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THE ENTROPY OF PREDICTING PERSONALITY FROM FUNNINESS SCORES

Faisal L. Kadri [1]

[1] PhD, Amman, Jordan

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Corresponding Author
Faisal L. Kadri,
faisal@artificialpsychology.com

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ABSTRACT

This investigation is a correlation and entropy study of two models of personality: The Big Five (B5) psychometric personality traits and the Age Trend Classification (ATC) model of artificial personality. ATC is based on a nonlinear dynamic model of animal motivation; the classification is computed *a posteriori* from funniness scores of arbitrary selected 100 humorous sentences. The purpose of the study is to assess the prediction of B5 traits by linear regression from funniness scores. The performance of prediction is measured by the Kullback-Leibler divergence (Kld) entropy of information loss.

The analysis is implemented in stages, the first computes the correlation of participants mean funniness score with B5 traits. The mean is a measure of personal bias in assessing humour and includes contributions from multiple biases, such as mood, insecurity, personality attributes and emotional states.

The analysis of the second stage is performed on scaled funniness scores and sentences with opposite orientation are aggregated and keyed, as is done in B5 assessment questionnaires. The graphic results show a repeating pattern of profiles not observed before.

Stage three involves splitting the data among age groups, the graphs roughly showed a general trend of declining correlation with age, which suggests that the influence of motivation over traits in general also declines with age.

The ATC model of artificial personality is intended as a counterpart of the personality of the user in a man-machine interface, where the machine could complement the user's personality in order to achieve higher learning, more entertainment and/or improve productivity.

Keywords: Personality Psychology, Cybernetics, Humour Research, Artificial Intelligence, Motivation

1. INTRODUCTION

The taking into account the participants themselves in the assessment of a social/scientific situation is an example of concrete science and of Second Order Cybernetics*. Letting the participants scores decide the classification of sentences rather than subjective self-appraisal is a distinguishing aspect of this work from other psychological research and justification of being concrete science.

The research on linking humour with personality is not new, Mendiburo-Seguel et al. (2015) surveyed 15 publications, the most referenced personality model was the Five Factor Model McCrae and Costa (1997) also known as the Big Five (B5)

traits Goldberg (1992) "The perspective of Martin et al. (2003) can be considered the most influential in current self-evaluative research" Isik and Cengiz (2018) Most existing studies classified humour according to the Humour Styles Questionnaire (HSQ) Martin et al. (2003) which classified the styles of humour as either Self-Enhancing, Aggressive, Affiliative or Self- Defeating. Later notable works on linking humour and personality focused on daily use of humour and its relation to personality Heintz (2017) Nezlek and Derks (2020). Nearly all above research is based on subjects self-appraising their own preferences.

This investigation depends on the classification of funniness scores according to age trend without requiring self-appraisal, this completely removes subjective judgment from the analysis and suggests concrete science. Age Trend Classification (ATC) was used in modelling artificial personalities Kadri (2010) sentences were categorizing into four classes: Constant, Falling, Peaking or Rising funniness scores with age. ATC classes parallel HSQ styles in trend and in interpretation Kadri (2013)

This work is an investigation of the link between the two models of personality: B5 psychometric personality traits and ATC dimensions of artificial personality. The purpose is to determine the reliability of predicting B5 scores from funniness ATC scores by linear regression. The reliability is to be assessed by computing the entropy of information loss or the Kullback-Leibler divergence (KLd) Kullback and Leibler (1951) The potential benefit is to automate the assessment of personality by processing funniness scores of sentences that match the user's age and personality for financial benefit, improved learning, or entertainment.

The next section contains the theory behind ATC model followed by explanation of the analysis procedure. Next comes the first stage of analysis; scaling of raw scores and correlating participant's mean scores with B5. Correlation coefficient values show small to medium significance but generally consistent with earlier research. The second stage correlates scaled ATC scores with B5 resulting in more significant links with three traits. The third adds age information.

* Louis Kauffman, past president of ASC, in a message to CybCom group on Feb 3, 2022

2. EXISTING RESEARCH

Most existing research used B5/FFM data as the personality and HSQ as the humour assessment for correlation Mendiburo-Seguel et al. (2015) The trait classification of B5 psychometric model is well known, the five traits: Extroversion, Agreeableness, Conscientiousness, Neuroticism and Openness to experience are computed by aggregating scores to carefully selected opposing questions, such as: Talk to a lot of different people at parties, vs. Am not really interested in others. The orientation of the above sentences may intuitively be interpreted as first having outward then inward focus of attention. The opposition of orientation is reflected in the title of a trait, as in Extroversion vs. Introversion. The traits of Agreeableness, Conscientiousness and Openness can easily be seen with opposing orientation. The exception is Neuroticism, which relates to insecurity without distinction between inward and outward orientation. The scoring of B5 sentences is keyed, so that opposite sentences had opposite signs when computing the aggregated score of a B5 trait.

