

Personality in Personalisation: A User Study with an Interactive Narrative, a Personality Test and a Personalised Short Story

ANONYMOUS AUTHOR(S)*

We present a user study developed to explore the use of psychological frameworks for the personalisation of narratives. Further, we explore using interactive narratives to understand the user's personality and how closely their in-narrative persona matches with our understanding of their personality. The study consists of three sections: an interactive narrative, a personality test, and a personalised short story.

CCS Concepts: • **Applied computing** → **Psychology**.

Additional Key Words and Phrases: personalisation, personality, narrative, interactive narrative

ACM Reference Format:

Anonymous Author(s). 2021. Personality in Personalisation: A User Study with an Interactive Narrative, a Personality Test and a Personalised Short Story. 1, 1 (January 2021), 10 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

1 INTRODUCTION

What makes a good story? Any subjective answer to the question would, by definition, be down to personal preferences, and ultimately to the kind of person that is answering the question. To present a suitable story to the person, we could either seek to find one that matches with their preferences, or, more intriguingly, make one fit them. This is what personalising narratives could do: alter a narrative to match with its reader's preferences. But the next question here is: how do we figure out their preferences? Perhaps the most intuitive approach would be to look at what else they have liked. However, this requires a lot of information: first, on what they have liked; and second, what the things they have liked are like; and third, how to make the new narrative similar in the right way. However, another approach is also possible, and this is what this study explores: trying to understand the person using methods from psychology. Then the narrative could be made to have different variations for different personalities. But how do we get an understanding of the person's personality? Using their social media data would be a common, well-established method, but not always possible or ethical. Using a personality test would be perhaps even more conventional, but not necessarily much fun to the user. Then, why not, if possible, use a method that should be fun for anyone interested in narratives: a narrative? That is what this study does: presents the users with an interactive narrative designed to capture their personality, and then personalises a narrative to match with their personality scores.

2 BACKGROUND

Player modelling has been widely used to adapt computer games, but relatively little to determine storylines, often using factorial models of user types, such as in Thue et al. [29], Barber and Kudenko [5], El-Nasr [11], and Sharma et al.

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.

© 2021 Association for Computing Machinery.

Manuscript submitted to ACM

Manuscript submitted to ACM

[26]. Such a model can easily be based on the five-factor model, as well. The five-factor model (FFM) [15] is considered by many researchers as the "gold standard" of personality psychology. It features five traits: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience. The Need for Affect (NFA), a less common metric, refers to how motivated people are to seek emotion-inducing situations and activities [16], and has also been used to predict engagement with negative and ambivalent emotion in narratives [6]. Therefore, using it in combination with the FFM could be helpful in determining possibly the most important issue in personalisation: whether the narrative should be ultimately happy or sad.

2.1 The Five-factor Model

The five factors have been found in many studies to influence preferences in narratives and media. Weaver [34] found that people with high scores in neuroticism, the reverse of emotional stability, had a strong preference for sad music and avoided lighthearted film genres, and psychoticism, an opposite of agreeableness, indicated a preference against comedy but one strongly in favour of graphically violent horror movies. Media preference profiles could also be used to successfully discriminate between different levels of neuroticism and psychoticism. Gunter [13] reported neuroticism to indicate less preference for violent film clips. Zuckerman and Litle [38] found evidence that sensation seeking (represented by openness and extraversion) involved a preference for novel and arousing media across genres. Many such correlations have also been found in other studies, such as Rawlings and Ciancarelli [21], Rentfrow, Goldberg and Zilca [22], Rentfrow and Gosling [23], Teng [28] and Zammitto [37]. Various other online activities, such as personal websites [32], Facebook profiles [4], emails [12] and even email addresses [3], can also reveal a person's personality to human observers. Computer-based personality judgments, however, are more accurate than those made by humans, according to Youyou, Kosinski and Stillwell [36], who created an algorithm they found to accurately predict FFM traits simply based on likes on Facebook. Computer-based judgments had higher correlation ($r=0.56$) with subjects' self-ratings than human judgments did ($r=0.49$).

