Persona Finetuning for Online Gaming Using Personalisation Techniques

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Abstract. Automatic persona generation has been shown to have specific measurable benefits for application creators and users. In most situations, personas are adequately descriptive and diversified to achieve user type accuracy and coverage. For specific market segments, such as online gaming, using personas may accurately describe existing user base but not changing habit and need that are introduced by the fluidity of the offerings and the delivery methods. Changes in the ways that applications are marketed, such as new payment methods, for example, subscription models, pay-to-play and pay-to-win, payment-driven-gamification, seriously affect user needs and result in direct impact on user acceptance. This work utilises structured user needs from online gaming players to augment personas using personalisation techniques. The personas are finetuned and de-diversified to result in concise personas, based on user needs that successfully convey information for creators and users alike.

Keywords: Persona · Online gaming · Diversification · Personalisation · Data-driven methods · Collaborative filtering · User study · Usability evaluation

1 Introduction

Data-driven automatic persona generation leverages data analysis and human insight and can be used for digital marketing personalisation [1]. Digital marketing user segments are constantly evolving, based on several factors, ranging from pandemics or other extreme non marketing related events, to the introduction and adoption of disruptive technologies, leading to innovative offerings, such as online music or the metaverse [2]. An illustrative example is online gaming, a domain that hosts thousands of users, applications/games, teams, and communities [3]. The complexity of the types of users in online gaming depends on several dimensions that include behavioural and psychographic variables [4].

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Online games can be clearly categorised according to genre, based on single or multiple parameters that represent aspects of gaming, as formulated by the designers. Social interaction is a major dimension that is used to classify online games, such as Massively-Multiplayer Online Role-Playing Games (MMORPGs) [5]. Effectively, online games may refer to multiple genres. However, they are commonly identified by a major genre and supplementally by one or two additional secondary genres. The genres are constructed on the basis of gaming dimensions that include technical factors such as achievement, social and immersion [6].

Depending on the dimensions, online games attract several types of players. The goal is to trigger and sustain the players' purchase motivation, which can depend on social interaction (I and my friends or co-players buy content to play together or in teams), unobstructed play (buy time or barrier lifts and progress through paywalls), and economical (investing in an entertaining activity, when pricing is judged to be reasonable) benefit [7].

Personas are user archetypes that are used to describe the user base for application, services and products [8]. In the era of big data, data-driven persona development utilised statistical analysis of data to create personas as a fast and accurate that corresponded to the quantified data [9]. Through the years, persona research shifted from data-driven quantification to digitalisation that uses a multitude of methods to model behavioural characteristics and interactivity into the personas [10].

Data-driven persona generation may accurately capture aspects that can be technically assessed at a point in time [11]. However, they may fail to sustain faithful descriptors due to inherent shortcomings, such as the persona diversification techniques [12]. A critical issue for online gaming, and online apps in general, are the new or shifting categories of applications that target multiple personas on specific aspects that cannot be quantified, such as the "respect of the user's time" and "pay once and play", which can also have specific effects on users [13].

The emerging categories refer to user needs or meta game genres that can be found in game reviews. Those are created by gamers and reviewers. For example, the term "gacha" refers to games that are designed to induce players to spend in-game currency to gain a relatively small chance to acquire game items. The need for a dedicated category name for gacha games was due to the fact that the nature of the game monetisation was an overarching descriptive factor that included several genres or other categories. This has also resulted in the formulation of other relevant categories, such as the "no in-app purchases", that describe the opposite game category. This is the result of expressing direct user needs that encompass other game preferences or needs, traditionally described by personas.

All the above indicate that personas may be descriptive enough to account for traditional user types, however emerging needs may require persona finetuning or even clustering to overarching personas, to accurately present the user types for online gaming.

This work explores how personas can be finetuned by users using real user needs that are pivotal to persona generation, such as gacha methods or no-ads preferences. The first research hypothesis (RH1) is that personalisation techniques can be used to create non-diversified personas that would potentially be used to mark seemingly minor user needs as important, through aggregation or collaborative filtering [14–16]. The second research hypothesis (RH2) is that users may successfully identify candidate personas and finetune them based on the marked user needs that would have been hidden, otherwise.

The rest of this paper is structured as follows: Sect. 2 introduces the related work in personas for online gaming, while Sect. 3 overviews the fundamental personalisation methods that are appropriate for this work. Section 4 describes the user study, that is the study setup and the experimental results. Finally, Sect. 5 concludes the paper and outlines the future work.

2 Personas in Online Gaming

Personas are used in user-centred game design to establish user narratives and marketing strategies during the design and development of games to model user behaviour [17]. Moreover, personas are useful for the monitoring and evaluation of user behavioural patterns during the experience with the games [18]. Personas have been an important tool for traditional marketing analysis experts and it has become even more crucial to business data analytics personalisation [19].