Psychometric personality models in general and B5 in particular did not demonstrate significant change with age Damian et al. (2019) However, the HSQ classification found systematic dependence on age; Martin et al. (2003) noted that

their Aggressive humour has a declining funniness appreciation with age while Self-Defeating increased.

Studies of humour preference changes in adults were "virtually nonexistent" McGhee et al. (1990) An early research proposed a developmental model based on prior cognitive studies of development in childhood McGhee et al. (1990) The present study does not challenge the cognitive basis of change in humour development but posits that changes in motivation are more significant contributors than cognition over adulthood.

3. THEORY BEHIND THE ARTIFICIAL PERSONALITY

The dimensions of ATC were interpreted as groups of animal motivations Kadri and Duncan (1995) Kadri (2022) Following the classification of animal motivation, funniness scores are categorized into four complex dimensions according to the trend of their average scores Kadri (2015) Constant, Falling, Peaking and Rising.

The design of the artificial personalities is built on projection of a dynamic animal motivation model Kadri and Duncan (1995) the model is a mathematical representation of priming and homeostatic motivations with four main animal motivations: self-preservation in the immediate sense, feeding, sociosexual and rearing motivations. Their projection on human behaviour has a slightly different nomenclature: the emotions, feeding, sociosexual and parenting.

Anecdotal observations suggested that motivations have age dependence in adult humans; feeding motivation, including aggression in the context of securing and defending resources, desire for growth and perhaps extremism, is predominant in young adults but gradually falls with age. Parenting motivation is the opposite; humans care for their offspring more and for themselves less as they age. Sociosexual desires peak around the time of maximum fertility and/or virility, while the emotions are equally likely to occur at any age, hence the emotions are anecdotally constant over adult age. The parallel in interpretation and in age trend with the HSQ styles is evident: Aggressive humour with Falling, self-defeating with Rising, Affiliative with Peaking and Self-Enhancing with Constant age trend. Age dependence was modelled as four repertoires of chatter sentences in artificial personalities Kadri (2010), Kadri (2013) each repertoire reflects insecurity in subjective context and orientation of response (either externalizing or internalizing the threat).

Previous work sought the link between ATC sentences and B5 traits, including signature analysis of funniness scores Kadri (2015) Earlier questionnaires used different languages with fewer sentences and participants than the present, leading to jagged, incoherent profiles indicating inadequate data to show trends Kadri (2021) This work is based on wider participation and leads to clearer patterns of gender and age links.

4. PROCEDURE

Online Big 5 funniness questionnaires were published through Google Mechanical Turk in 2020. The questionnaire was in English, had 100 B5 items and 100 arbitrarily selected humorous sentences for funniness scoring, the participants were asked to give a 1 to 5 mark to each sentence, a score of 1 for not funny and 5 for very funny. The questionnaire attracted 800 English language participants from around the world, of which 789 responses were validated, 310 female and 479 males. Age groups (18, 25, 30, 35, 45, 55) years, participation of females (98, 67, 35, 44, 31, 35) and males (107, 126, 83, 85, 53, 25) respectively.

Missing data were imputed, B5 scores with trend averages and funniness scores with participant score averages.

Procedures for filtering abnormal data were attempted, quantile filtering of B5 scores and Mardia test of funniness scores, such tests did not lead to substantial change in graphic patterns of correlation, in the end all validated 789 participants were included in the analysis.

The scaling and keying funniness scores distinguish the present analysis from other research. In justification, scaling aims to exclude two factors from further analysis. First factor, temporary personal bias which offsets all classes or types of humour equally, to make participant's score averages irrelevant to the ATC classification. Second factor, age group bias, in order to make score comparisons between age groups on the same basis of mean and standard deviation.

Keying of sentence scores is a practical necessity since loadings clearly shows positive and negative values. On inspecting to associate the orientation of sentences with the sign of loadings, subjective interpretation generally identified externalizing sentences had positive while internalizing had negative loadings. The 5 top and bottom sentences of the four ATC classification are included in the Appendix. Keying follows the sign of loading, +1 for positive and -1 for negative loadings.

