Comparing Persona Analytics and Social Media Analytics for a User-Centric Task Using Eye-Tracking and Think-Aloud

Joni Salminen
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha, Qatar; University of Turku, Turku, Finland, jsalminen@ @hbku.edu.qa

Sercan Şengün
Wonsook Kim College of Fine Arts, Illinois State University, Normal IL., USA
ssengun@ilstu.edu

Soon-Gyo Jung
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha, Qatar
sjung@hbku.edu.qa

Bernard J. Jansen
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha, Qatar
sjung@hbku.edu.qa

ABSTRACT

We compare a data-driven persona system and an analytics system for efficiency and effectiveness for a user identification task. Findings from the 34-participant experiment show that the data-driven persona system affords faster task completion, is easier for users to engage with, and provides better user identification accuracy. Eye-tracking data indicates that the participants focus most of their attention on the persona content while focusing more on navigation features when using the analytics system. The combined results provide empirical support for the use of data-driven personas for a user identification task, which we surmise to be a result of the persona system following a user-centered design paradigm instead of an information-centered paradigm. That analytics system afforded capabilities and insights that the persona system did not suggest that the triangulation of features may lead to a better overall user understanding.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction.

KEYWORDS

Analytics systems, data-driven personas, eye-tracking, mixed-method user study

ACM Reference Format:
Joni Salminen, Sercan Şengün, Soon-Gyo Jung, and Bernard J. Jansen. 2021. Comparing Persona Analytics and Social Media Analytics for a User-Centric Task Using Eye-Tracking and Think-Aloud. In *CHItaly 2021: 14th Biannual Conference of the Italian SIGCHI Chapter (CHItaly '21), July 11–13, 2021, Bolzano, Italy*. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3464385.3464734

CHItaly '21, July 11–13, 2021, Bolzano, Italy

ACM ISBN 978-1-4503-8977-8/21/07…$15.00
https://doi.org/10.1145/3464385.3464734

1 INTRODUCTION

A persona is a technique for giving personal characteristics to segments of an audience, user base, or customer segments [10]. Personas are employed for an enhanced understanding of user segments in many domains, including content creation [3, 26], marketing [9, 40], product design [12, 19, 25], and software development [10, 38]. Personas are often designed using user data composed via focus groups, face-to-face interviews, or online surveys [13, 35], although there is an increasing interest in algorithmic approaches for data-driven persona development [42]. Data-driven personas [21] are the specific focus of this research, as organizations are increasingly interested in leveraging big data for user understanding, and data-driven personas represent state-of-the-art approaches in persona development.

Personas, including data-driven personas, are usually presented as a set of persona profiles (also called 'descriptions', 'narratives') that are generally a page or two containing personal attributes, behavioral patterns, goals, skills, name, age, and a photo, all with the purpose of presenting the persona as a real person [35]. The aim of employing personas is to provide insights concerning the desires, goals, or needs of a targeted segment in an empathetic manner (i.e., another person) for aiding decisions regarding a product, service, or system [34]. In short, the employment of personas is presumed to be cognitively compelling for user understanding via placing a human face on user data.

Persona research is broad [10], with researchers claiming several benefits that are primarily about channeling the focus on and highlighting communication concerning users to improve crafting, design, and development activities in organizations and teams [1, 13, 15, 39, 41]. However, despite the claimed benefits in the extant human-computer interaction (HCI) literature [1, 11, 13] and the host of qualitative research concerning the employment of personas [1, 18, 23, 35, 38], there is scant quantitative research empirically addressing two essential questions: (1) *whether or not personas are beneficial*; and if they are beneficial, (2) *whether or not personas are better than other techniques for user-centric tasks.* Empirical and experimental research addressing these questions is needed because of the prevailing criticism of personas, both as concepts and as design tools, postulating that personas are not valid methods for understanding users and have limited practical value [7, 8], with some even questioning whether personas can be scientifically validated at all [8]. These criticisms apply across the range of personas, and also impact the design of data-driven persona systems.