Games have been used to research personality in several studies; Holmgård, Togelius and Henriksen [14], noting that games can have similar qualities to psychometric tests while being more engaging, propose a game for daily cognitive assessment. Many have noted that in-game behaviour might not match real-life behaviour [30], but many studies have found strong correlations between them [27, 35]. The Five Domains of Play theory [31] translates the FFM into five aspects of gaming motivation: people with a high score in openness to experience seek novelty; conscientiousness matches with challenge; extraversion with stimulation; agreeableness with harmony; and neuroticism with threat. De Vette et al. [9] tested the model, finding that for participants younger than 60, four out of five personality traits correlated significantly but weakly with their corresponding game preference domains ($r=0.13-0.30$, $p<0.05$). Nagle, Wolf and Riener [19] applied the FFM for adjusting difficulty in a first-person shooter game, with a linear regression model aiming to optimise enjoyment and gameplay duration. Van Lankveld et al. [30] found a correlation between gameplay metrics and all the five factors. De Lima, Feijó and Furtado [8] also created a method for generating a FFM profile during gameplay for the players, which is then used to define their quests.

There is also work on personalising language, typically with chatbots, such as in Ritschel, Baur and André [25] who used the user's FFM personality type. The Personage system [17] maps the five-factor model to a wide range of linguistic parameters. Rishes et al. [24] took use of Personage for creating variations of stories generated from a semantic representation composed of events and character intentions, with the results being the same regarding content, but slightly different stylistically, such as in the use of swear words, exclamation marks and shuttering.

2.2 Need for Affect

There have been various studies and versatile results on the topic of what sort of personal characteristics explain enjoyment of negative emotions in art. For example, De Wied, Zillmann, and Ordman [10] found that people with high empathy enjoyed tragic films more. Vuoskoski et al. [33] linked it to high openness to experience and empathy.

One promising approach could be the Need for Affect (NFA), which refers to how motivated people are to seek emotion-inducing situations and activities [16]. Media use or preference is not a part of its definition or operationalisation, but the study did have participants rate their willingness to see specific films after having read descriptions of how interesting, happy, and sad each of them was supposed to be. The willingness to see happy and sad films rather than less emotional films was higher for individuals with a strong NFA. They note that while sensation seeking is conceptually similar to the NFA, they found them empirically distinct.

Appel [1] found that high NFA scores matched with willingness to watch films with affectively negative content, but only in females. Bartsch, Appel and Storch [6] found that people with high NFA enjoyed horror films more. They found the NFA as the first personality trait found to be a consistent predictor of individuals' engagement with negative and ambivalent emotion experiences regardless of gender or genre.

3 METHODOLOGY

3.1 Study Outline

The first part of the experiment is an interactive narrative specifically written for this study. The user is presented as the protagonist and must choose one of presented options in 25 questions. All but one of the questions simulate a personality questionnaire on a five-point Likert scale, with the possible options ranging from one extreme to another, measuring either one of the factors in the Five-Factor Model (FFM) or the Need For Affect (NFA).

The participants then take a 10-item FFM questionnaire [20] and a 10-item NFA questionnaire [2]. Each question in both the narrative and the personality test is given a score from 0 to 4, and the total score for each trait is scaled in a normalised range from 0 to 1. Later, once enough people have participated, the scores for the questions in the narrative are readjusted with ridit scores [7] to take into consideration how specific questions tend to get answered. Here too, a normalised range from 0 to 1 is used.

In the final part, the users are presented with a short story written for the experiment and personalised to them. Users are defined as being either high or low in a given trait and are given a version that matches with that. Group 1 have this done according to the interactive narrative (IN) results, group 2 according to the personality test (PT), and one control group will get the opposite of what they'd get in group 1. Language style depends on extraversion, the protagonist's personality on the other FFM traits to match with the user, and the ending on NFA: a high NFA indicates a preference for a more emotional, tragic ending; a low NFA a less emotional, somewhat happy ending. The users are asked how much they liked the story and its language and how much they identified with the protagonist, which is used for measuring how useful the personalisation was.

