform. Therefore, we employ *Automatic Persona Generation* (APG) [3, 4], a data-driven persona system that generates personas from underlying online social media or user data. For this study, we use the same raw data as used by the YTA system for the analytics to create the APG personas. The APG system is reported in a variety of publications [3, 4, 37], and it can be considered as state-of-the-art for data-driven persona creation.

Specifically, with the aim of investigating personas, we pursue two research questions:

RQ01: Are personas more efficient than analytics?

RQ02: Are personas more effective than analytics?

For RQ01, we have the following hypotheses, all that deal with *efficiency* (benefit/criticism; metric in parentheses):

H01: Using personas results in *faster* task completion than analytics (addresses Evaluation; metric: task completion time).

H02: Using personas results in *fewer steps* for task completion than analytics (addresses Evaluation; metric: number of screen moves).

H03: Using personas results in *faster* segment location than analytics (addresses Evaluation; metric: time).

Task completion is when the participant determines they have enough information to address the study's work scenario or time expired for the study session. *Segment location* is when the participant first navigates to the correct persona/analytics segment (i.e., selected the correct persona or segment), which is a critical sub-set of the task.

For RQ02, we have the following hypotheses, all that deal with *effectiveness* (benefit/criticism; metrics in parentheses):

H04: Using personas results in the identification of more *correct* user attributes than analytics (addresses Envision; metric: success rate).

H05: Using personas results in *higher confidence* for correct user identification than analytics (c.f. self-efficacy [6]) (addresses Consideration; metric: confidence rating).

H06: Using personas results in *better communication* about the user attributes than analytics (addresses Communication; metrics: message).

Successful *user identification* takes place when the participant correctly identifies an attribute of the target user segment. *Confidence* is a self-reported level concerning the assurance of identified user attributes. We measure better communication in two ways, (a) *the number of correct user attributes conveyed in the message* and (b) *the number of words in the message*. Our premise is that more detailed user information would require a longer message.

METHODOLOGY

We conduct a within-participant controlled field experiment to address our research questions and hypotheses using APG for the persona system and YTA for the analytics platform. Both APG and YTA use the identical underlying data from the focal company, facilitating a comparison between the two methods.

Data Site and Participants

Our data collection site was a major international news and media company, and the study was conducted in the participants' workplace. For this company, understanding online users plays a pivotal role. Various teams within the company use both personas and analytics to infer insights about their online audience, including the YouTube social media users. These insights are used for daily content creation and strategic planning, involving crafting agendas to serve the stakeholder groups of the company better and communication among teams/groups. Thus, the application of user insights in this company is both wide and varied. The choice of this company is further supported by the fact that the organization has adopted both tested systems, APG and YTA, which are used for the purposes we mentioned.

There are 34 participants (see Table 2). The average age is 33 years, and the participants reflect the staff working with online content daily in various capacities. The participants are from a diverse background, coming from 21 countries (including Belgium, Canada, India, Lebanon, South Africa,

South Korea, Turkey, UK, USA, etc.). *Producers* are the primary content creators of news articles and videos both for web and television, whereas *Editors* prepare the content for final publication, mainly for social media channels. *Analysts'* primary job deals with analyzing quantitative data about the users. The participants' average experience is 3.65 years with the current company. Their experience with personas and analytics varies, with some not that familiar with the concepts before the study.

Gender	No.	%	Role	No.	%
Male	14	41%	Editor	10	29%
Female	20	59%	Producer	12	35%
			Analyst	5	15%
			Other	7	21%
Total	34	100%	Total	34	100%

Table 2. Participant information for the study. Participants in the role 'Other' include executive, programmer, etc.

Each participant rated their experience both with personas and analytics data on a three-point Likert scale. A chi-squared test showed no significant difference in experience levels between the two approaches (personas: mean=1.44, SD=0.67, analytics: mean=1.36, SD=0.12). However, we explained both concepts to each participant to ensure a level foundational understanding.

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, while *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.

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 software¹ for logging the visual engagement of the participants. Eye tracking is widely used to study website usability [22] and design recommendations [27]. In addition to eye-tracking and mouse-tracking data², we collected (a) think-aloud [25] voice recordings (that were transcribed), (b) survey data, and (c) observer notes.

We also used the *concurrent think-aloud method* [2], encouraging the participants to explain what they are doing and why. To not interfere with the task completion [23, 60], we only spoke to a participant when s/he stopped voicing his/her cognitive process. We did not opt for complete non-obstruction, since we specifically wanted to learn about the cognitive processes of the participants as a form of triangulating eye tracking with the think-aloud protocol [9].

¹ <https://cooltool.com/>

² See supplementary video

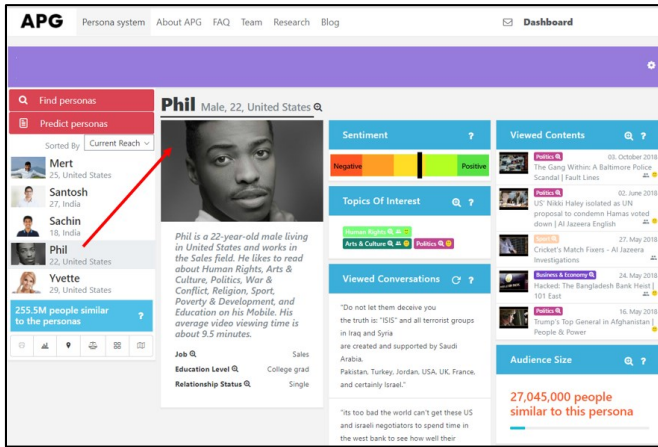


Figure 1. Example of persona treatment (Male, 18-24, USA). To locate the correct persona, the participant had to scan the list of personas and select the persona that fit the user segment criteria of (a) from the USA/Jordan, (b) 18-24 years of age, and (c) male. In the list of personas, there was only one correct persona (see red arrow). See <https://persona.qcri.org/> for example profile.