One reason for this lack of quantitative research is that traditionally assumption-based personas are notoriously difficult to evaluate quantitatively. However, the emergence of many online platforms permits the creation of data-driven personas that are created algorithmically. As with other types of personas, there is a limited quantitative evaluation of data-driven personas. The empirical validation of data-driven persona benefits is a pressing issue because a plethora of alternative online analytics systems, services, and tools have emerged since the initial introduction of personas within the HCI domain [6, 22]. These systems (e.g., IBM Analytics, Facebook Insights, Google Analytics, etc.) provide ample and competitive means for organizations to understand user segments using behavioral data [28] of remarkable volumes, varieties, and velocities [48]. Many contemporary organizations also have access to online user data at the individual level—referred to as 'personified big data' —which challenges the value of employing data-driven personas as a segment-based user representation rather than just employing individualized data or other forms of data aggregation (numbers, tables, and charts) to understand users in downstream tasks, such as personalization and recommendation [46].

Organizations are increasingly operating wholly or partially online, and they desire to understand their users in digital environments, including the foundational task of *identifying* target users for a specific design task, whether this task relates to development, design, advertising, or communication. If the data-driven persona approach is not competitive in terms of inferring user understandings easily and reliably, personas (data-driven or not) will simply be discarded as redundant and *passé* relative to data analytics systems. Consequently, there are realistic apprehensions about data-driven personas offering practical value relative to the other available analytics services [9] for understanding online users [44]. The essential question is *whether, in this day and age of user analytics systems, data-driven personas are, in fact, useful for understanding users.* It is this question that motivates our research.

Addressing this fundamental question informs the ongoing efforts to define the value of data-driven personas for the increased understanding of users in the digital era. Intrinsically, addressing this question has broad and impactful implications for HCI and related fields, including marketing, recruiting, advertising, health informatics, and other domains routinely deploying user analytics and personas [26]. Hence, this question is worthwhile to pursue, particularly because we could not locate any prior research that rigorously compared data-driven personas to other approaches to user-centric tasks. The prior literature regarding the benefits of data-driven personas is primarily anecdotal, composed of case studies and qualitative studies, with little to no quantitative comparisons of data-driven personas to alternative methods used in the industry.

2 LITERATURE REVIEW

Data-driven personas are, naturally, based on the persona concept. Introduced for the software design field, personas gained popularity in the late 1990s [1]. Pruitt and Adlin [38], with others [34-36, 39, 45], expanded the persona's best practices and techniques. Since personas were introduced, HCI researchers have highlighted both their positive and negative aspects. We first present these positive and negative aspects and then explore the underlying assumptions of both, as the research at hand specifically addresses the foundational assumptions of persona.

2.1 Reported Positives of Personas

The proposed positive aspects of personas can be summarized into the groupings of Communication, Consideration, and Concentration.

Communication: Personas reportedly offer collaboration benefits derived from the personas' ability to encapsulate user information into the intuitive representation of a real person that can be readily communicated to the various stakeholders within organizations [31] and is more immersive than analytics data [20].

Consideration: Personas supposedly have psychological benefits that are rooted in the natural emotional identification with people represented by personas [32], helping decision-makers understand and predict user behavior under different contexts [39].

Concentration: Personas can allegedly facilitate concentrating on the most significant user segments [32] by isolating an archetype user for the development of products and services.

2.2 Reported Negatives of Personas

There are substantial negative aspects of personas detailed in the HCI literature. We tag these negatives into Envision, Execution, and Evaluation (labeled as the 3Es).

Envision: Chapman and Milham [7] contend that personas have no direct association with real user data and that they represent few actual users [7] and are not scientifically valid [13] because a persona is not falsifiable in any meaningful way [37].

Execution: Hill et al. [20] highlight that it takes considerable effort, money, and time to create high-quality personas. Accordingly, as Rönkkö [41] reports, the volume of effort leads many to question the return on investment (ROI) of a persona-development project.

Evaluation: Rönkkö reports how organizational factors often led to limited persona usage [41]. Also, numbers-oriented end users may consider personas as little more than "nice narratives" while resisting their adoption for practical use in day-to-day decision-making [30].

