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Exploring the associations between personality and response speed trajectories in low-stakes intelligence tests

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ABSTRACT

Previous research suggests a negative relationship between test taking speed and performance in mental ability testing, inviting researchers to explore the origin of individual differences in test taking speed. We investigate how personality could explain both one's initial speed and its evolution through test completion. 555 adult participants responded the Big Five personality items from the Synthetic Aperture Personality Assessment (SAPA) and a progressive matrices test created with IMak. We used the joint hierarchical response-response time model with variable speed to estimate individual speed parameters (as well as ability). We use Latent Profile Analysis on these person speed estimates, which suggest three distinct profiles. We then interpret these three speed profiles and investigate their relations with Big Five traits. Classes significantly differ on agreeableness, conscientiousness and openness – as well as the matrices test ability. "Hasty" (class 1) individuals are characterized by low openness and ability, "absorbed" (class 2) individuals by high ability and openness, low agreeableness and conscientiousness, and "precautious" (class 3) individuals by high agreeableness and conscientiousness. We conclude that response speed trajectories are associated with ability and personality traits, warranting future investigations.

1. Introduction

A seminal study conducted by Klein Entink et al. (2009) suggests a strong negative relation between speed and ability (i.e., a between-individual speed-accuracy trade-off) in mental ability tests: For a given item, slower respondents have an increased probability to respond correctly. Several studies have pointed to how a person's response speed varies during tests and how it impacts test performance (Goldhammer et al., 2015; Goldhammer & Klein Entink, 2011; Must & Must, 2018), but which individual characteristics explain test taking speed? In this paper, we investigate the role of personality in a person's speed trajectory when taking intelligence tests. We propose that personality may explain how one's response speed dynamically evolves through test taking.

1.1. *Studying response speed dynamically*

The relation between the speed to complete a task and performance has been the focus of many studies, particularly in the context of the investigation of speed-accuracy trade-off, both within- and between-persons (Fox et al., 2007; van der Linden & Fox, 2016). Investigating the links between speed and performance not only solves practical issues – for example, by detecting cheating or aberrant response patterns (Fox & Marianti, 2016), or understanding how motivational aspects of tests impact performance (Shaw et al., 2020) – but also questions test validity (Myszkowski, 2019).

Modern approaches to the speed-accuracy relation in intelligence tests have indicated that the modeling framework should disentangle person characteristics (speed and accuracy) and item characteristics (Fox et al., 2007; van der Linden & Fox, 2016). Indeed, from only raw response times, we would, for example, not distinguish a person responding slowly from the item being more time consuming. As a consequence, a joint hierarchical modeling approach for responses and response times was proposed and has gained popularity (Fox et al., 2007; van der Linden & Fox, 2016), mainly – but not only (Myszkowski, 2019) – in reasoning tests. Consistent with this work, throughout this paper, we use the term *speed* to refer to a person's latent speed