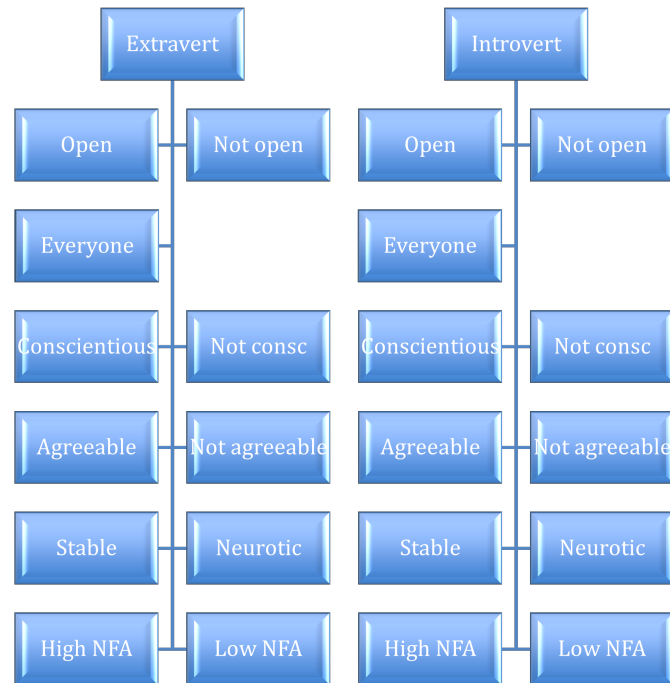
There were 59 participants (17 women and 36 men), volunteers who were found on internet discussion boards on interactive narratives and other relevant topics.

3.2 Narrative Structures

The IN questions relating to FFM are about how the protagonist responds to the situation, for example in a very extraverted or a very introverted manner, and the questions measuring NFA are about what happens next, ranging

157 from something lighthearted to something very dark. Most choices do not affect the direction of the IN, except for
 158 three questions. In question 23, the user is asked whether to slip a housemate's medications into his drink, like another
 159 housemate previously asked the user to do. The choice is presented only to add to the user experience and the user's
 160 sense of control, and has no influence on the user's personality scores, but does affect the situation in the next question.
 161 In Q24, the user is given five choices on the housemate's condition, one of which is that he's fine, one that he's dead,
 162 and three are different levels of illness. Both Q24 and Q25 also measure NFA. In Q25, 5 different options are offered
 163 for the ending by asking for the topic of a newspaper article. Therefore, there are $2 \times 3 \times 5 = 30$ different ways the story
 164 could end up.
 165
 166

167 In the personalised short story, there are two different versions from the start: high and low extraversion. This
 168 affects the use of language throughout every section. The story is then split into six different sections, and, apart from
 169 the section that is the same for everyone in the same extraversion pathway, there are two versions of each section
 170 under both extraversion pathways depending on whether the user has a high or low score in a given trait. The FFM
 171 traits influence how the protagonist is presented, and NFA defines whether the ending is tragic, or moderately happy.
 172 Therefore, there are $2^6 = 64$ different versions of the story.
 173
 174
 175



199
 200 Fig. 1. The structure of the personalised short story. Extravert and introvert version are different throughout, and consist of sections
 201 depending on whether a trait is above or below 0.5
 202

203 FFM traits have been found to have various correlations with what sort of language people use, and here it is
 204 hypothesised that people would also like to read the sort of language they prefer to use. The most important FFM trait
 205 in this and many other respects has been found to be extraversion [18], and therefore, to avoid complicating things, it
 206 is the only trait used for personalising language in this study. Since it is used for this purpose, it is not used in other
 207
 208 Manuscript submitted to ACM

forms of personalisation; e.g. adjusting the protagonist’s personality, to separate the effect of personalising language from that of personalising the character. Nevertheless, since extraversion is arguably the most important and the most widely understood FFM trait, it is the most likely one to affect identifying with the character, so if the other traits are helpful at all, extraversion would be highly likely to be so as well.

The way the use of language is personalised here is based on previous studies that have shown that people with high extraversion write using simple constructions; short sentences; few quantifiers; informal, affective language; the pronouns “we” and “which”; confident language featuring much words such as “want” and “need”; stylistic expressions such as “catch up” and “take care”; and a lot of semantic errors. Introverts, on the other hand, prefer the reverse: more long, formal and complex sentences; few errors; the pronoun “I”; negations; quantifiers; and less confident language such as “trying” and “going to” [18].

4 RESULTS

4.1 Interactive Narrative

The personality scores given by the interactive narrative (IN) had varying correlations with the personality scores given by the personality test (PT), slightly improved by the ridit analysis. The Spearman correlations are displayed in Table 1 below.