Surveys on game preference can be deployed to adequate numbers of players to collect data that can be used to generate player personas [20]. Surveys collect both standard user demographic information, as well as personal preferences and needs. Apart from the qualitative methods, quantitative and mixed methods are used to create or enhance personas, each to their own merit [21].

Personas can be matched to game types for targeted marketing and monetisation decisions [22]. Personas are the amalgamation of user needs and games characteristics, requiring user behaviour research and quantitative analysis or the collected user data [23]. However, depending on the game type, certain aspect of the user base may be biased or under-represented [24].

Data-driven personas can be constructed fast and with relative accuracy, since they utilise existing data from application stores, such as user standard demographic data and user entered reviews [25]. Automatic persona generation from large datasets can lead to a very high number of personas, depending on the generation method that is applied. Accordingly, this requires appropriate techniques to reduce the number of personas [26]. For instance, hierarchical clustering can be applied to the generated non-final personas to create a manageable number of representative personas [27].

By design, data-driven personas may include a lot of information that is hard to formally evaluate through users, since the templates provide the structured means to create the persona but do not offer a trustworthy method to assess and evaluate the data [28]. Therefore, data-driven personas would not be easy to curate for user experience evaluation of real-time applications using standard usability metrics [29]. Evaluation becomes more complex in situations where personas are generated from both standard data and high level user interaction information [30].

The above become more apparent when the data that are collected for persona construction is unstructured and informally collected, as in the case of social media [31]. Social media data aggregation for persona generation is a method that requires collection, analysis and processing of social media data, creating a real time representation of the user population [32]. It can be used to create and update personas as the pool of data can be augmented by additional sources or additional data at a future time [33]. Persona analytics is key to modelling personas by understanding how users interact with personas, thereby founding a basis on which to evaluate the complexity and accuracy to real life user types of personas [34].

Personas can be further enriched by automatically or semi-automatically selecting trivial information to eject and impactful information to insert to the generated personas [35]. Persona enrichment with non-standard descriptors may be very useful for marketing products that require user behaviour descriptions [36]. Social media contains implicit information regarding user behaviours as well as explicit user needs as expressed by user opinions, reviews and comments [37]. Social media data can be used to process standard demographics and segment customer types based on product parameters and market analysis [38]. In this case, persona evaluation becomes a study in complexity, since the human evaluator is faced with a mix of artificially generated data, such as pictures [39], automatically collected standard user demographic data, and post-processed information from various sources of user interaction from linguistically rich environments [40].

3 Personalisation

Personalisation is a research field that has attracted numerous research works over the last years. Rhee and Choi [41] explore the product recommendation persuasion mechanism produced by a conversational agent and examine the importance of types of social roles to the shopping of items using voice. They design an experimental study to test the effects of friends' role of a voice agent with low and high item involvement, as well as personalised content that reflected the users' preferences for item characteristics. The results show an important interaction effect for the social involvement and role. Xiao et al. [42] introduce a personalization model that explores higher-order friends in a social media to support recommendation of content. In the exploration and model designs, they consider the effects for both consumers and content creators in the social network platform. As a result, the platform can be benefited to encourage additional interactions between clients and creators, as well as attract more innovative content creators. Park et al. [43] introduce a personalised social learning companion system which modulates children's engagement and maximize their long-term learning gains, by using nonverbal and verbal affective cues. They present a reinforcement learning method which, for each student during an educational activity, trains a personalised policy. Aivazoglou et al. [44] introduce a social ecosystems fine-grained recommender system, which recommends media content (online clips, music videos, etc.) published by friends of the users. The design was based on the findings of a qualitative user study, which investigate both the requirements and the value of a recommendation component within a social media. The core idea of the recommender system is to create interest profiles, to calculate similarity scores between social media users at a fine-grained level. Metz et al. [45] explore both the consequences and use of self-personalisation on the Facebook social media platform. A content analysis of posts from politicians reveals that they often use self-personalisation, as a communication style, which is often presented in visual communication. They show that the use of a more private and emotional style benefits impression management. Furthermore, by suggesting the demands of the audiences for more emotional and intimate impressions of public figures, positive effects on audience engagement are achieved.

User classification and user clustering are important aspects of personalisation. Ferrari et al. [46] define a validation model to assess the performance of machine learning personalisation algorithms. They also assess the public datasets of a personalisation model, taking into account both the aspect of the physical similarity between people (height, weight, age, etc.) and the activity-based similarity aspect (based on the signals produced by people when performing). Last, they develop a personalisation model that takes into account both the aforementioned similarities.