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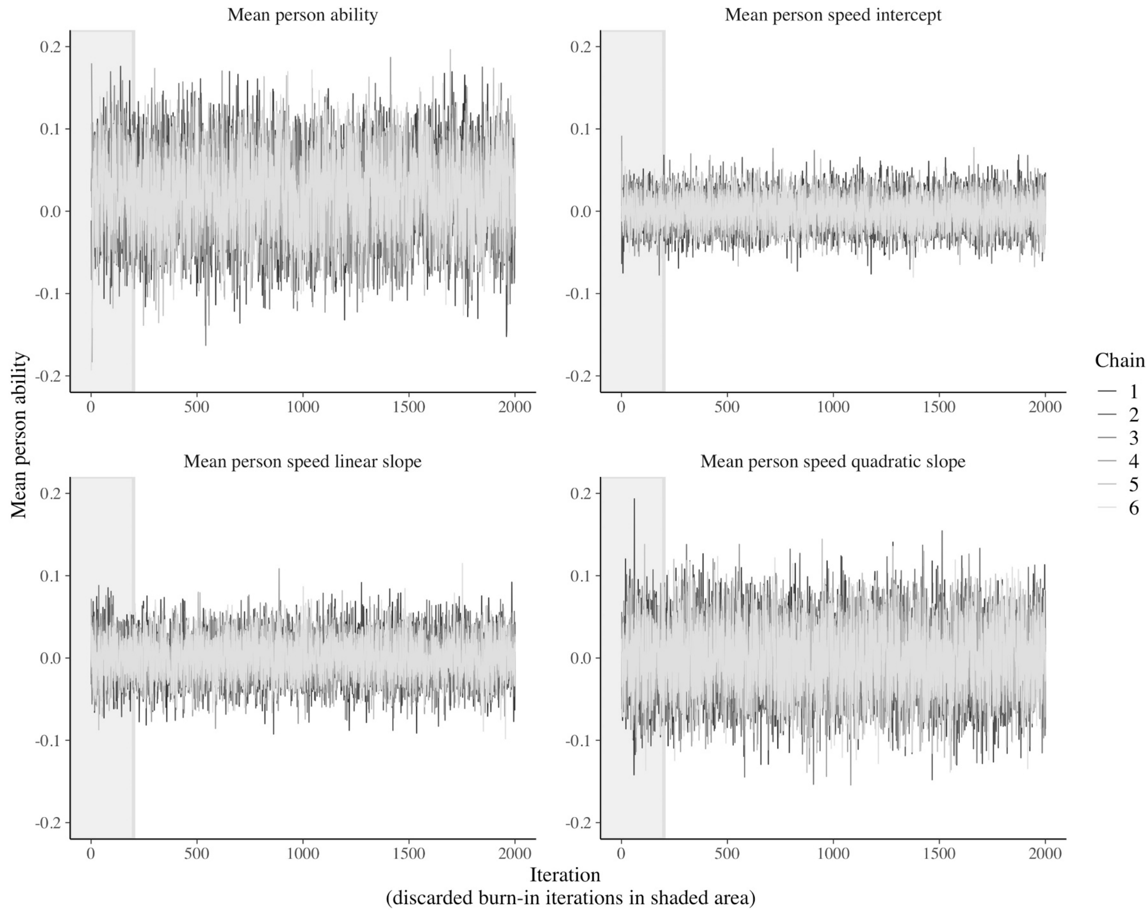

Fig. 1. MCMC chains trace plots.

(controlling for item effects), as opposed to predicted or observed response times (in seconds). Further, in this study, speed does not refer to the speed of information processing, but to the speed at which one gives responses to a test. To note, speed is here studied using an online low-stakes test.

In many reasoning tests, individuals are not speeded: Even when examinees are materially constrained in time, time is not considered a central aspect of the test. In these tests, however, studies using the joint hierarchical model have indicated a between-person speed-accuracy trade-off, indicated by a negative between-person correlation between speed and accuracy – controlling for item effects. This suggests that test takers who are fast to respond are usually less accurate (Klein Entink et al., 2009). In other words, even without being speeded, examinees may speed themselves, and this impacts performance in the test.

Most studies using the joint hierarchical approach have assumed the speed of test takers to remain constant during the test. Because this approach accounts for item effects, a constant speed does not imply constant response times for a person, but that the variation in response times across items for a given examinee is only explained by item differences. But the constant speed assumption may be unrealistic (Fox & Marianti, 2016): Respondents who have a positive experience may increase their effort, leading to decreases in speed. Others may be bored or discouraged by the first items, leading to increases in speed. More generally, examinees may experience increases or decreases in their intellectual engagement in the test, leading to speed variations. As a consequence, a *variable speed model* has been proposed, which allows both linear and quadratic speed variations through test completion (Fox & Marianti, 2016).

1.2. The aims of this research

There is limited evidence on the relations between personality traits and response speed in mental ability tests (Shaw et al., 2020). We aim to better understand these relations by accounting for variations in speed. In other words, we propose that personality traits predict speed trajectories.

To investigate this question, after extracting speed trajectories with the model previously discussed, we used Latent Profile Analysis (LPA) to identify speed trajectory classes. We used a latent class approach because research suggests that test takers vary qualitatively in problem-solving strategies when taking intelligence tests. For example, in reasoning matrices, eye-tracking studies (Hayes et al., 2011) suggest a systematic strategy, based on an analytical processing of the matrix, and a toggling strategy, based on a global and disorganized processing of the matrix. Qualitatively different strategies may have a qualitatively different speed trajectory signature.