Internal cohesion of data was computed, raw funniness scores have robust Cronbach's alpha Christmann and Van-Aelst (2006) of over 0.9, which is higher than B5 trait scores for the same participants of 0.82. However, scaling and keying of aggregated scores reduce the Cronbach's Alpha value to just over 0.6, which indicates lower coherence after scaling.

5. RESULTS

People like to give their opinion and mostly enjoy humour! Grading humorous sentences is an easy unobtrusive request. The next sections show numeric and graphic results of the prediction of personality traits from funniness scores.

5.1. FUNNINESS AVERAGE SCORES OF INDIVIDUALS CORRELATE WITH BIG FIVE TRAITS

A participant's average score is calculated in the process of scaling data, scaled scores replace raw scores when personal bias is skimmed off; the average or mean individual score represent common bias of participants.

Searching for interpretation of the measure of personal bias, terms with close meaning include mood, the emotions, affect, motivation and individual sense of humour.

Mood states are "momentarily stable response dispositions that vary among and within individuals" Deckers (2010) and "Moods are the affective states of mind that underlie our subjective mental life" Brown and Astell (2012) An early tool for the quantitative assessment of mood followed 12 factor adjective self-rating questionnaires Nowlis (1965) Personal bias certainly includes momentary stable responses, the similarity suggests that personal bias could qualify as a direct measure of mood that does not involve self-assessment. However, Brown and Astell (2012) investigated several mood assessing methods and found that mood is a complex phenomenon, and it may not be possible to distinguish between mood, the emotions, wellbeing, and long-term aspects of personality, and admit that "most of our knowledge about the nature and content of mood experiences has been determined through introspection and subjective report".

The emotions are also temporary dispositions with high interest to model in AI as is the affect Wilson (2010) Fahn (2019) cites "Affect, emotion, and mood are critical yet under-emphasized elements. were never really separate in the first place". Which can be understood as the three elements are not distinct from each other, and perhaps affect includes the emotions and mood. Therefore, mood and the emotions could be part of the definition of affect.

Motivation is an inclusive term of animal and human drives; it is distinct from cognition in being variable with time. Variability can be fast, medium, or slow. Fast motivations, such as the emotions, medium as in mood, slow as in age dependent human drives. Personal bias includes factors from all three, scaling removes fast and medium variability when comparing age group scores, thus amplifying age dependent factors when analysing scaled data. Therefore, motivation includes longer term changes in addition to the affect.

The most intuitive interpretation of bias is probably as a measure of personal sense of humour; lower average means less, higher means more appreciation of humour. Yet, the interpretation of personal score average has no exclusive meaning; all of the above may be valid to certain degrees. The following result shows assessment of predicting Big Five trait dimensions from individual reading of average funniness scores. It should not come as a big surprise that all traits are correlated; the computed value of the robust Cronbach's Alpha for the five traits of the 789 participants is just over 0.8 Christmann and Van-Aelst (2006)

Table 1

Table 1 Correlation coefficients of personal bias with B5 traits, numbers in parenthesis indicate the Kullback-Leibler divergence in bits

	Extroversion	Agreeableness	Conscientiousness	Neuroticism	Openness
Females	0.15(1.4)	-0.14(2.9)	-0.15(2.9)	-0.07(2.8)	-0.07(3.2)
Males	0.17(1.1)	-0.03(4.2)	-0.24(1.8)	-0.31(1.1)	-0.14(2.1)
Both Genders	0.16(1.2)	-0.10(2.9)	-0.21(2.1)	-0.21(1.5)	-0.11(2.5)

Table 1 above shows gender dependence with medium significance Cohen (1992) highest with Conscientiousness and Neuroticism in males. The Kullback-Leibler divergence helps in measuring how much information/entropy is lost in the prediction, the lower the number the closer the prediction.

Notice the above values processes raw scores with no scaling or keying of externalizing/internalizing jokes, in the following sections correlation will be computed on scaled, keyed scores.

5.2. KEYED AGGREGATED FUNNINESS CORRELATES WITH THREE OF THE BIG FIVE TRAITS

Scaling and keying of raw data removes score averages and exploits the orientation of sentences in order to produce clearer profiles of correlation. The processing does not alter pre-existing links, it mainly makes common features clearer when plotting the graphics.