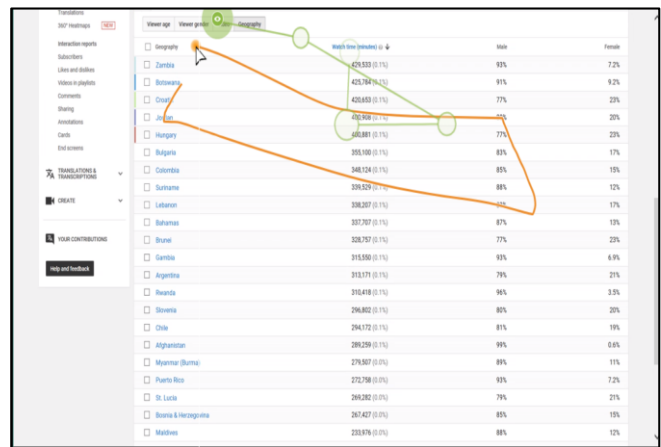


Figure 2. Example of YouTube treatment (Male, 18-24, Jordan). To locate the correct user segment, the participant had to select Analytics from the list of reports, then select Demographics, and then filter for the user segment criteria of (a) from the USA/Jordan, (b) 18-24 years of age, and (c) male. Note: Extra lines are eye and mouse movements.

The collected data permitted us to explore the aspects of persona and analytics use for efficiency and effectiveness for both inferring insights and communicating about users. Given the combination of eye-tracking, mouse-tracking, think aloud, and survey data, we believe we have a rich data set with triangulation along multiple collections avenues for a robust data analysis to address our research hypotheses.

Experimental Design

In the within-participants experiment, participants use personas and analytics to (a) locate an audience segment, (b) identify key attributes of that audience segment, (c) communicate a plan for targeting this segment to other members of a team, (d) crafting content targeted for this segment, and (e) recalling at the end of the session key attributes of the segment.

We show each of the participants both APG and YTA with one of the two audience segments chosen for the study representing an actual audience segment of the company. The participants were each assigned both possible conditions, persona or analytics. We pilot tested the experimental design with four test subjects, who did not participate in the actual experiment, making minor wording changes to the instructions based on their feedback.

The two treatments were the APG (personas) and the YTA (analytics) (see Figures 1³ and 2⁴). For this experiment, APG generated the personas using data gathered via the API from the organization’s YouTube channel. For the analytics system, YTA showed audience statistics from the same YouTube channel data. YTA is the analytical backend provided to the owners of specific YouTube channels, and

it provides a host of demographic and behavioral user information and reporting.

In the work task scenario employed, participants had to engage with the systems to locate the correct persona (on APG) or user segment (on YTA). For APG, the participants had to navigate three screens (*three steps*) to get to the correct persona. For YTA, the participants had to navigate two screens and set three filters (*five steps*) to get to the correct user segment (i.e., these steps represent the “minimum effort” required to complete the task successfully). As such, the minimum effort to locate the correct user segment was similar for both systems.

There were two user segments that we pilot tested on both systems to ensure that each was nearly identical in terms of task difficulty: (a) *men, age 18-24, from the United States* and (b) *men, age 18-24, from Jordan*. We manually created four different sequences showing the segments in the eye-tracking software for counterbalancing (e.g., in *Sequence 1* the participant first sees segment (a) using APG and then segment (b) using the YTA). An equal number of participants doing each sequence ensures all factors are counterbalanced, mitigating possible order effects. For each treatment, the participant was presented a pilot tested work scenario before being shown the system.

Data Collection

The experiment was conducted in the participants’ workplace. The entire user study took approximately forty minutes per participant (P). We instructed all participants in the same way at the beginning of the experiment about the usage of the devices and the procedure. To begin each trial, we welcomed the participant, introduced the study (i.e., using eye tracking to investigate how they use the systems), and answered any questions. After completing an institutional review board (IRB) consent form, we assigned

³ See supplementary video
⁴ See supplementary video

each participant a unique ID and calibrated the devices. Then, each participant was shown one of the two user segments. Depending on the condition (persona or analytics), the participant was shown the pilot tested work scenario task. The first work task scenario was:

Your team is preparing a YouTube marketing campaign to increase audience engagement.

In this campaign, it has been decided that you want to target “men, age 18-24, from the United States” [or the other treatment, “men, age 18-24, from Jordan”].

Your task is to use persona analytics [or the YouTube Analytics system] to learn more about this user segment.

Instructions:

- 1. Access the Persona Analytics [or the YouTube Analytics] system.*
- 2. Analyze the analytics information while *thinking aloud*.*
- 3. Write a description of the user segment using the information you've learned.*

After completing the first task, the participants then had to implement the segment information they gathered first into an email to their team members and then into a social media posting. The second work task scenario instructions were:

Please write an email to your team in which you (a) describe the most important characteristics of the user segment “men, age 18-24, from the Jordan” [or the other treatment, “men, age 18-24, from the United States”] and (b) explain why these characteristics are important.

NOTE: Mention at least three characteristics.

Once the participant composed the email message, they also ranked on a seven-point Likert scale, expressing how confident they were of their response. The participant then composed a social media posting targeted at the specific user segment. At this point, the participant would continue the session on the other system (either persona or analytics) and the other segment ([men, age 18–24, from the United States] or [men, age 18–24, from Jordan]), and again asked to complete the same tasks.

Once the participant had used both systems, the participant completed a post-questionnaire on recall of the user segment (again counterbalanced) and a demographic survey. This survey ended the session; we thanked the participant and addressed any questions. The participants were rewarded with a gift card (value of USD \$27.40) to show gratitude for their time.

QUANTITATIVE ANALYSIS AND RESULTS

We performed parametric validity checks. The data passed with a bit of skewness; however, prior work has shown that ANOVA methods are robust to such skewness [34].