In the variable speed model of speed trajectories (Fox & Marianti, 2016), a speed trajectory is characterized by three distinct parameters: Initial speed, acceleration, and acceleration in the acceleration. If test takers rely on qualitatively different problem-solving strategies, we propose that the three parameters of speed trajectories form different profiles. Although previous research suggests there could be different speed trajectory profiles, it does not suggest an a priori number of profiles, so we first focused on identifying a number of trajectory profiles.

Our next aim was to investigate the links between speed trajectory profiles and personality traits. We speculated that certain personality traits would be especially relevant in the understanding of speed trajectory profiles. Our main hypothesis here was that high speed could be a proxy for low intellectual engagement in the test (Myszkowski, 2019;

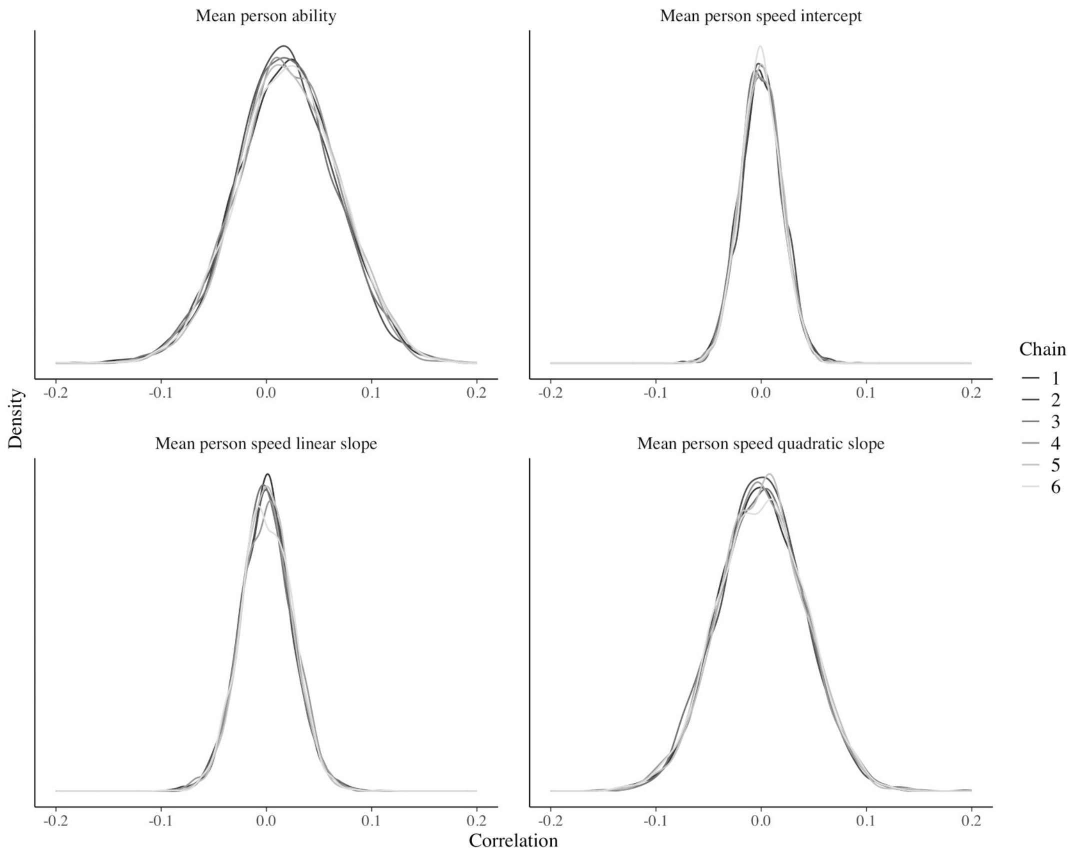

Fig. 2. MCMC chains density plots.

van der Linden & Fox, 2016), and that speed trajectories could indicate strategy changes (Fox & Marianti, 2016), such as, slowing down to improve accuracy, or moving to guessing strategies.

An important methodological note is that the test used in this study was – as most matrices tests, and as many mental ability tests – of increasing difficulty. While we used models that already account for item effects, this is relevant, because, even accounting for item characteristics, personality could possibly impact how respondents react to this increasing difficulty (e.g., by being more cautious, giving up, or gaining interest in the test).