Rajawat et al. [47] present a personalisation model for user preference, based on the Semi Supervised Support Vector Machines (S3VM) concept and apply it to online newspaper information, targeting at classification and recommendation improvement. They achieve an increase of the behaviour prediction performance and information classification, when compared with techniques using traditional machine learning algorithms. Margaris et al. [48] introduce a personalisation algorithm with clustering for recommending web services, to realise tailoring of business process execution. To produce recommendations, their algorithm takes into account the QoS values and functionality of the services, QoS weights and limits defined by the users, and the business processes past the execution history. Furthermore, they use a similarity metric in their collaborative filtering process, which extends the ones used in related works by considering both the QoS attributes' closeness and functionality resemblance. Last, the presented algorithm employs a clustering scheme that achieves both to improve recommendation time and leverage scalability.

Shamrat et al. [49] introduce a system which, out of all people registered, presents the suitable ones for a job. It helps job seekers, relate to the notification, and find jobs efficiently. More specifically, only the candidates that match the job title, expected experience and salary, based on their profile, get an email notification for the job. The system uses a decision tree which checks the data through a set of conditions, where their fulfilment determines whether a candidate is suitable for a job or not. Vijayalakshmi and Jena [49] present a web search approach based on the individual clustering and classification method. Their approach classifies the cluster data using multilevel association rules for recurring relationship and frequent pattern mining, and cluster the web usage using hierarchical methods with the personalisation user interest and navigating site. Furthermore, that approach supports real time personalisation and maximises the personalisation resource cost reduction.

Online gaming personalisation is a field that has attracted considerable research attention over the recent years. Naudet et al. [50] present and analyse experimental results obtained towards museum visit personalisation using a personal mobile guide, as well as an approach based on social networks gaming, user cognitive style and recommendations. The presented personalisation system is based on a Facebook game to infer the users' visiting and cognitive styles and interests, and a recommendation algorithm offering sequences of points of interests for a visitor to visit. Harteveld and Sutherland [51] present and analyse the need to personalise gamified research environments in order to motivate participation, by illustrating a playful platform, which allows users to create behavioural and social studies. Their work both contributes to theory-informed approaches to gamified personalisation technologies, as well as contributes to existing theories on player motivation. Raptis et al. [52] explore the interplay among cultural heritage gaming activities and human cognitive differences, towards visual behaviour and player performance. They conduct user studies under the field dependence/independence theory, which underpin cognitive differences in handling contextual of information and visual perception. Their findings provide useful insights for both researchers and practitioners, aiming at designing playful cultural activities based on the users' cognitive preferences. Jamil et al. [53] discuss the influence of the age and gender factors on user performance in gaming environments. They investigate the user performance on commonly used tasks (typing, pointing and clicking) using a gaming prototype, in controlled laboratory experiments. The user performance is analysed using multiple statistical methods. Significant differences between male and female participants are observed during interaction with the computer, similar to the ones found in the spectrum of age groups.

4 User Study

4.1 Experiment Setup

This paper reports on the user study of 44 computer science literate participants (68% male and 32% female) that are adept to online/mobile gaming. All participants were recruited from the university undergraduate and postgraduate course, though a departmental open call. The participant selection was based on the online gaming self-reported engagement. The participants that were recruited reported to have been engaging in online games (mobile or other) for at least five hours per week during the last three months, on average.

The facilitators collected the participants' player information. The player information included user and gaming data. Gaming data were collected through lists that the users submitted in their application. The user information included standard user data, as well as structured user needs. The user needs were collected through questionnaires that the users were asked to complete within seven days. The users were asked to fill in information regarding their experience with online games, their needs and fulfilment level, and their desired characteristics for their future gaming endeavours.

The participants were asked to validate automatically generated personas for the twenty most used games, as aggregated from the lists that the users provided as part of the experiment setup. No other artificially generated data regarding persona enrichment, such as pictures and gender categories, were used.

Collaborative filtering and user aggregation [54–57] were used to create user near neighbours, based on both data and needs. Two user representations were constructed, one using the standard user data as primary category points and one using the user needs as primary points. The participants were presented with the generated personas in a random order and were asked to evaluate them in terms of congruency (the level of correspondence to the users), transparency (the level of understandability of the information) and usefulness [58]. The participants could accept-as-is, accept-and-finetune (using either user representation data or both), or reject the personas. The accepted and finetuned personas were then aggregated, to merge duplicates or very similar personas, calculating the quantified percentage of information from the user needs and the standard user data between the finetuned and the accepted/rejected personas.

4.2 Results

The users reported a high number of persona rejection due to missing information on user needs, rendering the personas ineffective. On average, only 7% of the automatically generated personas were accepted without the need for augmentation by the majority of the participants (>50% of the participants). On the other hand, 27% of the personas were rejected by the majority of the participants (>50% of the participants).