Figure 1 is a scale representation of gender correlation coefficients using 5 pairs of selected ATC sentence scores. Notice near zero values of female correlation with Neuroticism and Extroversion, and conformity of female profiles compared with males. Additive (not keyed) correlation profiles are also generally close to zero, indicating that keying is a significant step in defining the link.

Table 2 contains the numerical values of correlation and corresponding KL divergence; lower values are more favourable for predictions. Notice males in many instances have a lower KL divergence figure than females, suggesting more reliable prediction of B5 traits despite lower correlation coefficients.

Neuroticism in particular, females and both genders have noticeably higher KL figures than males, signifying weaker link.

Table 2

Table 2 Correlation coefficients of B5 traits with aggregated scaled keyed ATC funniness scores. KL divergence in brackets

Kulback-Leibler	Extrov.	Agree.	Consc.	Neuro.	Openness
Constant Female	-0.11(2.11)	0.31(1.98)	0.26(2.22)	-0.04(3.95)	0.17(2.14)
Falling Female	-0.01(4.95)	0.3(1.84)	0.26(2.26)	0.03(2.82)	0.29(1.52)
Peaking Female	-0.01(1.87)	0.29(2.08)	0.22(2.41)	0.05(3.90)	0.27(1.76)
Rising Female	-0.14(2.1)	0.34(2.02)	0.27(2.26)	0.01(3.95)	0.25(2.24)
Constant Male	-0.09(1.32)	0.26(1.47)	0.27(1.81)	0.13(2.04)	0.3(1.15)
Falling Male	-0.13(1.25)	0.09(3.18)	0.08(3.49)	0.15(2.02)	0.23(1.76)
Peaking Male	-0.04(1.30)	0.14(1.57)	0.23(1.71)	0.15(1.9)	0.17(1.09)
Rising Male	-0.07(1.35)	0.06(1.73)	0.03(2.68)	0.11(2.12)	0.1(1.24)
Constant F+M	-0.09(1.48)	0.31(1.49)	0.29(1.88)	0.05(2.62)	0.25(1.43)
Falling F+M	-0.08(2.09)	0.20(2.09)	0.18(2.61)	0.09(2.35)	0.26(1.56)
Peaking F+M	-0.02(1.46)	0.24(1.64)	0.24(1.95)	0.1(2.58)	0.22(1.28)
Rising F+M	-0.09(1.59)	0.22(1.70)	0.17(2.31)	0.05(2.86)	0.17(1.53)

Figure 1

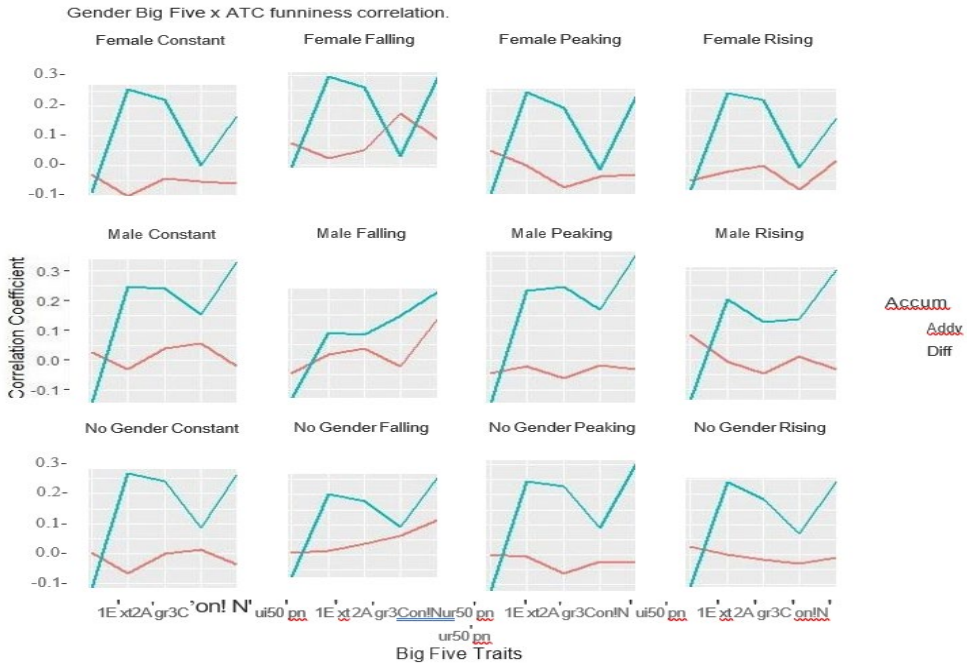

Figure 1 Gender correlation of B5 traits with aggregated ATC keyed scores

It is no surprise that the traits of Agreeableness, Conscientiousness and Openness are correlated with keyed externalizing-internalizing humour sentences.