H01. Using personas results in faster task completion than analytics (effort). We conducted a paired sample t-test to compare task completion time (seconds) using the persona and the analytics systems. There was a significant difference in the task completion time for the persona system (M=417.30 seconds, SD=144.08) and the analytics system (M=552.96, SD=115.97); $t(33)=4.29$, $p<0.01$. Thus, H01 is fully supported. *It is faster to complete a user identification task completion using the persona system than the analytics system.*

H02. Using personas results in fewer steps for task completion than analytics (effort). We conducted a paired sample t-test to compare the number of steps employed using the persona and the analytics conditions. There was a significant difference in the steps for the persona system (M=10.48, SD=7.13) and the analytics system (M=17.21, SD=7.35); $t(33)=5.40$, $p<0.01$. Thus, H02 is fully supported. *It takes less effort to gather attributes for a user identification task using the persona system than the analytics system.* We also normalized for the difference in steps (3 for APG; 5 for YTA), resulting in no significant difference. However, this is non-realistic as they are both operational systems. The number of steps are what they are. Also, as discussed below (H04), the majority of participants using the analytics system never actually located the correct user segment during the session.

For additional insight, each participant rated both systems on a five-point Likert scale of 1 (*not difficult at all*) to 5 (*very difficult*). We conducted a paired-samples t-test to compare the rating of the persona and analytics systems on the difficulty of use. There was a significant difference in the ratings for the persona system (M=1.85, SD=0.66) and the analytics system (M=3.54, SD=1.43); $t(33)=5.46$, $p<0.01$. As a corollary to H02, *it is easier to locate user attributes about a specific audience segment using the persona system than the analytics system.*

H03. Using personas results in faster segment location than using analytics (effort). We conducted a paired sample t-test to compare the time (seconds) needed to locate the targeted segment using the persona system and the analytics system. There was a significant difference in the times for the persona system (M=111.1, SD=58.9) and the analytics system (M=319.0, SD=131.1); $t(33)=4.30$, $p<0.01$. Thus, H03 is fully supported. *It is faster to locate the correct audience segment using the persona system than the analytics system.*

H04. Using personas results in more correct user attributes than analytics (success). We found that 25 (73.5%) of the participants were able to locate the user segment successfully using the persona system and 8 (23.5%) using the analytics system.

We employed McNemar’s test to assess the significance of the difference between two correlated proportions, where there are two possible outcomes (e.g., success or failure).

The p-value was calculated for the McNemar's test with continuity correction. There were 19 discordant pairs (i.e., participants that were successful with one system but not the other). There were 18 (94.7%) pairs where the participants were successful with the persona system but not with the analytics system, and 1 (5.26%) pair where the participant was successful with the analytics system but not with the persona system. There was a significant difference in outcomes between the two systems (McNemar's test(1) = 13.47, $p < 0.01$). Therefore, H04 is fully supported: *Using the persona system results in more correct user segment identifications relative to the analytics system.*

H05. Using personas results in higher confidence for correct user identification than analytics (*self-efficacy*).

We conducted a paired sample t-test to compare the confidence rating by the participants of the persona and the analytics conditions of messages containing user attributes. There was a significant difference in the scores for the persona system (M=6.93, SD=1.29) and the analytics system (M=5.83, SD=2.05); $t(33) = 2.85$, $p < 0.01$. Thus, H05 is fully supported. *Communication using the persona system was rated with higher confidence than the analytics.*

H06. Using personas results in better communication about the user segment than analytics (*communication*).

Each participant composed an email to their team members, where they provided three characteristics of the user and informed their teammates why they thought these attributes were important. We then conducted two evaluations: (a) a manual assessment where each correct user characteristic was awarded one point (0 = no attributes mentioned were correct to N = all the attributes mentioned were correct), and (b) total word count per email message, where our premise is that *a message with more words conveys more detailed information*, which seems a reasonable assumption given the work scenario task. However, we acknowledge that this assumption may not be valid in all cases.

To address H06a, we first conducted a paired sample t-test to compare the number of correct user attributes used in participant email messages of the persona and the analytics conditions. There was a significant difference in the scores for the persona system (M=3.03, SD=1.28) and the analytics system (M=2.08, SD=1.25); $t(35) = 4.19$, $p < 0.01$. H06a is fully supported: *The persona system produced more accurate communication than the analytics system.* In addition to identifying more correct user attributes (H06a) with the persona system, the participants were also more confident in their responses when using personas (H05).

To address H06b, we conducted a paired sample t-test to compare the number of terms used in email messages by the participants of the persona system and the analytics system conditions. Our premise is that, given the task, it seems reasonable that a more detailed description of the user segment would contain more terms. However, there was not a significant difference in the scores for the persona system (M=75.31, SD=55.23) and the analytics system (M=81.39,

SD=75.12) ($p = 0.69$). Therefore, H06b is not supported. The persona system did not result in more detailed communication than the analytics system as measured by the number of words in the email message.

QUALITATIVE ANALYSIS OF THINK-ALOUD

The qualitative analysis of the think-aloud transcripts was performed based on a codebook created from two usability frameworks: *HCI standards* [7] and *Usability in E-learning Context* [69]. We chose these frameworks because of their focus on designing information content for users. These frameworks provided us with six *functional* and four *affective* dimensions that we used as a matrix to identify and isolate segments that displayed specific affective responses on specific functions. We coded two affective dimensions (attention and relevance) into positive or negative sentiments. The remaining two affective dimensions were already either positive (satisfaction) or negative (dissatisfaction). A second researcher coded 100 transcripts comments resulting in a Cohen's kappa of 0.84.

Functional Dimensions

The six functional dimensions are interactivity, media use, navigability, learnability, consistency, and visual design⁵. These were coded in parallel to their affective context.