Figure 1 depicts the evaluation results on the acceptance of the personas by the participants, based on four factors: congruency, transparency, usefulness, and overall acceptance. The participants rated each persona using the Likert scale 1 to 7 (low-high). The user representation sources were hidden from the participants to ensure unbiased evaluation.

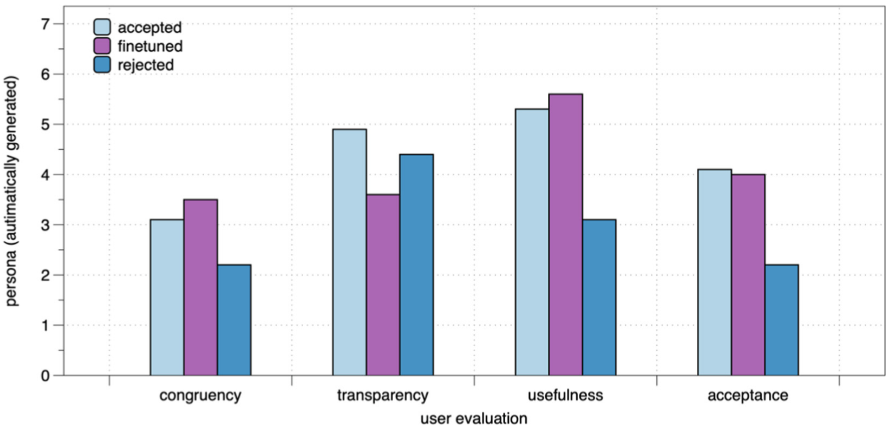

Fig. 1. User evaluation of automatically generated personas. Personas were either accepted as they were, accepted as candidate for finetuning, or rejected.

The users were then asked to finetune at least three personas of their choice, each, out of the pool of the personas deemed appropriate for finetuning. Peer review was used for the re-evaluation of the finetuned personas. Two random users (excluding the users that finetuned the persona) were asked to evaluate the finetuned personas.

Figure 2 depicts the user evaluation outcome of the personas finetuned by the users using the information collected from the user needs against the originally accepted-as-is personas from the first evaluation round. The participants reported that the finetuned personas rated higher than the accept-as-is personas. Especially for congruency, the evaluation result average for the finetunes personas was significantly higher. This may be partially explained by the overall low rating (3.1 on the scale) average of the accepted personas.

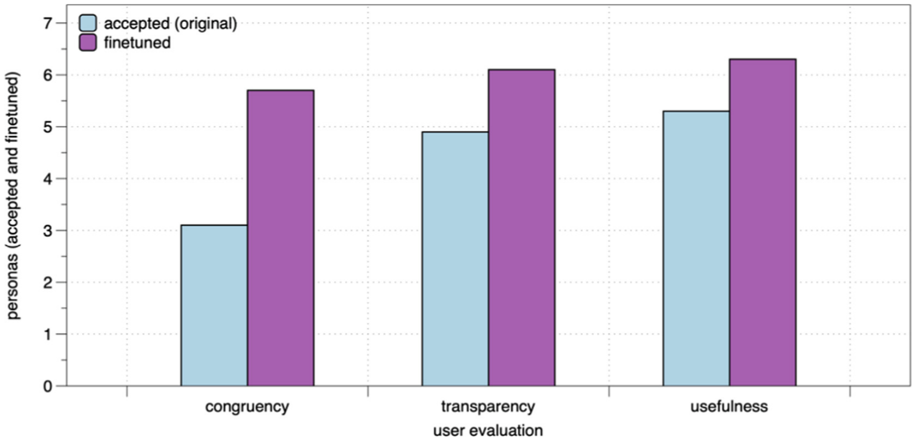

Fig. 2. User evaluation of the finetuned personas using the proposed method against the originally accepted automatically generated personas.

RH 1 was found true to a significant extent. The users reported to have successful and very positive results in finetuning using the data from the user needs representation (78% of the users). Additionally, user data were useful for validation and transparency verification, when used in conjunction with the user needs (49% of the finetuned personas).

RH2 was found to be true. The 11 personas finetuned by the users were aggregated to 5 (automatically) and down to 4 (collectively, by the users). The users reported that this was an equivalent approach to de-diversification based on explainable user need information, present in the finetuned personas.

Achieving representative personas that directly respond to user needs would be very beneficial to providers to understand potentially business and user base harming practices and decide on mitigation actions [59].

5 Conclusion and Future Work

This work reported on a user study that examined the level of which automatically generated personas based on user needs and standard user information are complete and fully accepted by real users. It also examined whether personas can be manually finetuned with low labour cost, when potentially important content can be recommended to users for use in the finetuning process.