Table 1. Correlations of traits as judged by IN and PT, readjusted with ridit scores

Trait	Spearman correlation	P value
Extraversion	0.425	0.001
Emotional stability	0.323	0.012
Conscientiousness	0.155	0.241
Agreeableness	0.128	0.335
Need for affect	0.035	0.791
Openness to experience	0.018	0.89

It appears the IN was able to make an approximate assessment of the user’s extraversion and emotional stability, but not the other traits. NFA(IN), or NFA according to the IN, did not have any significant correlations with anything, especially with NFA(PT), but got close to significant correlations with agreeableness(PT), $\rho=-0.233$, $P=0.076$, and with openness(PT), $\rho=-0.211$, $P=0.108$, both negative but not quite significant at $p<0.05$.

The IN also appears good at judging openness in those identifying as women ($\rho=0.469$, $P=0.058$), but for men the correlation is actually negative ($\rho=-0.273$, $P=0.107$); neither are quite statistically significant. Particularly for women, statistical significance was hard to reach due to the small number of participants who identified as women (17).

4.2 Personalised Short Story

Some people took the experiment rather quickly and presumably carelessly, and one person confessed to just skim-reading the personalised narrative. Therefore, we exclude from the personalised short story analysis the 14 people who spent less than ten minutes on the test. As a result, we find the liking of the short story (3.56 vs. 3.2 on a scale 1-5) and its language (3.55 vs. 3.1) greatly increased in group 1, where taking the experiment very quickly was oddly common (ten individuals – this can only be down to chance).

Table 2. Average scores by group, scale 1-5

Group	Liking story	Relating	Liking language
1 [n=9] (IN)	3.56	2.78	3.55
2 [n=19] (PT)	3.37	3.00	3.58
3 [n=17] (Control, IN)	3.00	2.35	3.00
Kruskal-Wallis p value	0.342	0.197	0.022

We can note that extraversion according to the PT had 0.387 correlation with relating with the protagonist in the high-extraversion version (n=21), but -0.24 in the low-extraversion version (n=24), meaning that the more extraverted the user is, the more they relate with the protagonist if the language used is extraverted, but if the language is introverted, the reverse happens: the more introverted the user is, the more they relate! The p value for such a difference in correlations is 0.021. There were many such correlation differences, with only the statistically significant ones presented in Table 3.

Table 3. Significant correlation pairs, comparing groups presented with different version of the short story

Trait	Rating	IN			PT		
		Corr (high-trait group)	Corr (low-trait group)	p	Corr (high-trait group)	Corr (low-trait group)	p
Extraversion	Relating with protagonist				0.387 [n=21]	-0.24 [n=24]	0.021
Extraversion	Liking the language	0.136 [n=24]	-0.41 [n=21]	0.037	0.389 [n=21]	-0.638 [n=24]	0
Conscientiousness	Relating with protagonist	0.381 [n=29]	-0.176 [n=16]	0.044	0.109 [n=29]	-0.426 [n=16]	0.048
Stability	Relating with protagonist	0.104 [n=26]	-0.422 [n=19]	0.044			
Openness	Liking sad ending				-0.364 [n=25]	0.333 [n=20]	0.012
NFA	Relating with protagonist more in sad ending	0.169 [n=25]	-0.382 [n=20]	0.038			

Gender was also a major factor with the ending. For men, the ending made little to no difference, as versions with the happy ending were found just marginally better (3.27 [n=15] vs. 3.07 [n=15], Mann Whitney U p=0.24). However, for women, the sad ending was greatly preferred (3.71 [n=7] vs. 2.6 [n=5], Mann Whitney U p=0.014).

Table 4. Ratings by gender

	Men			Women		
	Happy ending [n=15]	Sad ending [n=15]	Mann Whitney U p	Happy ending [n=7]	Sad ending [n=5]	Mann Whitney U p
Liking	3.27	3.07	0.24	2.6	3.71	0.014
Relating	3.0	2.4	0.071	2.4	3.0	0.11
Language	3.4	3.33	0.41	3.0	3.57	0.043

5 DISCUSSION

5.1 Interactive Narrative

As noted above, the IN was able to make an approximate assessment of the user’s extraversion and emotional stability, but not the other traits. It should be noted that its way of measuring NFA did not match with the way NFA is tested, but with the way the authors of NFA describe the preferences for art that people with high NFA are expected to have: the more emotional and intense, the better. This study would give some indication that this is not necessarily the case.