The *interactivity* dimension refers to the general use of the system (UX) and interface components (UI). These codes contain information on whether these components were:

- **interesting:** attention; *"if I don't have patience, I would have clicked on the cross"* (P1)
- **helpful:** relevance; *"I'm just scrolling down and looking at [average duration...] I'm just trying to find out where I can locate..."* (P23), or, generally,
- **positive or negative sentiments:** *"I don't know what I just did, do I drag this thing here? That doesn't really tell me anything, so what was I supposed to do"* (P2)

The *media use* dimension collects the participant comments about the use of images, videos, charts, and tables in the system. Again, these would refer to:

- **attention:** *"one was more of graphs [but] you had to get in two different places to search."* (P9),
- **relevance:** *"usually there's just like bars here where you can break things down [...]"* (P23), and
- **positive or negative sentiments:** *"the picture coincides with most of the information that is provided in the short description"* (P12) or *"I'm looking at a graph that doesn't really say much to me"* (P2).

The *navigability* dimension highlights issues related to traversing the data through links, views, and pages. This dimension is differentiated from interactivity as it focuses on how the data is presented and navigated rather than how it is interacted with. For example:

⁵ We originally coded for an *accessibility* dimension, but it did not produce any segments, so we exclude it from the analysis reporting.

- “it took me a while to understand [the] architecture of the page to see what’s where” (P9) or
- “in the persona system you were able to see stuff clearly [...] without having to do too much digging [...] you know, clicks and stuff to try to get this” (P27).

The *learnability* dimension is about sentiments on how easy or how hard it was to adopt the system. These segments were collected under the affective dimensions of:

- **attention:** “it’s interesting because you get insight” (P29),
- **relevance:** “it’s refined here [...] understanding those details” (P9), and
- **positive or negative sentiments:** P15 on YTA: “I don’t recall anything [...] overwhelmed by numbers” (P15) vs. P15 on APG: “I can write more [about the persona], I remember a lot about [the persona]” (P15).

We used the *consistency* dimension in two contextual categories: (1) the system works (or not) as expected in terms of providing information (e.g., “I just want to focus on him and [the system gives] me all the topics [...] that he’s interested in...” (P28)) and (2) the information provided by the system is consistent (or not). Some negative examples are: “I don’t think [the persona] is an average US person” (P2), and “I guess I’m really not sure what this information is really telling me, it seems a little conflicting” (P3). The comment of P2 is interesting, as it is somewhat similar to statements that personas actually represent few real users [13, 14]. Some positive examples are: “demographics seems logical to me” (P2), “that immediately narrows it down, great” (P3), and “good, that’s to be expected” (P20).

Finally, the *visual design* codes referred to the general visual feeling of the systems. There were very few codes regarding this dimension. The limited codes from this dimension are: “It’s just the color [...] I think it would be better if when you select, it highlights and then you’d know what options you have” (P26), “with few icons, very straight...” (P29), and “the design is a bit too blocky” (P26). Therefore, we do not analyze this dimension further.

Affective Dimensions

The four affective dimensions are attention, relevance, satisfaction, and dissatisfaction. The code *attention* was used when there was curiosity or interest (or lack of) from the participant toward the interaction or information at-hand. Typically, these segments were not overlapping with any strong positive (satisfaction) or negative (dissatisfaction) sentiments. Some examples are:

- (positive) “[the persona] uses the shorthand quite a bit, which is interesting” (P20) and
- (positive) “okay, so the persona seems to be watching far less content or [...] shorter content—this is interesting” (P27).

- (negative) “[the persona’s] quotes are.... no, I won’t remember them” (P15) and
- (negative) “I didn’t pay attention to the quote....” (P4).

The code *relevance* was used when the participant points out that they are able or not able to access the information that is related to their task goals and that the information makes sense to them toward their motives. Once more, these segments did not overlap with strong sentiments but merely constructed statements of availability, as in:

- “I can see here some of what I’m looking for” (P19) vs.
- “I want to know like what kind of content is most popular to this demographic, but I don’t know if [...] the option [exists]” (P31).

The *satisfaction* and *dissatisfaction* codes were used when the participants made explicit judgments about the functions of the systems. Some examples are:

- “that demo didn’t really speak to me” (P3, dissatisfaction),
- “it’s annoying me [...] I don’t know anything.” (P14, dissatisfaction),
- “I can see them [the personas] in front of my eyes” (P20, satisfaction), and
- “those statistics are perfect” (P13, satisfaction).

Comparative Results

We used our coding results by normalizing the positive vs. negative sentiments for each functional dimension using:

$$score_{normalized} = [n_{total\ positive\ codes} - n_{total\ negative\ code}] / n_{total\ codes}$$

where n = instances. See Table 3 for top-level results.

Functional Dimension	Persona System	YouTube Analytics
Interactivity	-1 (n=9)	-1 (n=5)
Media use	-1 (n=4)	-1 (n=7)
Navigability	-0.33	-0.63
Learnability	+0.23	-0.68
Consistency	-0.18	-0.59

Table 3. Normalized scores for our coding of the think-aloud transcriptions for participants using personas and analytics.

A score of +1 would mean that all the codes were positive, a score of -1 would mean that all the codes were negative, and a score of 0 would mean that the number of positive vs. negative codes were equal.

The scores indicated a clear distinction between the persona and the analytics systems in terms of learnability. The only positive score was for the learnability of APG. The personified data in the persona system garnered more positive comments:

- “it was a little bit more intuitive than YouTube” (P3),
- “this is more to me, it’s very easy to see” (P22), and
- “I understood about [the persona]” (P24).

Quotes from several participants highlight the challenges of the numbers-based information in YTA:

- “I need someone to explain things to me so I can understand how to use this data because now I don’t know what this number means” (P5),
- “I have zero confidence [...] because I don’t have the experience [of] reading this data” (P7),

APG performed better than YTA on consistency too, although the scores of both systems were negative, highlighting some issues raised in prior literature concerning coherent information in personas profiles [10].