The information that was presented to the participants was aggregated using personalisation methods. This method of content recommendation was also useful for persona aggregation, enabling the participants to aggregate personas based on important information, ensuring the sustainment of critical descriptors during the manual process.

The results from this study indicate that automatically generated personas can be contextually analysed for enhancement. Essentially, persona descriptors can be checked against information highlighted through personalisation methods to allow potential enhancement.

The results are encouraging for aiming to research toward a model for automatic comparison of persona information bits from recommender systems and other data-driven methods, such as clustering. A semi-automatic approach for persona finetuning would be useful for fast and accurate persona validation and enhancement.

The future work will also focus on the longitudinal effects of online gaming to specific user types based on the personas that describe them. The ultimate marketing use of personas is monetisation via long-term user engagement [60]. Therefore, based on the results from the persona data correlation, it would be interesting to examine which personas correspond to players that are most likely to commit themselves to long term money spending, or even be exploited by gacha mechanics [61, 62].

References

1. Jansen, B.J., Salminen, J.O., Jung, S.-G.: Data-driven personas for enhanced user understanding: combining empathy with rationality for better insights to analytics. Data Inf. Manage. **4**, 1–17 (2020). https://doi.org/10.2478/dim-2020-0005
2. Xu, Y., Lee, M.J.: Identifying personas in online shopping communities. MTI. **4**, 19 (2020). https://doi.org/10.3390/mti4020019
3. Goodman, W., McFerran, E., Purves, R., Redpath, I., Beeken, R.J.: The untapped potential of the gaming community: narrative review. JMIR Serious Game. **6**, e10161 (2018). https://doi.org/10.2196/10161
4. Hamari, J., Tuunanen, J.: Player types: a meta-synthesis. ToDIGRA. 1 (2014). https://doi.org/10.26503/todigra.v1i2.13
5. Granic, I., Lobel, A., Engels, R.C.M.E.: The benefits of playing video games. Am. Psychol. **69**, 66–78 (2014). https://doi.org/10.1037/a0034857
6. Yee, N.: Motivations for play in online games. Cyberpsychol. Behav. **9**, 772–775 (2006). https://doi.org/10.1089/cpb.2006.9.772
7. Hamari, J., Alha, K., Järvelä, S., Kivikangas, J.M., Koivisto, J., Paavilainen, J.: Why do players buy in-game content? An empirical study on concrete purchase motivations. Comput. Hum. Behav. **68**, 538–546 (2017). https://doi.org/10.1016/j.chb.2016.11.045
8. Nielsen, L, Nielsen, K.S., Stage, J., Billestrup, J.: Going Global with Personas In: Kotzé, P., Marsden, G., Lindgaard, G., Wesson, J., Winckler, M. (eds.) Human-Computer Interaction – INTERACT 2013. Lecture Notes in Computer Science, vol. 8120, pp. 123–133. Springer, Heidelberg (2019).https://doi.org/10.1007/978-1-4471-7427-1_7
9. McGinn, J., Kotamraju, N.: Data-driven persona development. In: Proceeding of the Twenty-Sixth Annual CHI Conference on Human Factors In Computing Systems - CHI 2008, p. 1521. ACM Press, Florence, Italy (2008). https://doi.org/10.1145/1357054.1357292
10. Salminen, J., Guan, K., Jung, S.-G., Jansen, B.J.: A survey of 15 years of data-driven persona development. Int. J. Hum.-Comput. Interact. **37**, 1685–1708 (2021). https://doi.org/10.1080/10447318.2021.1908670
11. Salminen, J.O., Jung, S., Jansen, B.J.: Are data-driven personas considered harmful?: Diversifying user understandings with more than algorithms. Pers. Stud. **7**, 48–63 (2021). https://doi.org/10.21153/psj2021vol7no1art1236
12. Salminen, J., Jansen, B.J., An, J., Kwak, H., Jung, S.-G.: Automatic persona generation for online content creators: conceptual rationale and a research agenda. In: Personas - User Focused Design. Human–Computer Interaction Series, pp. 135–160. Springer London (2019).https://doi.org/10.1007/978-1-4471-7427-1_8