It is also not surprising to observe near zero correlation of Neuroticism with keyed sentences; the interpretation of Neuroticism seemingly relates to a sense of insecurity without the externalizing-internalizing orientation. However, it is surprising that Extroversion also has near zero correlation. The interpretation of Extroversion describes a concept with verbal similarity to externalizing, it is counter intuitive to expect negative or no correlation between the two.

A possible explanation maybe a conflation between Extroversion and Neuroticism; some items seem to carry similar meanings, such as: "Often feel uncomfortable around others" (Extroversion) and "Feel threatened easily" (Neuroticism) and "Don't like to draw attention to myself" (Extroversion) and "Take offence easily" (Neuroticism). Such conflation may explain the low correlation of Extroversion to some extent but not the negative sign. The subject is certainly worth further investigation.

5.3. AGE MAY REDUCE THE DEPENDENCE OF HUMOUR ON PERSONALITY

Figure 2

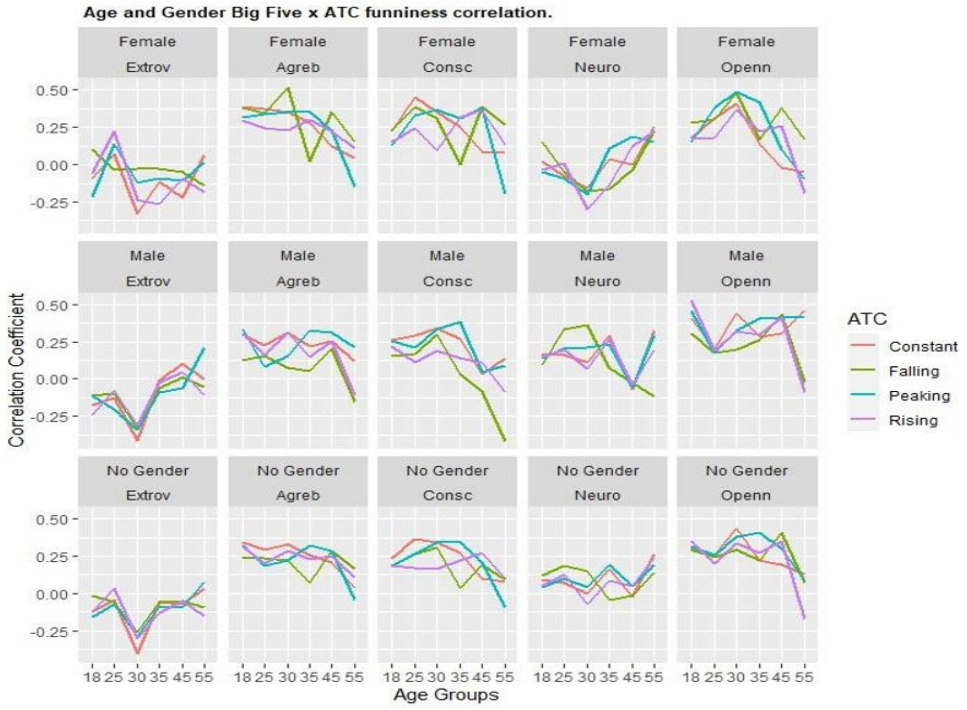

Figure 2 Age and gender correlation of B5 traits with aggregated ATC keyed scores

Lower count of participants invariably reduces the smoothness of profiles and leads to jagged curves in Figure 2 above, and possibly to worse performance of prediction models. Participants are divided among six age groups in order to draw age profiles, the resulting profiles are not easy to draw accurate conclusions, more participation is necessary. However, a human observer may be inspired to see features to suggest direction for further investigation without rigorous statistical tests, such as correlation values near zero for no gender profiles of Neuroticism and Extroversion (except for age group 30 years for Extroversion). And a general trend of declining correlation with age. There certainly no clear distinction between the different ATC classes and their link to B5 traits.