Summary of Research Findings

The major research findings from the quantitative analysis are that (a) personas are more efficient for user identification relative to analytics, and (b) personas are more effective for user identification relative to analytics. A summary of the hypotheses tested is presented in Table 4.

	Result	Implication
H01	✓ Fully Supported	Personas result in faster task completion than analytics (effort)
H02	✓ Fully Supported	Personas result in fewer steps for task completion than analytics (effort)
H03	✓ Fully Supported	Personas result in faster segment location than using (effort)
H04	✓ Fully Supported	Personas result in more correct user identification than analytics (success).
H05	✓ Fully Supported	Personas create more confidence in user identification than analytics (self-efficacy)
H06	Partially Supported	Personas result in better messaging about user segment than analytics (communication)

Table 4. Summary of hypotheses results and findings of personas vs. analytics for efficiency and effectiveness.

User identification is the core aspect of employing nearly all types of personas, including design, advertising, marketing, ad hoc, primary, audience, collaborative, or any other of the multitude of persona types proposed in the literature. User identification is also an essential component of communication about users for implementing user focus design or for directing decision makers to emphasize the users during product, system, or content development. As such, user identification is a needed task for the employment of either personas or analytics methodologies in most domains. As shown in Table 4, personas outperformed analytics for this central foundational task.

First, personas were more efficient for user identification both in terms of time and number of steps required, both for the critical location of the user segment and for the overall work task. Personas were more efficient than analytics in these regards, requiring less time and effort than analytics.

Second, personas were more effective for user identification in terms of accuracy, the ability to craft messages concerning those user attributes, and confidence in that communications. Along all measures (success, self-efficacy, and communication), personas were more effective than analytics in these regards. These quantitative findings were further supported by the qualitative analysis indicating the superiority of personas for the user identification task.

DISCUSSION AND IMPLICATIONS

Positioning Findings to Persona Benefits and Criticism

Our research addresses the widely cited criticism in the field of HCI that personas are not scientifically validated (‘Evaluation’ aspect of the 3Es) [15]. We show how to quantify and measure the value of personas relative to the widely used method of user analytics. *This approach can be adopted by further studies to validate persona benefits for different use cases.* While HCI researchers [12, 14, 67, 71] have evaluated the *accuracy* of personas relative to the underlying data, there has been little progress reported in the literature evaluating the *value* of personas using quantitative user studies. The research presented here shows that personas can be evaluated in comparison to other methods, especially when both systems have an identical underlining data source, also addressing the ‘Execution’ aspect of the 3Es.

Our findings also question statements made in prior work that personas cannot replace the employment of actual user data for inferring user insights [45]. Most notably, the reduced time and number of steps while using personas did not negatively impact the ability of the participants to complete the task. In fact, personas resulted in participants generating more accurate user segment descriptions (H04) with higher confidence (H05) (e.g. “*Honestly I can, I can imagine a day in the life of this persona, how he behaves, how he works.*” (P33)). This supports the ‘Consideration’ aspect of the 3Cs.

All participants spent significantly less time to complete the overall task (i.e., gather enough information about users for team communication) (H01) and to locate information about the user segment (H03) using personas than using analytics. Participants similarly used fewer steps to complete the targeted user segment task (H02) using personas than analytics. Participants also rated personas easier for locating information about a specific user segment than analytics. This is most likely because the information in a persona is presented in a user-centric way (i.e., the persona profile is the focal point), whereas in analytics systems, the information about specific user segments tends to be scattered across many reports, tables, and graphs, requiring the advanced use of filters (“*it’s hard to get a lot of information [because it’s fragmented under many sections]*” (P32 on YTA)). We note that this platform is an industry standard service, with features common in many other analytics systems. These findings support the

‘Concentration’ aspect of 3Cs, as they imply personas helped participants focus on the specific user segment.

Additionally, the participants were more effective in communicating about the user segment in a rich description format (H06a), which supports the ‘Communication’ aspect of the 3Cs. We note that, counter to our premise, the descriptions were not lengthier. However, our assumption for this hypothesis may have been incorrect in that the task may not require lengthier descriptions.

The research reported here highlights the advancements made possible by leveraging forms of online user data [39] for persona creation with the increasing power of analytics systems [32]. Data-driven personas capture the coverage of aggregated data representations while retaining the *interpretability* of human-like user depictions (e.g., “*I could tell that in the persona system you were able to see stuff clearly like right... without having to do too much digging ‘cause usually you have to do a lot of like, you know, clicks and stuff to try to get this information out*” (P27)). The results imply that personas can provide insights as good as analytics in a more effective and efficient manner.

Practical Implications for Personas and Analytics Use

We highlight three practical take-aways for organizations.

Use Personas for User Identification Related Tasks:

Personas appear ideally suited for user segment location, inferring insights about user segments, and then communicating about these segments with others (e.g., “*It did seem like a very authentic person actually, I think that was really well done [...] I know how to target that person.*” (P34)). This holds regardless of end user experience-level. We initially suspected that there would be some ‘analytically challenged’ and ‘analytically sophisticated’ participants. However, this was not the case, as the experience level of either personas or analytics was not a significant control variable. Participant comments supported this (e.g., “*I don’t know what is happening, this is my first time to open analytics on YouTube. [...] I understand how to use a persona, but here I don’t know, this is certainly difficult*” (P05); “*Ok, I think I’m done, this was easier*” (P02 about personas)). Generally, *when participants of whatever experience used the persona system, they were both more effective and more efficient*. We argue that, as personas support a user-centric information discovery process using big data [5], they result in a significantly higher success rate.

Deploy Personas in Conjunction with Support: Personas do appear to require possible accompanying education for end users. Some participants were thrown off by the easiness of the persona system (“*it was so easy I thought I did something wrong*”) (P3 on APG). Some participants expected to see more personas from the same user segment (e.g., P3), indicating some disorientation about what the system affordances are, what personas are, and how to incorporate the persona approach. It shows that, for

personas to be used effectively, workshops and training on the concept should be provided to end users of an organization before persona employment and use.