2.3 Motivation for Research

We note that prior literature is lacking in empirical support for the claimed positives or negatives of data-driven personas (or personas in general). Long [29] evaluated personas using students completing a course assignment. Long [29] reported that persona use resulted in slightly more user-friendly solutions than an alternative user-centered method. Equally, with the exception of Chapman et al. [7], who conducted a probabilistic evaluation of persona representativeness relative to baseline data, we also locate no quantitative research of the negatives of personas or comparison of personas using an alternative technique. However, [43] report research results showing that a persona analytics system is more effective and efficient than a standard analytics system. In the research reported here, we employ eye-tracking data and qualitative analysis of think-aloud data to shed light on *why* and *by what means* a persona analytics systems perform more effectively and efficiently, which builds on research in [43].

For the analytics system, we employ *YouTube Analytics* (YTA), the *de facto* standard for video analytics that is largely comparable in design and breadth to other common analytics platforms (i.e., Adobe Analytics, Facebook Analytics, Google Analytics, IBM Analytics, etc.). In sum, as an industry-standard approach for user insight, it is a challenging competitor for a comparison with personas. For the persona analytics system, we use *Automatic Persona Generation* (APG) [3], a persona system that generates data-driven personas from primary online user data. The APG system is discussed in a variety of previous publications [3, 24], and it can be considered as state-of-the-art for creating data-driven personas from online analytics data. For this research, we use identical raw data to create data-driven personas corresponding to the user information available in the YTA system.

Specifically, we pursue the research question: ***RQ01: What makes analytics or data-driven personas more efficient and effective?*** We employed two mutually supporting methods. First, we conducted an n-gram analysis of the collected eye-tracking data to determine how the participants interacted with the APG and YTA systems and to shed insight on the information processed by the participants, providing indications concerning the efficiency and effectiveness of the persona and analytics approaches. Second, we performed a qualitative analysis of think-aloud transcripts based on two usability frameworks codebook and then employed the AFINN-165 dictionary for valence analysis to compare the persona and analytics approaches. Efficiency is the number of actions or amount of time to complete the task. Effectiveness is the success in accomplishing the task.

3 METHODOLOGY

To address the research question, we conducted a within-participant experiment with 34 participants in an organization workplace using the APG persona and YTA analytics systems. APG and YTA both leveraged identical underlying user data from the companies in question, making the assessment between the two approaches fair. Both are analytics systems, but their design paradigm is different: with the persona system, the user is in the center (i.e., the user-centered design paradigm), whereas with YTA, numbers, tables, and charts are in the center (i.e., the information-centered design paradigm).

3.1 Focal Organization and Participants

Our data collection organization is a major international news and media company. For this organization, understanding their online users in social media channels has a pivotal role. Various divisions within the company employ both analytics and personas to glean insights concerning the online audience, specifically users of the organization's YouTube channel. These user insights are deployed for daily content creation and longer-term strategic planning, including crafting agendas to address the stakeholder groups of the organization better and to communicate among groups.

As shown in Table 1, there are 34 participants. The participants are reflective of the staff working daily with online content in various company capacities. The participants are from a diverse background, being from 21 countries (including, USA, UK, Turkey, South Korea, South Africa, Lebanon, India, Canada, Belgium, etc.). Producers are the primary media content creators of news articles and videos both for online and broadcast, whereas Editors make the content for final publication, mainly for social media channels. Analysts' primary tasks deal with analyzing the quantitative user data. All participants were explained the concept of data-driven personas prior to engaging the user study to ensure a foundational level of understanding. A chi-square test showed no significant difference between the experience level between personas and analytics (personas: M=1.44, SD=0.67, analytics: M=1.36, SD=0.12).

3.2 Data Collection

We collected two primary types of data from the study participants: (a) *explicit feedback* via quantitative measures during the study task and from amassing the participants' opinions, reported in [xx] and (b) *implicit feedback* via the eye- and mouse-tracking that records the gaze and mouse movements of the participants with diverse information screen elements.