The scores given by the IN followed a more standard distribution than those from the PT, particularly with ridit scores. According to the PT, the participants had a particularly low average score in extraversion (0.32) whilst being high in openness to experience (0.77), for example, which makes sense given the way they were recruited, but this could skew the results given by the IN, which had all of the average scores between 0.43 and 0.54 before ridit, and 0.45 and 0.50 after ridit. Some choices in the IN were far more popular than others, typically with bias in favour of the middle options. When the bias was away from the middle options, however, the ridit scores pulled the scoring closer to the middle.

Interestingly, almost half of the users (26/59) decided to slip the housemate his medications, and of those who did, few (8/26) wanted to see him unwell afterwards, though this was very common (28/33) in the group that chose not to slip them! This was the only question where previous choices could have such influence on answers, being avoided specifically for issues like this. This gives some clue that while people often want to see suffering in interactive narratives, they don’t want to feel like it’s their fault.

5.2 Personalised Short Story

According to Kruskal-Wallis tests, the only statistically significant difference between the ratings in the groups (Table 2) was with the language, $p=0.022$. However, the scores between the groups are not directly comparable; for example, group 2 got the sad ending much more than others, which could skew the results slightly in their favour, since that ending was more liked on average. This is because users tended to get high NFA scores in the PT (average 0.61), which defined the personalisation of group 2, but the results were more balanced in the IN (average 0.45), which was used in group 1. Nevertheless, it is easy to note that the control group performed the worst in every aspect, suggesting the personalisation did improve the experience. Like in group 1, the personalisation in the control group was based on the IN, meaning the different versions were more evenly represented than in group 2.

Looking at Table 3, we can note that adjusting the language depending on level of extraversion worked well regarding liking the language, and, in the case of the PT, also with respect to relating with the protagonist (who was also the narrator). However, this did not appear to translate to liking the story more. Personalisation based on conscientiousness

365 and emotional stability(IN) also worked particularly well in making the protagonist relatable. Openness(PT) indicated
366 liking the happier, less emotional ending, and therefore would apparently have been better for personalising the
367 ending than NFA was, though NFA(IN) appeared to work too, but did not quite reach significance (-0.028 vs. -0.45,
368 $p=0.079$). NFA(PT) seemed to have the opposite effect, which would have reached significance without removing the
369 fast experiment takers. However, NFA(IN) did work in making the protagonist relatable. Generally, the IN worked in
370 many ways much better than the PT, though many correlations weren't found quite significant and therefore weren't
371 mentioned here.
372
373
374

375 6 CONCLUSIONS

376
377 It was found that extraverted people appear to prefer reading narratives with less formal language, and introverts
378 prefer narratives with more formal language, or specifically, the types of language extraverts and introverts have been
379 found to write; this does not appear to have been tested before. Whilst it would appear that at least this interactive
380 narrative could not be used as a personality test per se, it was able to capture some traits, specifically extraversion and
381 emotional stability. It is possible that with agreeableness, conscientiousness and openness to experience, people might
382 indeed have a preference to act within fiction differently from how they would in reality; for example, someone who is
383 agreeable in reality might want to get a safe experience of what it is like to be rude. Whether they would then want to
384 see protagonists behaving like this as well, or preferably like they would in reality, is an open question. We should also
385 consider the possibility that the personality tests did not measure traits ideally. Short versions were used to not bother
386 the participants too much, but longer versions might have been more accurate. On the other hand, some people could
387 have been rather uninterested in the personality test section and clicked through it rather carelessly, and making it
388 longer could have exacerbated such a problem. It is therefore possible that interactive narratives could capture at least
389 some aspects of personality even better than personality tests, particularly as questions in personality tests tend to be
390 rather abstract and open to interpretation, even ambiguous, but in an interactive narrative, the user is put into a specific
391 situation in a rather concrete manner. In other contexts, verifying this could be difficult, but personalising a narrative is
392 a creative way of attempting to do this, and in fact the IN was at least as good as the PT for personalisation, despite, for
393 the most part, having rather low correlations with the PT. NFA, however, did not appear to work as intended, except
394 with the way the IN interpreted it. Therefore, perhaps NFA(IN) could be re-defined simply as a preference for tragic
395 rather than lighthearted themes in narratives– perhaps this could be called Preference for Tragedy, or PFT.
396
397
398
399
400