Leverage Analytics Capabilities Along with Personas:

This research examined one user-centric task in which personas performed better. However, this does not mean that analytics is not valuable, as these platforms offer an array of functions and reports beyond the scope of personas. In fact, for the analytics system, some participants highlighted the range of metrics provided (e.g., “*YouTube analytics is giving me more details about the target audience and their behavior on our content*” (P35)).

Limitations

Concerning the limitations of the research, there may be possible mitigating aspects of the analytics system. However, YTA is state of the art, so it has features common in many other analytics platforms. The time limit possibly affected the participants’ behavior compared to a naturalistic setting (i.e., “*would choose more metrics but cannot due to time limit*” (P12)). However, time pressures are a normal occurrence in many organizations, making our experimental results practical and valid. Nevertheless, the study could be repeated in a fully naturalistic setting. Another possible limitation is that YTA has additional features concerning users and user segments, while the persona system is focused on the presentation of user segmentation. For tasks other than user identification, analytics might provide affordances that personas cannot.

Future Work

Concerning future research, replication studies comparing data-driven personas to other types of user segmentation platforms (e.g., Google Analytics, Facebook Analytics), to other tasks (e.g., user understanding, user prediction), to other methods for user focusing (e.g., scenarios, use cases, user profiling, participatory design), and in other domains would be productive pursuits. It would also be good to do a study with traditionally created personas and the underlying data, although there may be challenges for such a study.

CONCLUSION

To our knowledge, this is one of the first quantitative evaluations of personas relative to another method for understanding users. We conducted a quantitative experiment using workplace participants, a work task, and real systems for the validity of the findings. The persona and analytics systems employed identical user data and were evaluated using both effectiveness and efficiency for user identification. Findings make a strong case for the advantages of personas and provide foundational support for the benefits of personas as a user focus methodology.

ACKNOWLEDGMENTS

We thank the 34 participants of this study for taking time from their extremely busy workday to participate in this research and the anonymous reviewers for comments that greatly enhanced the quality of this manuscript.

REFERENCES

- [1] T. Adlin and J. Pruitt, *The Essential Persona Lifecycle: Your Guide to Building and Using Personas*: Morgan Kaufmann Publishers Inc., 2010.
- [2] O. Alhadreti and P. Mayhew, "To Intervene or Not to Intervene: An Investigation of Three Think-aloud Protocols in Usability Testing," *Journal of Usability Studies*, vol. 12, pp. 111–132, 2017.
- [3] J. An, H. Kwak, J. Salminen, S. G. Jung, and B. J. Jansen, "Customer segmentation using online platforms: isolating behavioral and demographic segments for persona creation via aggregated user data," *Social Network Analysis and Mining*, vol. 8, p. 54, 2018.
- [4] J. An, H. Kwak, J. Salminen, S. G. Jung, and B. J. Jansen, "Imaginary People Representing Real Numbers: Generating Personas from Online Social Media Data," *ACM Transactions on the Web*, vol. 12, p. Article 27, 2018.
- [5] M. I. Baig, L. Shuib, and E. Yadegaridehkordi, "Big data adoption: State of the art and research challenges," *Information Processing & Management*, vol. 56, p. 102095, 2019.
- [6] A. Bandura, "Self-efficacy mechanism in human agency," *American Psychologist*, vol. 37, pp. 122–147, 1982.
- [7] N. Bevan, "Human-computer interaction standards," in *Advances in Human Factors/Ergonomics*. vol. 20, ed, 1995, pp. 885-890.
- [8] H. Beyer and K. Holtzblatt, *Contextual Design: Defining Customer-centered Systems*: Morgan Kaufmann Publishers Inc., 1998.
- [9] T. Blascheck, M. John, S. Koch, L. Bruder, and T. Ertl, "Triangulating User Behavior Using Eye Movement, Interaction, and Think Aloud Data," in *The Ninth Biennial ACM Symposium on Eye Tracking Research & Applications*, 2016, pp. 175–182.
- [10] S. Bødker, E. Christiansen, T. Nyvang, and P. O. Zander, "Personas, people and participation: challenges from the trenches of local government," in *Proceedings of the 12th Participatory Design Conference: Research Papers (PDC '12)*, 2012, pp. 91-100.
- [11] R. Boghrati, J. Hoover, K. M. Johnson, J. Garten, and M. Dehghani, "Conversation level syntax similarity metric," *Behavior Research Methods*, vol. 50, pp. 1055-1073, 2017.
- [12] J. Brickey, S. Walczak, and T. Burgess, "Comparing Semi-Automated Clustering Methods for Persona Development," *IEEE Transactions on Software Engineering*, vol. 38, pp. 537–546, 2012.
- [13] D. G. Cabrero, H. Winschiers-Theophilus, and J. Abdelnour-Nocera, "A Critique of Personas as representations of "the other" in Cross-Cultural Technology Design," in *Proceedings of the First African Conference on Human Computer Interaction (AfriCHI'16)*, 2016, pp. 149-154.
- [14] C. N. Chapman, E. Love, R. P. Milham, P. ElRif, and J. L. Alford, "Quantitative Evaluation of Personas as Information," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2008, pp. 1107–1111.
- [15] C. N. Chapman and R. P. Milham, "The Personas' New Clothes: Methodological and Practical Arguments against a Popular Method," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2006, pp. 634–636.
- [16] M. F. Clarke, "The Work of Mad Men that Makes the Methods of Math Men Work: Practically Occasioned Segment Design," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*, 2015, pp. 3275-3284.
- [17] T. B. Clarke and B. J. Jansen, "Conversion potential: a metric for evaluating search engine advertising performance," *Journal of Research in Interactive Marketing*, vol. 11, pp. 142–159, 2017.
- [18] A. Cooper, *The Inmates Are Running the Asylum: Why High Tech Products Drive Us Crazy and How to Restore the Sanity (2nd Edition)*: Pearson Higher Education, 2004.
- [19] P. Dharwada, J. S. Greenstein, A. K. Gramopadhye, and S. J. Davis, "A Case Study on Use of Personas in Design and Development of an Audit Management System," in *Human Factors and Ergonomics Society Annual Meeting Proceedings*, Baltimore, Maryland, 2007, pp. 469-473.
- [20] J. Dong, K. Kelkar, and K. Braun, "Getting the most out of personas for product usability enhancements," *Usability and Internationalization, HCI and Culture*, vol. 4559, pp. 291–296, 2007.
- [21] V. L. Drego and M. Dorsey, "The ROI Of Personas," Forrester Research 3 Aug. 2010.
- [22] A. T. Duchowski, *Eye Tracking Methodology: Theory and Practice*. London: Springer, 2009.
- [23] K. A. Ericsson and H. A. Simon, "Verbal reports as data," *Psychological Review*, vol. 87, pp. 215-251, 1980.
- [24] E. Eriksson, H. Artman, and A. Swartling, "The Secret Life of a Persona: When the Personal Becomes Private," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Paris, France, 2013, pp. 2677-2686.
- [25] M. E. Fonteyn, B. Kuipers, and S. J. Grobe, "A description of think aloud method and protocol analysis," *Qualitative Health Research*, vol. 3, pp. 430-441, 1993.