For the eye-tracking sessions, we employ two indistinguishable laptop workstations (HP Studio G4 laptops with 15" screens) and a myGaze eye-tracking device with associated software[1] for logging the visual engagement of the participants. Eye-tracking is extensively used for insights regarding UX design [17] and website usability [14], among other domains [27]. Along with eye-tracking and mouse-tracking data[2], we collect (1) observer notes, (2) survey data, and (3) think-aloud [16] voice recordings that were transcribed.

We also leverage the *concurrent think-aloud method* [2] by encouraging participants to clarify what they are doing and why. To minimize interference with task completion, we only spoke to the participants if they stopped voicing their cognitive processes. We did not opt for complete non-obstruction, as we specifically wanted to learn about the participants' cognitive processes as part of triangulating eye tracking with the think-aloud protocol [5] for greater system usability insights. The combination of eye-tracking data and talking aloud provided a rich data set for triangulation along multiple data collection paths.

3.3 Experimental Design

For the within-participants experiment, the participants employ both personas and analytics to (a) find a user segment; (b) identify the important attributes of that user segment; (c) communicate to team members a plan for targeting this segment; (d) craft targeted content for this segment; and, finally, (e) recall key segment attributes. For each of the participants, we show both APG and YTA using one of the two user segments selected for the study, which are actual user segments of the organization. We assigned the participants both potential conditions, data-driven personas or analytics. APG (data-driven personas) and the YTA (analytics) were the two experimental levels (see Figure 1 and Figure 2). For this user experiment, APG generated the data-driven personas using data gathered via the API from the organization's YouTube channel.

[1]https://cooltool.com/

[2]See supplementary video at https://dl.acm.org/doi/abs/10.1145/3313831.3376770

Table 1: User study participant information. "Other" includes the participant roles of the executive, programmer, etc.

Gender	Number	Percentage	Role	Number	Percentage
Female	20	59%	Analyst	5	15%
Male	14	41%	Editor	10	29%
			Producer	12	35%
			Other	7	21%
Total	34	100%	Total	34	100%

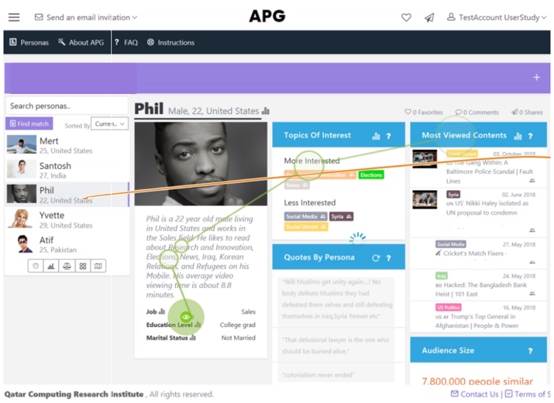

Figure 1: Data-driven persona treatment example (Male, 18–24, USA). To locate the right persona, participants needed to scan the persona list and choose the persona suitable to the user segment criteria: (a) male, (b) 18–24 years of age, and (c) from the USA or Jordan. The extra lines are eye and mouse movements.

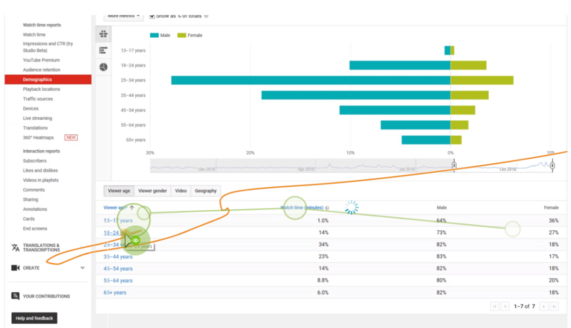

Figure 2: YouTube treatment example (Male, 18–24, Jordan). To locate the right user segment, participants needed to select Analytics and then Demographics, then filter for (a) male, (b) 18–24 years of age, and (c) USA or Jordan. Note: The extra lines are eye and mouse movements.