Openness is generally considered as the Big Five personality trait that tends to overlap the most with intelligence (Ackerman & Heggestad, 1997). Generally speaking, open individuals tend to be motivated to process complex stimuli and solve problems (Furnham et al., 2005). In the context of a reasoning test, open individuals can therefore be expected to be more intellectually engaged, and thus to process the items in a careful – and thus, slow – manner. From this, we anticipated that openness could be related to being slow and slowing down through test completion.

Previous research (Ackerman & Heggestad, 1997) suggests that there is a positive relationship between emotional stability and intelligence test performance, which may be explained by how stable individuals efficiently regulate test anxiety. Therefore, emotional stability may be associated with changes in speed. More specifically, we hypothesized here that profiles characterized by positive speed variations when taking an intelligence tests are found among individuals scoring low on emotional stability.

We also hypothesized that individuals would differ in how cautious they would be when responding, as precautionary measures (e.g., double-checking) would decrease speed. We here anticipated that profiles suggesting precautious responding – that is, profiles characterized by overall slower responses – would be found especially among individuals scoring high on conscientiousness, emotional stability and agreeableness, which are traits usually associated with lower risk taking (Nicholson et al., 2005). Interestingly here, openness is, in general, also positively related to risk taking, which would suggest that open individuals would respond faster – in contradiction with our previous hypothesis on openness. Because we used a test of progressive difficulty, we thus anticipated that open individuals would in fact be especially characterized by slowing down (because the test is, to them, increasingly engaging), but not necessarily starting slowly.

2. Method

2.1. Participants and procedure

We recruited participants registered on an e-assessment application matching job applicants and recruiters. A link to the study was sent via email to the last 11,000 users of the e-assessment application, who had previously taken an online Computerized Adaptive Test (CAT) of intelligence, and had indicated that they consented to be contacted for scientific studies after taking assessments on the website. The email indicated that the new survey would be connected to the intelligence test that they had already taken on the assessment platform, but that their responses and results would only be used for scientific study, with no impact on their assessment profile online, and no communication to external companies. For this reason, this study represents a low-stakes context. 7.4% of the users voluntarily responded.

Because the intelligence test was not optimized to be displayed on smartphone screens, we removed participants who had completed the survey on a smartphone and retained only those who had taken it on a computer. In this final sample (N=555), 53.5% participants identified as female and 46.5% as male, with a mean age of 38.9.