13. Shibuya, A., Teramoto, M., Shoun, A., Akiyama, K.: Long-term effects of in-game purchases and event game mechanics on young mobile social game players in Japan. Simul. Gaming **50**, 76–92 (2019). https://doi.org/10.1177/1046878118819677
14. Xu, Z., Dukes, A.: Personalization from customer data aggregation using list price. Manage. Sci. **68**, 960–980 (2022). https://doi.org/10.1287/mnsc.2021.3977
15. Margaris, D., Spiliotopoulos, D., Vassilakis, C.: Social relations versus near neighbours: reliable recommenders in limited information social network collaborative filtering for online advertising. In: Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, pp. 1160–1167. ACM, Vancouver British Columbia Canada (2019). https://doi.org/10.1145/3341161.3345620
16. Kluver, D., Ekstrand, M.D., Konstan, J.A.: Rating-Based Collaborative Filtering: Algorithms and Evaluation. In: Brusilovsky, P., He, D. (eds.) Social Information Access. LNCS, vol. 10100, pp. 344–390. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-90092-6_10
17. Tychsen, A., Canossa, A.: Defining personas in games using metrics. In: Proceedings of the 2008 Conference on Future Play Research, Play, Share - Future Play 2008, p. 73. ACM Press, Toronto, Ontario, Canada (2008). https://doi.org/10.1145/1496984.1496997
18. Canossa, A., Drachen, A.: Play-Personas: Behaviours and Belief Systems in User-Centred Game Design. In: Gross, T., et al. (eds.) INTERACT 2009. LNCS, vol. 5727, pp. 510–523. Springer, Heidelberg (2009). https://doi.org/10.1007/978-3-642-03658-3_55
19. Amyrotos, C., Andreou, P., Germanakos, P.: Human-centred persona driven personalization in business data analytics. In: Adjunct Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization, pp. 175–180. ACM, Utrecht Netherlands (2021). https://doi.org/10.1145/3450614.3462241
20. Salminen, J., Vahlo, J., Koponen, A., Jung, S.-G., Chowdhury, S.A., Jansen, B.J.: Designing prototype player personas from a game preference survey. In: Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems, pp. 1–8. ACM, Honolulu HI USA (2020). https://doi.org/10.1145/3334480.3382785
21. Jansen, B.J., Jung, S.-G., Salminen, J., Guan, K.W., Nielsen, L.: Strengths and weaknesses of persona creation methods: guidelines and opportunities for digital innovations. In: Presented at the Hawaii International Conference on System Sciences (2021). https://doi.org/10.24251/HICSS.2021.604
22. Vahlo, J., Koponen, A.: Player personas and game choice. In: Lee, N. (ed.) Encyclopedia of Computer Graphics and Games, pp. 1–6. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-08234-9_149-1
23. Zhang, X., Jia, Z., Jia, S.: User research and persona building method in mobile games. J. Phys.: Conf. Ser. **1168**, 032043 (2019). https://doi.org/10.1088/1742-6596/1168/3/032043
24. Rogstad, E.T.: Gender in eSports research: a literature review. Eur. J. Sport Soc. **19**, 1–19 (2021). https://doi.org/10.1080/16138171.2021.1930941
25. Park, D., Kang, J.: Constructing data-driven personas through an analysis of mobile application store data. Appl. Sci. **12**, 2869 (2022). https://doi.org/10.3390/app12062869
26. Jansen, B.J., Jung, S., Salminen, J.: Creating manageable persona sets from large user populations. In: Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1–6. ACM, Glasgow Scotland UK (2019). https://doi.org/10.1145/3290607.3313006
27. Zhang, X., Brown, H.-F., Shankar, A.: Data-driven personas: constructing archetypal users with clickstreams and user telemetry. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, pp. 5350–5359. ACM, San Jose California USA (2016). https://doi.org/10.1145/2858036.2858523
28. Salminen, J., Guan, K., Nielsen, L., Jung, S.-G., Jansen, B.J.: A Template for Data-Driven Personas: Analyzing 31 Quantitatively Oriented Persona Profiles. In: Yamamoto, S., Mori,