The YTA analytics system showed user statistics from the same YouTube channel data.

We employed a work task scenario for which participants had to use both systems to locate the exact persona (on APG) or user segment (on YTA). We pilot-tested two user segments on both the APG and YTA systems to ensure that they were nearly identical in terms of the difficulty of locating and reviewing (i.e., (a) '*men, age 18–24, from Jordan*' and (b) '*men, age 18–24, from the United States*.' We produced four altered sequences in the eye-tracking software, showing the segments in a different order for counterbalancing (e.g., in *sequence 1,* the participant first sees segment a using APG and then segment b using the YTA). This ensures that all factors are counterbalanced and that an equal number of participants are doing each sequence, mitigating possible ordering effects.

3.4 Experiment Walkthrough

We conducted the experiment in the workplace of the participants. The complete user study required about forty minutes for participants (P). We initiated all participants in the same manner at the start of the session about the procedure and the use of the devices. To start each trial, we welcomed the participant, introduced the experimental setting (i.e., using eye-tracking to investigate how they use the systems), and responded to any questions. After completing an institutional review board (IRB) consent form, we then gave each participant a unique id and adjusted the devices. We showed each participant one of the user segments. Dependent on the condition (persona or analytics), we showed the participant a pilot tested work-task scenario, which 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 opening task, the participants then implemented the segment information they collected first into an email to team members and then into drafting a social media posting.

The next work task scenario instructions were:

> Please write an email to your team in which you (a) describe the most important characteristics of the user

Table 2: User study participant information concerning states and areas of interest (AOIs) when interacting with the persona and analytics systems. Each state is labeled as either Content (providing task information) or Navigation (used to move to another screen or AOI).

APG State	Type	No.	%	YTA State	Type	No	%
Persona in Listing	Content	153	44.2	Overview	Navigation	46	10.6
Persona Listing	Navigation	34	9.8	Search	Navigation	35	8.0
Search	Navigation	27	7.8	Demographics	Navigation	33	7.6
Filter	Navigation	28	8.1	More Metrics	Navigation	33	7.6
Reach	Content	13	3.8	Menu	Navigation	31	7.1
Comparison	Content	10	2.9	Demographics—age	Content	31	7.1
Contents	Content	7	2.0	Demographics—geography	Content	29	6.7
Sort by Content	Navigation	8	2.3	Overview/Demographics—male	Navigation	17	3.9
Chronology	Content	4	1.2	Demographics—gender	Content	16	3.7
All Others		62	17.9	All Others		165	37.8
		346	100.0			436	100.0

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.

After the participants drafted the email message, they then ranked the confidence of their response on a seven-point Likert scale. Each participant also crafted a social media post targeted at their explicit user segment. Then, the participant continued the experiment using the other system (either persona or analytics) and addressed the user segment ([men with the age of 18-24, from the United States] or [men with the age of 18-24, from Jordan]). Afterward, the participant completed the same tasks. These actions ended the experimental session. We answered any questions and thanked the participant, following the provision of a gift card with a value equivalent of $27,00 USD, as an expression of gratitude for volunteering.

4 RESULTS

4.1 Eye-Tracking Analysis

We used the eye-tracking data to identify each of the major states (n-grams) that participants used while interacting with both the APG and the YTA systems in order to assist in explaining why the persona system was more efficient and effective compared to the analytics system. To do this, we counted the number of moves to a particular screen or area of interest (AOI) and classified each screen or AOI as primarily either content (i.e., providing information related to task accomplishment) or navigation (i.e., moving from one screen to another or AOI within the system), with results shown in Table 2.

As indicated in Table 2, which shows the more frequently occurring states, 54.1% of these were Content states for APG (vs. 28.1% for Navigation). Conversely, for YTA, only 17.5% of the most frequently occurring states dealt with Content (vs. 44.8% for Navigation). These findings shed light on why the participants were more efficient and more effective with the persona system. Most of their interactions with APG tackled task-supporting information, while most of the participants' interactions with YTA dealt with moving among system components, obviously a hindrance to task accomplishment.