Table 3

Table 3 Kullback-Leibler divergence figures in bits for no-gender ATC/B5 age group prediction by linear regression

Age Group	18	25	30	35	45	55
ConsXExtv	2.26	3.59	3.41	2.71	3.64	3.11
ConsXAgree	4.35	5.55	5.9	4.89	5.98	4.92
ConsXConsc	4.41	5.25	5.41	5.05	5.79	5.08
ConsXNeuro	3.06	3.81	4.09	3.21	4.16	3.88
ConsXOpenn	4.62	5.07	6.12	5.27	5.84	4.91
FallXExtv	4.03	2.85	3.97	3.09	3.62	2.84
FallXAgree	5.79	4.43	5.66	4.94	4.98	5.19
FallXConsc	5.65	4.2	5.76	4.86	4.73	5.31
FallXNeuro	4.28	3.02	3.82	3.18	3.63	2.99
FallXOpenn	5.83	4.41	5.81	5.4	4.88	5.38
PeakXExtv	3.17	3.56	3.89	2.85	3.21	2.96
PeakXAgree	5.69	5.61	5.39	5.08	5.65	5.37
PeakXConsc	5.65	5.87	5.11	5.21	5.64	5.3
PeakXNeuro	3.85	3.85	4.06	3.46	3.81	3.68
PeakXOpenn	5.89	5.97	5.32	5.74	5.67	5.4
RiseXExtv	2.38	3.41	2.29	2.97	3.51	3.69
RiseXAgree	4.31	5.05	4.56	5.23	5.41	6.19
RiseXConsc	4.34	4.82	3.99	5.01	5.83	6.02
RiseXNeuro	2.68	3.6	2.46	3.31	4.18	4.21
RiseXOpenn	4.67	5.07	4.52	5.36	6.03	6.21

Performance data given in Table 3 show, as expected, lower quality of prediction in the direction of ATC to B5 traits. The table is the computed KLd values in bits from combining both genders, correlation coefficients are drawn to scale in the bottom 5 graphs in Figure 2

6. CONCLUSIONS

The Kullback-Leibler divergence (KLd), also known as the relative entropy, is a measure of the difference between a predictor and predicted probability distributions. The predictor is usually data computed using specific mathematical models, the lower KLd value the closer the prediction model to the predicted reality. Here, correlation and KLd are used to assess the link between personality and humour.

This investigation shows that it is possible to predict the Big Five traits of a person by linear regression models from his/her funniness scores of arbitrary humorous sentences. This can be done in three stages. The first predictor is the linear regression model of average raw funniness scores. The second is from the aggregated, scaled, and keyed scores of Age Trend Classification (ATC) sentences. The third is with scores divided over age groups.

The KLd computations of the three stages show that the Big Five traits correlate with funniness scores in two distinct groups. Extroversion and Neuroticism correlate significantly with average raw funniness scores while Agreeableness, Conscientiousness and Openness correlate less significantly, with notable gender differences.

On the other hand, Agreeableness, Conscientiousness and Openness correlate significantly with aggregated, scaled, and keyed ATC scores while Extroversion and Neuroticism have near zero correlation coefficients and higher KLd values.

The lower correlation coefficients of Extroversion with the scaled, keyed scores is particularly surprising, because it suggests that the Extroversion-Introversion trait is not linked to the externalizing- internalizing context of sentences despite the obvious semblance in the meaning. The division of the participants by six age groups and the subsequent reduction in statistical bases probably caused the correlation profiles to be jagged, yet a visual inspection suggests a falling dependence of humour appreciation on personality. These two areas, the distinctive behaviour of Extroversion and age dependence, are probably worth investigating in the future with more participants.

The age dependent artificial personality model is designed to be a tool for man-machine interaction, where machines could emulate or complement the user's personality in order to achieve higher learning, more entertainment or improve productivity. The elucidation of the link with personality traits validates the model and points the way to calculating exact conversion parameters for practical application.

CONFLICT OF INTERESTS

None.

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APPENDIX

Examples of selected externalizing-internalizing sentence keying

10-At every party there are two kinds of people: Those who want to go home and those who don't. The trouble is, they are usually married to each other. Constant Externalizing

67- One's own simple bread is much better than someone else pilaf. Constant Internalizing

100- A bank is a place that will lend you money, if you can prove that you don't need it. Falling Externalizing

75- A woman confused her Valium with birth control pills, now she has 10 kids and doesn't care. Falling Internalizing

6- Diplomacy is the art of telling someone to go to hell in such a way that he looks forward to the trip. Peaking Externalizing

41- A fair face may fade, but a beautiful soul lasts forever. Peaking Internalizing
83- Never ask a barber if he thinks you need a haircut. Rising Externalizing

43- Better a diamond with a flaw than a pebble without. Rising Internalizing