401 The personalisation with individual FFM traits also appeared to work well for relating with the protagonist. However,
402 the effect could have been limited by the fact that the sections displaying the protagonist's personality were rather
403 brief. Therefore, that a type of personalisation did not appear to work with this story does not mean that it could not
404 work when done better or with more participants, and that it did appear to work here could in some cases be down
405 to just chance. Similarly, at least some of the questions in the interactive narrative could have been just poorly made.
406 Therefore, more similar studies would be helpful.
407
408
409

410 REFERENCES

- 411 [1] Markus Appel. 2008. Manche mögen's heiß. *Diagnostica* 54, 1 (2008), 2–15.
412 [2] Markus Appel, Timo Gnams, and Gregory R Maio. 2012. A short measure of the need for affect. *Journal of personality assessment* 94, 4 (2012),
413 418–426.
414 [3] Mitja D Back, Stefan C Schmukle, and Boris Egloff. 2008. How extraverted is honey. bunny77@ hotmail. de? Inferring personality from e-mail
415 addresses. *Journal of Research in Personality* 42, 4 (2008), 1116–1122.

417
418
419
420
421
422
423
424
425
426
427
428
429
430
431
432
433
434
435
436
437
438
439
440
441
442
443
444
445
446
447
448
449
450
451
452
453
454
455
456
457
458
459
460
461
462
463
464
465
466
467
468

[4] Mitja D Back, Juliane M Stopfer, Simine Vazire, Sam Gaddis, Stefan C Schmukle, Boris Egloff, and Samuel D Gosling. 2010. Facebook profiles reflect actual personality, not self-idealization. *Psychological science* 21, 3 (2010), 372–374.

[5] Heather Barber and Daniel Kudenko. 2007. A user model for the generation of dilemma-based interactive narratives. In *Workshop on Optimizing Player Satisfaction at AIIDE*, Vol. 7.

[6] Anne Bartsch, Markus Appel, and Dennis Storch. 2010. Predicting emotions and meta-emotions at the movies: The role of the need for affect in audiences' experience of horror and drama. *Communication Research* 37, 2 (2010), 167–190.

[7] I Bross. 1958. How to use ridit analysis, *Biometrics Magazine*, 14. (1958).

[8] Edirlei Soares de Lima, Bruno Feijó, and Antonio L Furtado. 2018. Player behavior and personality modeling for interactive storytelling in games. *Entertainment Computing* 28 (2018), 32–48.

[9] Anna Frederiek Alberdien de Vette, Monique Tabak, MGH Dekker-van Weering, and Miriam MR Vollenbroek-Hutten. 2016. Exploring Personality and Game Preferences in the Younger and Older Population: A Pilot Study.. In *ICT4AgeingWell*. 99–106.

[10] Minet De Wied, Dolf Zillmann, and Virginia Ordman. 1995. The role of empathic distress in the enjoyment of cinematic tragedy. *Poetics* 23, 1-2 (1995), 91–106.

[11] Magy Seif El-Nasr. 2007. Interaction, narrative, and drama: Creating an adaptive interactive narrative using performance arts theories. *Interaction Studies* 8, 2 (2007), 209–240.

[12] Stephen D Gladis. 1993. *WriteType: Personality types and writing styles*. Human Resource Development.

[13] Barrie Gunter. 1985. Dimensions of television violence. New York: St.

[14] Christoffer Holmgård, Julian Togelius, and Lars Henriksen. 2016. Computational intelligence and cognitive performance assessment games. In *2016 IEEE Conference on Computational Intelligence and Games (CIG)*. IEEE, 1–8.

[15] Oliver P John, Eileen M Donahue, and Robert L Kentle. 1991. Big five inventory. *Journal of Personality and Social Psychology* (1991).

[16] Gregory R Maio and Victoria M Esses. 2001. The need for affect: Individual differences in the motivation to approach or avoid emotions. *Journal of personality* 69, 4 (2001), 583–614.

[17] François Mairesse and Marilyn A Walker. 2010. Towards personality-based user adaptation: psychologically informed stylistic language generation. *User Modeling and User-Adapted Interaction* 20, 3 (2010), 227–278.

[18] François Mairesse, Marilyn A Walker, Matthias R Mehl, and Roger K Moore. 2007. Using linguistic cues for the automatic recognition of personality in conversation and text. *Journal of artificial intelligence research* 30 (2007), 457–500.

[19] Aniket Nagle, Peter Wolf, and Robert Riener. 2016. Towards a system of customized video game mechanics based on player personality: Relating the Big Five personality traits with difficulty adaptation in a first-person shooter game. *Entertainment computing* 13 (2016), 10–24.