4.2 Think-Aloud Analysis

The qualitative analysis of the think-aloud transcripts was performed based on a codebook created from two usability frameworks: HCI standards [4] and Usability in E-learning Context [47]. We selected them based on their focus on designing informational content for users. These frameworks provided us with seven functional and four affective dimensions, which we used as a matrix to identify and isolate segments that displayed specific affective responses to certain functions. Furthermore, we manually coded two affective dimensions ('attention' and 'relevance') into positive or negative sentiments. The primary coding was performed by one researcher and then validated by two other researchers. The remaining two affective dimensions were always positive ('satisfaction') or negative ('dissatisfaction').

4.2.1 Functional Dimensions. The six functional dimensions examined are 'interactivity,' 'media use,' 'navigability,' 'learnability,' 'consistency,' and 'visual design'[3], which were coded in parallel to their effective context. The *interactivity* dimension is for the overall use of the system (UX) and the interface components (UI), containing information on whether these components with example comments by participant (P):

- **interesting**: attention – "It's a lot. I can't scroll down in here?" (P14)
- **helpful**: relevance – "It's just a highlighter?" (P26), or, generally,
- **sparked positive or negative sentiments**: "I don't see Jordan. Sorry. I'm looking for a search tab where I can just type in the name of the country and find out because . . . there's Jordan. There's no save button" (P22).

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

The *media use* dimension gathers the participant comments concerning the use of charts, images, tables, and videos, in the systems, referring to:

- **attention**: "It took a while to understand that the is a pattern that is yeah, it's supposed to be some sort of graph, but it wasn't clear" (P09),
- **relevance**: "If this pie chart was correct, or if that's what I think it means then they're just 1/100th of the audience" (P02), and
- **positive or negative sentiments:** "The picture coincides with most of the information that is provided in the short description" (P12) or "I am, umm, confused about the statistics between the graph and the [status] results. So, I am here." (P13).

The *navigability* dimension pinpoints issues connected to examining the data via links, pages, and views. We differentiated the *navigability* dimension from interactivity, given its focus on how data is presented and navigated versus how data is interacted with. For example:

- "I did not see what videos they were interested in, only the topics" (P4).
- "I'm going to traffic sources to see if they're using their phone or their laptop, but I have a strong feeling I cannot see this data using the demographic ... Yeah, I'll try it. So I'm going to just go back" (P31).

The *learnability* dimension concerns sentiments based on how hard or easy it was to adopt the system. These sentiments were collected using the affective dimensions of the following:

- **Attention**: "I know what he's interested in. That's going to stick to me, not his name but his interests" (P01).
- **Relevance**: "I guess I don't really know exactly how to apply this specifically to my demographic" (P03).
- **Positive or negative sentiments**: P13 on YTA: "Let's see the audience retention. No, we don't have so many details here in that category" (P13) versus P13 on APG: "Personas? Very easy" (P13).

We employed the *consistency* dimension in two contextual categories: (1) whether or not the system works as expected in terms of providing information (e.g., "Can you speak to the fact of whether or not this is like actual . . . this is an actual representation of this service?" (P03) and (2) whether the information provided by the system is consistent). Some negative examples are: "I'm trying to see if we can get the content consumption by the target personas, but it seems that we can only get it by geography" (P08), and "But [I've] not seen anybody has the time or the mental capacity to spend all this energy focusing on one particular video." (P16). Some positive examples are: "I'm very confident, I would say probably I'm 8 out of 10" (P09), "Wow, this is good" (P12), and "It's a very detailed information about him" (P22).

Lastly, the *visual design* codes are the general visual feeling of the two systems. As there were very few codes regarding this dimension, we did not analyze this dimension further.