- [26] E. Friess, "Personas and Decision Making in the Design Process: An Ethnographic Case Study," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Austin, Texas, USA, 2012, pp. 1209-1218.
- [27] J. H. Goldberg, M. J. Stimson, M. Lewenstein, N. Scott, and A. M. Wichansky, "Eye Tracking in Web Search Tasks: Design Implications," in *The 2002 Symposium on Eye Tracking Research & Applications*, New York, NY, 2002, pp. 51–58.
- [28] K. Goodwin and A. Cooper, *Designing for the Digital Age: How to Create Human-Centered Products and Services*. Indianapolis, IN: Wiley, 2009.
- [29] J. Grudin and J. Pruitt, "Personas, participatory design and product development: An infrastructure for engagement," in *Participatory Design Conference*, 2002, pp. 144-152.
- [30] R. Guðjónsdóttir and S. Lindquist, "Personas and Scenarios: Design Tool or a Communication Device," in *8th International Conference on Cooperative Systems (COOP'08)*, Carry-le-Rouet, France, 2008, pp. 165-176.
- [31] F. Y. Guo, S. Shamdasani, and B. Randall, "Creating Effective Personas for Product Design: Insights from a Case Study," in *International Conference on Internationalization, Design and Global Development (IDGD 2011)*, 2011, pp. 37-46.
- [32] B. A. Hammou, A. A. Lahcen, and S. Mouline, "Towards a real-time processing framework based on improved distributed recurrent neural network variants with fastText for social big data analytics," *Information Processing & Management*, vol. 57, p. 102122, 2020.
- [33] C. G. Hill, M. Haag, A. Oleson, C. Mendez, N. Marsden, A. Sarma, *et al.*, "Gender-Inclusiveness Personas vs. Stereotyping: Can We Have it Both Ways?," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, Denver, Colorado, USA, 2017, pp. 6658-6671.
- [34] D. Hull, "Using statistical testing in the evaluation of retrieval experiments," in *Proceedings of the 16th annual international ACM SIGIR conference on Research and development in information retrieval (SIGIR '93)*, 1993, pp. 329-333.
- [35] J. Järvinen and H. Karjaluo, "The use of Web analytics for digital marketing performance measurement," *Industrial Marketing Management*, vol. 50, pp. 117–127, 2015.
- [36] I. Jensen, H. Hautopp, L. Nielsen, and S. Madsen, "Developing international personas : A new intercultural communication practice in globalized societies," *Journal of Intercultural Communication*, vol. 43, p. Article 01, 2017.
- [37] S. Jung, J. An, H. Kwak, M. Ahmad, L. Nielsen, and B. J. Jansen, "Persona Generation from Aggregated Social Media Data," in *ACM Conference on Human Factors in Computing Systems 2017 (CHI2017)*, Denver, CO, 2017, pp. 1748-1755.
- [38] S. G. Jung, J. Salminen, and B. J. Jansen, "Personas Changing Over Time: Analyzing Variations of Data-Driven Personas During a Two-Year Period," in *ACM CHI Conference on Human Factors in Computing Systems (CHI2019) (Extended Abstract)*, Glasgow, United Kingdom, 2019, p. LBW2714.
- [39] J. H. Kim and Y. Kim, "Instagram user characteristics and the color of their photos: Colorfulness, color diversity, and color harmony," *Information Processing & Management*, vol. 56, pp. 1494-1505, 2019.
- [40] S. D. Krashen, "Immersion: Why it works and what it has taught us', Language and Society," *Language and Society*, vol. 12, pp. 61–64, 1984.
- [41] F. Long, "Real or Imaginary; The Effectiveness of Using Personas in Product Design," in *The Irish Ergonomics Society Annual Conference*, Dublin, 2009, pp. 1–10.
- [42] J. Ma and C. LeRouge, "Introducing User Profiles and Personas into Information Systems Development," in *AMCIS 2007 Proceedings*, 2007, p. Article 237.
- [43] J. Ma and C. LeRouge, "Introducing User Profiles and Personas into Information Systems Development," in *AMCIS 2007 Proceedings*, 2007.
- [44] A. L. Massanari, "Designing for Imaginary Friends: Information Architecture, Personas, and the Politics of User-Centered Design," *New Media & Society*, vol. 12, pp. 401-416, 2010.
- [45] T. Matthews, T. Judge, and S. Whittaker, "How Do Designers and User Experience Professionals Actually Perceive and Use Personas?," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2012, pp. 1219–1228.
- [46] T. Miaskiewicz, S. J. Grant, and K. A. Kozar, "A Preliminary Examination of Using Personas to Enhance User-Centered Design," in *AMCIS 2009 Proceedings*, 2009, p. Article 697 <http://aisel.aisnet.org/amcis2009/697>.
- [47] T. Miaskiewicz and K. A. Kozar, "Personas and user-centered design: How can personas benefit product design processes?," *Design Studies*, vol. 32, pp. 417–430, 2011.
- [48] T. Miaskiewicz, T. Sumner, and K. A. Kozar, "A latent semantic analysis methodology for the identification and creation of personas," in *SIGCHI Conference on Human Factors in Computing Systems*, Florence, Italy, 2008, pp. 1501–1510.