[20] Beatrice Rammstedt and Oliver P John. 2007. Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of research in Personality* 41, 1 (2007), 203–212.

[21] David Rawlings and Vera Ciancarelli. 1997. Music preference and the five-factor model of the NEO Personality Inventory. *Psychology of Music* 25, 2 (1997), 120–132.

[22] Peter J Rentfrow, Lewis R Goldberg, and Ran Zilca. 2011. Listening, watching, and reading: The structure and correlates of entertainment preferences. *Journal of personality* 79, 2 (2011), 223–258.

[23] Peter J Rentfrow and Samuel D Gosling. 2003. The do re mi's of everyday life: the structure and personality correlates of music preferences. *Journal of personality and social psychology* 84, 6 (2003), 1236.

[24] Elena Rishes, Stephanie M Lukin, David K Elson, and Marilyn A Walker. 2013. Generating different story tellings from semantic representations of narrative. In *International Conference on Interactive Digital Storytelling*. Springer, 192–204.

[25] Hannes Ritschel, Tobias Baur, and Elisabeth André. 2017. Adapting a Robot's linguistic style based on socially-aware reinforcement learning. In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (ro-man)*. IEEE, 378–384.

[26] Manu Sharma, Santiago Ontañón, Manish Mehta, and Ashwin Ram. 2010. Drama management and player modeling for interactive fiction games. *Computational Intelligence* 26, 2 (2010), 183–211.

[27] Shoshannah Tekofsky, Jaap Van Den Herik, Pieter Spronck, and Aske Plaat. 2013. Psyops: Personality assessment through gaming behavior. In *Proceedings of the International Conference on the Foundations of Digital Games*. Citeseer.

[28] Ching-I Teng. 2009. Online game player personality and real-life need fulfillment. *International Journal of Cyber Society and Education* 2, 2 (2009), 39–50.

[29] David Thue, Vadim Bulitko, Marcia Spetch, and Eric Wasylishen. 2007. Interactive Storytelling: A Player Modelling Approach.. In *AIIDE*. 43–48.

[30] Giel Van Lankveld, Pieter Spronck, Jaap Van den Herik, and Arnold Arntz. 2011. Games as personality profiling tools. In *2011 IEEE Conference on Computational Intelligence and Games (CIG'11)*. IEEE, 197–202.

[31] Jason VandenBerghe. 2012. The 5 domains of play: Applying psychology's big 5 motivation domains to games. In *Game Developers Conference, GDC Vault*.

[32] Simine Vazire and Samuel D Gosling. 2004. e-Perceptions: Personality impressions based on personal websites. *Journal of personality and social psychology* 87, 1 (2004), 123.

[33] Jonna K Vuoskoski, William F Thompson, Doris McIlwain, and Tuomas Eerola. 2011. Who enjoys listening to sad music and why? *Music Perception* 29, 3 (2011), 311–317.

- 469 [34] James B Weaver III. 1991. Exploring the links between personality and media preferences. *Personality and individual differences* 12, 12 (1991),
470 1293–1299.
- 471 [35] Nick Yee, Nicolas Ducheneaut, Les Nelson, and Peter Likarish. 2011. Introverted elves & conscientious gnomes: the expression of personality in
472 world of warcraft. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 753–762.
- 473 [36] Wu Youyou, Michal Kosinski, and David Stillwell. 2015. Computer-based personality judgments are more accurate than those made by humans.
474 *Proceedings of the National Academy of Sciences* 112, 4 (2015), 1036–1040.
- 475 [37] Veronica Lorena Zammito. 2010. *Gamers' personality and their gaming preferences*. Ph.D. Dissertation. Communication, Art & Technology: School
476 of Interactive Arts and Technology.
- 477 [38] Marvin Zuckerman and Patrick Litle. 1986. Personality and curiosity about morbid and sexual events. *Personality and Individual Differences* 7, 1
478 (1986), 49–56.
- 479
- 480
- 481
- 482
- 483
- 484
- 485
- 486
- 487
- 488
- 489
- 490
- 491
- 492
- 493
- 494
- 495
- 496
- 497
- 498
- 499
- 500
- 501
- 502
- 503
- 504
- 505
- 506
- 507
- 508
- 509
- 510
- 511
- 512
- 513
- 514
- 515
- 516
- 517
- 518
- 519
- 520