4.2.2 A ective Dimensions. The four affective dimensions are attention, relevance, satisfaction, and dissatisfaction. The code *attention* was used when there was curiosity/interest, or lack thereof, from a participant to the information or interaction at hand. Normally, these segments did not overlap with any strong positive (satisfaction) or negative (dissatisfaction) sentiments. Some examples are:

- (**positive**) "I know because on Facebook anything above a minute is a miracle, so this is very interesting to me" (P04) and
- (**negative**) "I did not see what videos they were interested in, only the topics," (P04) and

We used the code relevance to indicate that the participants were or were not able to access the information relating to the goals of the task or that the information made sense to them in terms of their motives. Again, these segments did not intersect with strong sentiments but simply constructed statements of readiness, such as:

- "I need to know where is he; where in the US is he from? He doesn't say, just United States. So that's not specific, so I don't know, east coast, west coast?" (P04) vs.
- "Is there any way that I could maybe save this group, so I can see, for example, all the things that they do? Let me see if there is any way I can save this segment" (P27).

We used *satisfaction* and *dissatisfaction* when the participants completed explicit decisions concerning the system functions. Examples are:

- "I'm trying to see if we can get the content consumption by the target personas, but it seems that we can only get it by geography" (P08, *dissatisfaction*),
- "whereas in the other one, it was straight in front of me. Here's the persona. In the other one, it gave me some information." (P29, *satisfaction*).

4.2.3 Comparative alitative Outcomes of APG and YTA. To compare the performance of two systems (data-driven persona vs. analytics), we mobilized the AFINN-165 textual valence analysis codebase [33] to compute the valence scores of interview transcriptions. For this analysis, we ran the interview transcriptions of each participant for each system through the AFINN-165 valence analysis, calculating: (a) a *valence score* and (b) a *comparative score*. The valence score is computed by adding the scores of each word to a total number, and the comparative score is calculated by averaging the mean score for all the words. The results of this analysis are given in Table 3. They support the conclusion of the n-gram analysis and the hypotheses that the APG system performed more positively than the YTA system in many functionalities and created more positivity in general.

5 DISCUSSION, IMPLICATIONS, AND CONCLUSION

Based on the insights from the eye-tracking and the qualitative analysis, the persona analytics system affords the participants the opportunity to directly move to task-supporting information, while the YTA interactions mostly dealt with navigation. From our findings, while YTA provides many reports and a high volume of information, it may not be an optimal system for learning about *specific* target groups relative to a persona system. Regarding the

Table 3: Measures of central tendency of the AFINN-165 analysis.

AFINN-165 Metric	x̄	x̃	s	r
Data-driven Persona Valence	84.26	57	82.63	15:437
Data-driven Persona Comparative	.08695	.08483	.02754	.038 : 0.150
YouTube Analytics Valence	70.13	50	71.85	3:375
YouTube Analytics Comparative	.06961	.0695	.0336	.009 : 0.192

generalizability of this conclusion, we speculate that it is generalizable to other similar analytics systems that have many reports, tables, graphs, and filters. There is an abundance of information, but these analytics systems do not display that information in a customer-centric way (such as in the form of user or persona profiles). Future research should be directed to merging functionalities between information-centered and user-centered analytics systems for supporting different types of user-centric tasks.

This eye-tracking and qualitative analysis added nuanced support our earlier quantitative evaluation of personas relative to another the analytics method for user understanding [43]. We conducted this mixed methods experiment employing workplace participants in a real work task on real systems for the enhanced validity of the findings. Both the persona and analytics systems engaged identical foundational data of users, and the systems were evaluated using both effectiveness and efficiency for user segment identification. These mixed methods findings are strong support for the advantages of personas and provide practical support for the user of personas as a user understanding methodology for design and other tasks.

We employed a within-subjects experimental design, workplace participants, a work task, and real persona and analytics systems to enhance the research validity. The findings support the advantages of using data-driven personas. The evidence points in the direction that, even in the age of analytics, personas offer a valuable conceptualization for understanding users.

ACKNOWLEDGMENTS

We thank all the thirty-four participants for volunteering for this research study and taking precious time from their busy work schedules. Their contributions and engagement made this research study possible and will hopefully benefit the organization going forward.

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, "Imaginary People Representing Real Numbers: Generating Personas from Online Social Media Data," *ACM Transactions on the Web,* vol. 12, p. Article 27, 2018.