- [49] L. Nielsen, *Personas - User Focused Design*. London: Springer-Verlag, 2013.
- [50] L. Nielsen, K. S. Hansen, J. Stage, and J. Billestrup, "A Template for Design Personas: Analysis of 47 Persona Descriptions from Danish Industries and Organizations," *Int. J. Sociotechnology Knowl. Dev.*, vol. 7, pp. 45-61, 2015.
- [51] J. E. Nieters, S. Ivaturi, and I. Ahmed, "Making personas memorable," in *CHI '07 Extended Abstracts on Human Factors in Computing Systems*, San Jose, CA, USA, 2007, pp. 1817-1824.
- [52] D. Norman. (2004, 1 Sep). *Ad-Hoc Personas & Empathetic Focus*. Available: http://www.jnd.org/dn.mss/personas_empath.html
- [53] R. Pichler. (2012, 14 Aug). *A template for writing great personas*. Available: <http://www.romanpichler.com/blog/persona-template-for-agile-product-management/>
- [54] K. Popper, *The Logic of Scientific Discovery*. Abingdon-on-Thames: Routledge, 1959.
- [55] J. Pruitt and T. Adlin, *The Persona Lifecycle: Keeping People in Mind Throughout Product Design*: Morgan Kaufmann, 2006.
- [56] J. Pruitt and J. Grudin, "Personas: Practice and Theory," in *Proceedings of the 2003 Conference on Designing for User Experiences*, San Francisco, California, 2003, pp. 1-15.
- [57] A. Revella, *Buyer Personas: How to Gain Insight into Your Customer's Expectations, Align Your Marketing Strategies, and Win More Business*: Wiley, 2015.
- [58] K. Rönkkö, "An Empirical Study Demonstrating How Different Design Constraints, Project Organization and Contexts Limited the Utility of Personas," in *Proceedings of the 38th Annual Hawaii International Conference on System Sciences*, 2005, pp. 1530-1605.
- [59] K. Rönkkö, M. Hellman, B. Kilander, and Y. Dittrich, "Personas is Not Applicable: Local Remedies Interpreted in a Wider Context," in *Proceedings of the Eighth Conference on Participatory Design: Artful Integration: Interweaving Media, Materials and Practices*, New York, NY, USA, 2004, pp. 112-120.
- [60] J. E. Russo, E. J. Johnson, and D. L. Stephens, "The validity of verbal protocols," *Memory & Cognition*, vol. 17, pp. 759-769, 1989.
- [61] J. Salminen, S. G. Jung, and B. J. Jansen, "Detecting Demographic Bias in Automatically Generated Personas," in *ACM CHI Conference on Human Factors in Computing Systems (CHI2019) (Extended Abstract)*, Glasgow, United Kingdom, 2019, p. LBW0122.
- [62] J. Salminen, H. Kwak, J. An, S. G. Jung, and B. J. Jansen, "Are personas done? Evaluating their usefulness in the age of digital analytics," *Persona Studies*, vol. 4, pp. 47-65, 2018.
- [63] J. Salminen, L. Nielsen, S.-G. Jung, J. An, H. Kwak, and B. J. Jansen, "Is More Better?: Impact of Multiple Photos on Perception of Persona Profiles," presented at the Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, Montreal QC, Canada, 2018.
- [64] W. R. Smith, "A product differentiation and market segmentation as alternative marketing strategies," *Journal of Advertising*, vol. 21, pp. 3-8, 1956.
- [65] P. D. Stevenson and C. A. Mattson, "The Personification of Big Data," in *Proceedings of the Design Society: International Conference on Engineering Design*, 2019, pp. 4019-4028.
- [66] C. J. Vincent and A. Blandford, "The challenges of delivering validated personas for medical equipment design," *Applied Ergonomics*, vol. 45, pp. 1097-1105, 2014.
- [67] Y. Watanabe, H. Washizaki, K. Honda, Y. Noyori, Y. Fukazawa, A. Morizuki, *et al.*, "ID3P: Iterative Data-driven Development of Persona Based on Quantitative Evaluation and Revision," in *The 10th International Workshop on Cooperative and Human Aspects of Software Engineering*, 2017, pp. 49-55.
- [68] J. B. Wendell, K. Holtzblatt, and S. Wood, *Rapid Contextual Design: A How-to Guide to Key Techniques for User-centered Design*: Morgan Kaufmann, 2004.
- [69] P. Zaharias, "Usability in the context of e-learning: A framework augmenting 'traditional' usability constructs with instructional design and motivation to learn," *International Journal of Technology and Human Interaction*, vol. 5, pp. 37-59, 2009.
- [70] X. Zhang, H.-F. Brown, and A. Shankar, "Data-driven Personas: Constructing Archetypal Users with Clickstreams and User Telemetry," in *In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*, 2016, pp. 5350-5359.
- [71] H. Zhu, H. Wang, and J. M. Carroll, "Creating Persona Skeletons from Imbalanced Datasets - A Case Study using U.S. Older Adults' Health Data," in *The 2019 on Designing Interactive Systems Conference (DIS '19)*, 2019, pp. 61-70.