H. (eds.) HCII 2020. LNCS, vol. 12184, pp. 125–144. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-50020-7_8
29. Kouroupetroglou, G., Spiliotopoulos, D.: Usability methodologies for real-life voice user interfaces: Int. J. Inf. Technol. Web Eng. **4**, 78–94 (2009).https://doi.org/10.4018/jitwe.2009100105
30. Zhang, G.: Creating Enhanced User Experience Through Persona and Interactive Design: A Case of Designing a Motion Sensing Game. In: Marcus, A., Wang, W. (eds.) HCII 2019. LNCS, vol. 11583, pp. 382–394. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-23570-3_28
31. An, J., Cho, H., Kwak, H., Hassen, M.Z., Jansen, B.J.: Towards automatic persona generation using social media. In: 2016 IEEE 4th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW), pp. 206–211. IEEE, Vienna, Austria (2016). https://doi.org/10.1109/W-FiCloud.2016.51
32. Jung, S.-G., An, J., Kwak, H., Ahmad, M., Nielsen, L., Jansen, B.J.: Persona generation from aggregated social media data. In: Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems, pp. 1748–1755. ACM, Denver Colorado USA (2017). https://doi.org/10.1145/3027063.3053120
33. Salminen, J., Jung, S., Jansen, B.: The future of data-driven personas: a marriage of online analytics numbers and human attributes: In: Proceedings of the 21st International Conference on Enterprise Information Systems, pp. 608–615. SCITEPRESS - Science and Technology Publications, Heraklion, Crete, Greece (2019). https://doi.org/10.5220/0007744706080615
34. Salminen, J., Jung, S.-G., Jansen, B.: Developing persona analytics towards persona science. In: 27th International Conference on Intelligent User Interfaces, pp. 323–344. ACM, Helsinki Finland (2022). https://doi.org/10.1145/3490099.3511144
35. Spiliotopoulos, D., Margaris, D., Vassilakis, C.: Data-assisted persona construction using social media data. BDCC. **4**, 21 (2020). https://doi.org/10.3390/bdcc4030021
36. Watanabe, Y., et al.: Retrospective based on data-driven persona significance in B-to-B software development. In: Proceedings of the 40th International Conference on Software Engineering: New Ideas and Emerging Results, pp. 89–92. ACM, Gothenburg Sweden (2018). https://doi.org/10.1145/3183399.3183410
37. An, J., Kwak, H., Jung, S., Salminen, J., Admad, M., Jansen, B.: Imaginary people representing real numbers: generating personas from online social media data. ACM Trans. Web. **12**, 1–26 (2018). https://doi.org/10.1145/3265986
38. An, J., Kwak, H., Jansen, B.J.: Validating social media data for automatic persona generation. In: 2016 IEEE/ACS 13th International Conference of Computer Systems and Applications (AICCSA), pp. 1–6. IEEE, Agadir, Morocco (2016). https://doi.org/10.1109/AICCSA.2016.7945816
39. Salminen, J., Jung, S., Kamel, A.M.S., Santos, J.M., Jansen, B.J.: Using artificially generated pictures in customer-facing systems: an evaluation study with data-driven personas. Behav. Inf. Technol. **41**, 905–921 (2022). https://doi.org/10.1080/0144929X.2020.1838610
40. Xydas, G., Spiliotopoulos, D., Kouroupetroglou, G.: Modeling Prosodic Structures in Linguistically Enriched Environments. In: Sojka, P., Kopeček, I., Pala, K. (eds.) TSD 2004. LNCS (LNAI), vol. 3206, pp. 521–528. Springer, Heidelberg (2004). https://doi.org/10.1007/978-3-540-30120-2_66
41. Rhee, C.E., Choi, J.: Effects of personalization and social role in voice shopping: an experimental study on product recommendation by a conversational voice agent. Comput. Hum. Behav. **109**, 106359 (2020). https://doi.org/10.1016/j.chb.2020.106359
42. Xiao, W., Zhao, H., Pan, H., Song, Y., Zheng, V.W., Yang, Q.: Beyond personalization: social content recommendation for creator equality and consumer satisfaction. In: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 235–245. ACM, Anchorage AK USA (2019). https://doi.org/10.1145/3292500.3330965