[4] N. Bevan, "Human-computer interaction standards," in *Advances in Human Factors/Ergonomics.* vol. 20, ed, 1995, pp. 885-890.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] V. L. Drego and M. Dorsey, "The ROI Of Personas," Forrester Research3 Aug. 2010.

[14] A. T. Duchowski, *Eye Tracking Methodology: Theory and Practice.* London: Springer, 2009.

[15] 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.

[16] 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.

[17] 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.

[18] J. Grudin and J. Pruitt, "Personas, participatory design and product development: An infrastructure for engagement," in *Participatory Design Conference*, 2002, pp. 144-152.

[19] 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.

[20] C. G. Hill, M. Haag, A. Oleson, C. Mendez, N. Marsden, A. Sarmam, *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.

[21] B. J. Jansen, J. Salminen, S. G. Jung, and K. Guan, *Data-Driven Personas* vol. 4. San Rafael, CA: Morgan-Claypool:, 2021.

[22] J. Järvinen and H. Karjaluoto, "The use of Web analytics for digital marketing performance measurement," *Industrial Marketing Management,* vol. 50, pp. 117–127, 2015.

[23] 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.

[24] 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.

[25] S. J. Kerr, O. Tan, and J. C. Chua, "Cooking personas: Goal-directed design requirements in the kitchen," *International Journal of Human-Computer Studies,* vol. 72, pp. 255-274, 2014/02/01/ 2014.

[26] M. Lee, J. Kwahk, S. H. Han, D. Jeong, K. Park, S. Oh, *et al.*, "Developing personas & use cases with user survey data: A study on the millennials' media usage," *Journal of Retailing and Consumer Services,* vol. 54, p. 102051, 2020.

[27] H. Li, J. Epps, and S. Chen, "Think before you speak: An investigation of eye activity patterns during conversations using eyewear," *International Journal of Human-Computer Studies,* vol. 143, p. 102468, 2020/11/01/ 2020.

[28] Y. Li, X. Yuan, and R. Che, "An investigation of task characteristics and users' evaluation of interaction design in different online health information systems," *Information Processing & Management,* vol. 58, p. 102476, 2021/05/01/ 2021.

[29] 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.

[30] 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.
[31] 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.
[32] 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.
[33] F. Å. Nielsen, "A new ANEW: Evaluation of a word list for sentiment analysis in microblogs," presented at the Proceedings of the ESWC2011 Workshop on Making Sense of Microposts, 2011.
[34] L. Nielsen, *Personas - User Focused Design*. London: Springer-Verlag, 2013.
[35] 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," *International Journal of Sociotechnology and Knowledge Development,* vol. 7, pp. 45-61, 2015.
[36] 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.
[37] K. Popper, *The Logic of Scientific Discovery*. Abingdon-on-Thames: Routledge, 1959.
[38] J. Pruitt and T. Adlin, *The Persona Lifecycle: Keeping People in Mind Throughout Product Design*: Morgan Kaufmann, 2006.
[39] 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.
[40] A. Revella, Buyer Personas: How to Gain Insight into Your Customer's Expectations, Align Your Marketing Strategies, and Win More Business: Wiley, 2015.
[41] 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.
[42] J. Salminen, K. Guan, S.-G. Jung, S. A. Chowdhury, and B. J. Jansen, "A Literature Review of Quantitative Persona Creation," presented at the Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA, 2020.
[43] J. Salminen, S.-G. Jung, S. Chowdhury, S. Sengün, and B. J. Jansen, "Personas and Analytics: A Comparative User Study of Efficiency and Effectiveness for a User Identification Task," presented at the Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA, 2020.
[44] 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.
[45] 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.
[46] Y. Wang and L. Han, "Adaptive time series prediction and recommendation," *Information Processing & Management,* vol. 58, p. 102494, 2021/05/01/ 2021.
[47] 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.
[48] K. Żbikowski and P. Antosiuk, "A machine learning, bias-free approach for predicting business success using Crunchbase data," *Information Processing & Management,* vol. 58, p. 102555, 2021/07/01/ 2021.