43. Park, H.W., Grover, I., Spaulding, S., Gomez, L., Breazeal, C.: A model-free affective reinforcement learning approach to personalization of an autonomous social robot companion for early literacy education. AAAI. **33**, 687–694 (2019). https://doi.org/10.1609/aaai.v33i01.3301687
44. Aivazoglou, M., et al.: A fine-grained social network recommender system. Soc. Netw. Anal. Min. **10**(1), 1–18 (2019). https://doi.org/10.1007/s13278-019-0621-7
45. Metz, M., Kruikemeier, S., Lecheler, S.: Personalization of politics on Facebook: examining the content and effects of professional, emotional and private self-personalization. Inf. Commun. Soc. **23**, 1481–1498 (2020). https://doi.org/10.1080/1369118X.2019.1581244
46. Ferrari, A., Micucci, D., Mobilio, M., Napoletano, P.: On the personalization of classification models for human activity recognition. IEEE Access. **8**, 32066–32079 (2020). https://doi.org/10.1109/ACCESS.2020.2973425
47. Rajawat, A.S., Upadhyay, A.R.: Web personalization model using modified S3VM algorithm for developing recommendation process. In: 2nd International Conference on Data, Engineering and Applications (IDEA). pp. 1–6. IEEE, Bhopal, India (2020). https://doi.org/10.1109/IDEA49133.2020.9170701
48. Margaris, D., Georgiadis, P., Vassilakis, C.: A collaborative filtering algorithm with clustering for personalized web service selection in business processes. In: 2015 IEEE 9th International Conference on Research Challenges in Information Science (RCIS), pp. 169–180. IEEE, Athens, Greece (2015). https://doi.org/10.1109/RCIS.2015.7128877
49. Javed Mehedi Shamrat, F.M., Tasnim, Z., Ghosh, P., Majumder, A., Hasan, Md.Z.: Personalization of job circular announcement to applicants using decision tree classification algorithm. In: 2020 IEEE International Conference for Innovation in Technology (INOCON), pp. 1–5. IEEE, Bangluru, India (2020). https://doi.org/10.1109/INOCON50539.2020.9298253
50. Naudet, Y., Antoniou, A., Lykourentzou, I., Tobias, E., Rompa, J., Lepouras, G.: Museum personalization based on gaming and cognitive styles: the BLUE experiment. Int. J. Virtual Communities Soc. Networking. **7**, 1–30 (2015). https://doi.org/10.4018/IJVCSN.2015040101
51. Harteveld, C., Sutherland, S.C.: Personalized gaming for motivating social and behavioral science participation. In: Proceedings of the 2017 ACM Workshop on Theory-Informed User Modeling for Tailoring and Personalizing Interfaces, pp. 31–38. ACM, Limassol Cyprus (2017). https://doi.org/10.1145/3039677.3039681
52. Raptis, G.E., Fidas, C., Avouris, N.: Cultural heritage gaming: effects of human cognitive styles on players' performance and visual behavior. In: Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization, pp. 343–346. ACM, Bratislava Slovakia (2017). https://doi.org/10.1145/3099023.3099090
53. Jamil, A., Nadeem Faisal, C.M., Habib, M.A., Jabbar, S., Ahmad, H.: Analyzing the Impact of Age and Gender on User Interaction in Gaming Environment. In: Khanna, A., Gupta, D., Bhattacharyya, S., Snasel, V., Platos, J., Hassanien, A.E. (eds.) International Conference on Innovative Computing and Communications. AISC, vol. 1087, pp. 721–729. Springer, Singapore (2020). https://doi.org/10.1007/978-981-15-1286-5_64
54. Barbiero, A., Blasi, S., Schwidtal, J.M.: The Impact of End-User Aggregation on the Electricity Business Ecosystem: Evidence from Europe. In: Sedita, S.R., Blasi, S. (eds.) Rethinking Clusters. SDGS, pp. 213–226. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-61923-7_15
55. Shi, L., Song, G., Cheng, G., Liu, X.: A user-based aggregation topic model for understanding user's preference and intention in social network. Neurocomputing **413**, 1–13 (2020). https://doi.org/10.1016/j.neucom.2020.06.099
56. Margaris, D., Kobusinska, A., Spiliotopoulos, D., Vassilakis, C.: An adaptive social network-aware collaborative filtering algorithm for improved rating prediction accuracy. IEEE Access. **8**, 68301–68310 (2020). https://doi.org/10.1109/ACCESS.2020.2981567

57. Cui, Z., et al.: Personalized recommendation system based on collaborative filtering for IoT scenarios. IEEE Trans. Serv. Comput. **13**, 685–695 (2020). https://doi.org/10.1109/TSC.2020.2964552
58. Salminen, J., Santos, J.M., Jung, S.-G., Eslami, M., Jansen, B.J.: Persona transparency: analyzing the impact of explanations on perceptions of data-driven personas. Int. J. Hum.-Comput. Interact. **36**, 788–800 (2020). https://doi.org/10.1080/10447318.2019.1688946
59. Salminen, J., Jung, S.-G., Chowdhury, S., Robillos, D.R., Jansen, B.: The ability of personas: an empirical evaluation of altering incorrect preconceptions about users. Int. J. Hum Comput Stud. **153**, 102645 (2021). https://doi.org/10.1016/j.ijhcs.2021.102645
60. Petrovskaya, E., Zendle, D.: Predatory monetisation? A categorisation of unfair, misleading and aggressive monetisation techniques in digital games from the player perspective. J Bus Ethics.1–17 (2021).https://doi.org/10.1007/s10551-021-04970-6
61. King, D.L., Delfabbro, P.H., Gainsbury, S.M., Dreier, M., Greer, N., Billieux, J.: Unfair play? Video games as exploitative monetized services: an examination of game patents from a consumer protection perspective. Comput. Hum. Behav. **101**, 131–143 (2019). https://doi.org/10.1016/j.chb.2019.07.017
62. Close, J., Spicer, S.G., Nicklin, L.L., Uther, M., Lloyd, J., Lloyd, H.: Secondary analysis of loot box data: are high-spending "whales" wealthy gamers or problem gamblers? Addict. Behav. **117**, 106851 (2021). https://doi.org/10.1016/j.addbeh.2021.106851