Once logged into the survey, participants first took a 17-item logical

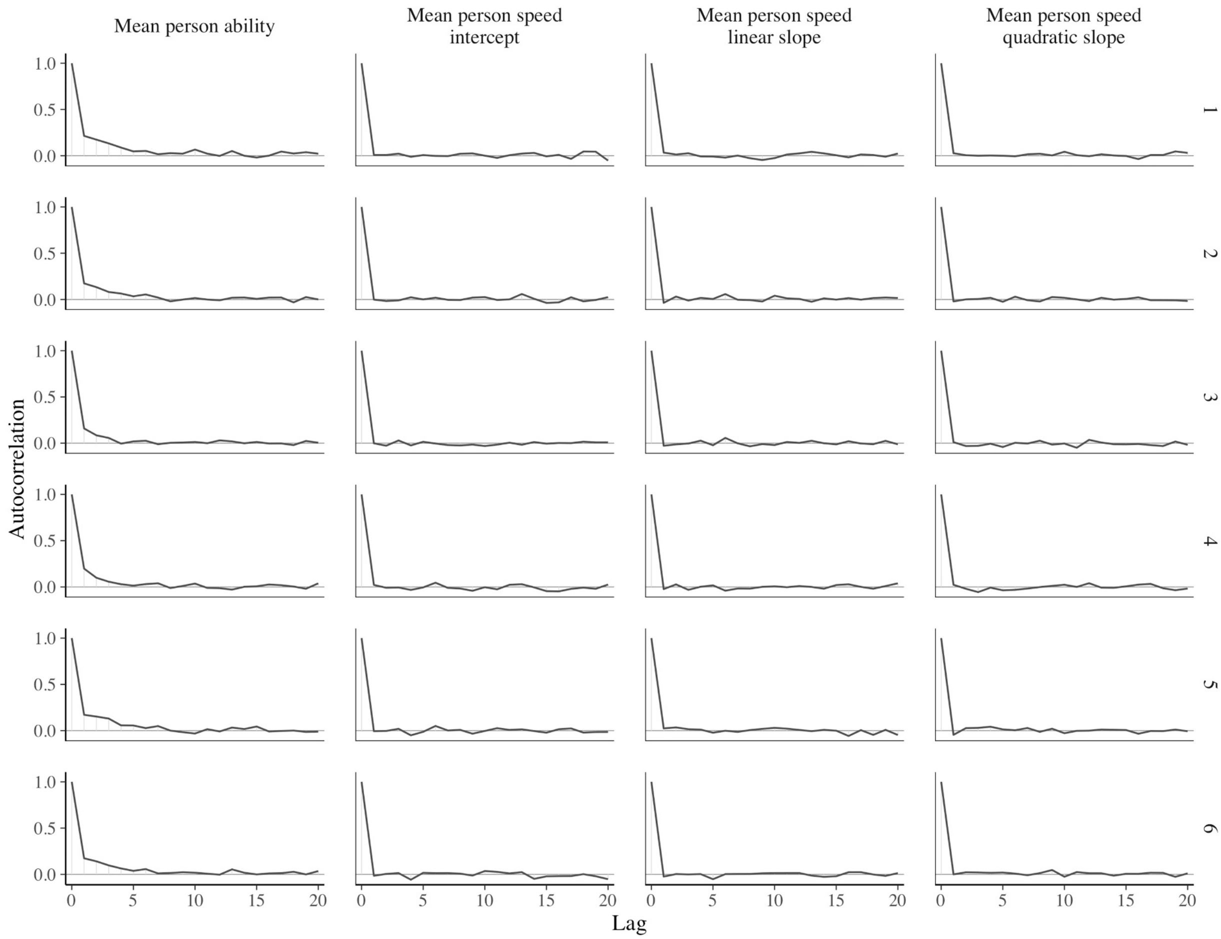

Fig. 3. MCMC chains autocorrelation plots.

reasoning matrices test and a 25-item personality questionnaire measuring the Big Five. The time spent to respond to each item of the matrices test was recorded together with the selected response option. Response times were recorded directly using the survey application used (SurveyGizmo), by calculating the difference (in seconds) between the time of display of the page (i.e., the item) and the time that the participant clicked to submitting their response.

Upon completion of the study, the participants' responses were linked to data from the e-assessment application, which allowed to use the CAT formerly taken as an external validity criterion for the matrices test.

The data, analysis code and the Imak-generated test are available at `https://osf.io/uge2w/?view_only=23a940d0460247509dd25ea50910fdef`. All conditions and data exclusions are reported in this paper. Participants were contacted based on them having previously responded to the CAT test, but some of them may have taken other measures on the online assessment platform, however these measures were not used because they were not relevant to the aims of this study.

2.2. Measures

2.2.1. Intelligence test

We used the library `IMak` (Blum & Holling, 2018) to generate figural analogies to assess intelligence. The final test consisted of 4 one-rule practice items, 4 one-rule items, 6 two-rule items, 6 three-rule items, and 1 four-rule item, presented in this order. We later refer to this as the IMak-17. Given that the number of rules is an indicator of item difficulty (Blum & Holling, 2018), this test can be considered a progressive matrices test. We estimated its reliability using McDonald's ω (Flora, 2020), which was 0.84.

Because we generated the matrices test for this study, we examined the validity of Imak-17 with an external criterion. For all participants, we collected the ability estimates from the Computerized Adaptive Test (CAT) of intelligence that the participants had taken on the e-assessment application. The CAT used for concurrent validity has not been the object of a psychometric validation study, but we can describe the items of this test as consisting of logical reasoning tasks, in which a series of figures and/or numbers is presented that have to be completed – similar to a matrix task. The test however differs from a matrix task, in that the response options often need to be combined together to complete the stimulus. We found a correlation of 0.41 between the two ability estimates. Usually, stronger correlations would be expected between two intelligence tests, but here, the correlation was probably attenuated by the time between the two measures, differences in item content (especially due to the combinatory aspect of the CAT test), and, more importantly, the fact that the IMak-17 is taken with low stakes, while the CAT test was taken in high stakes (as the results of the CAT test are used to populate one's online profile on the platform).

2.2.2. Big Five questionnaire

To assess personality, we used 25 items from the Synthetic Aperture Personality Assessment (SAPA) web-based personality assessment project (Revelle et al., 2010). The internal reliability of the 5 scales was acceptable considering their brevity (ω ranging from 0.61 to 0.81).

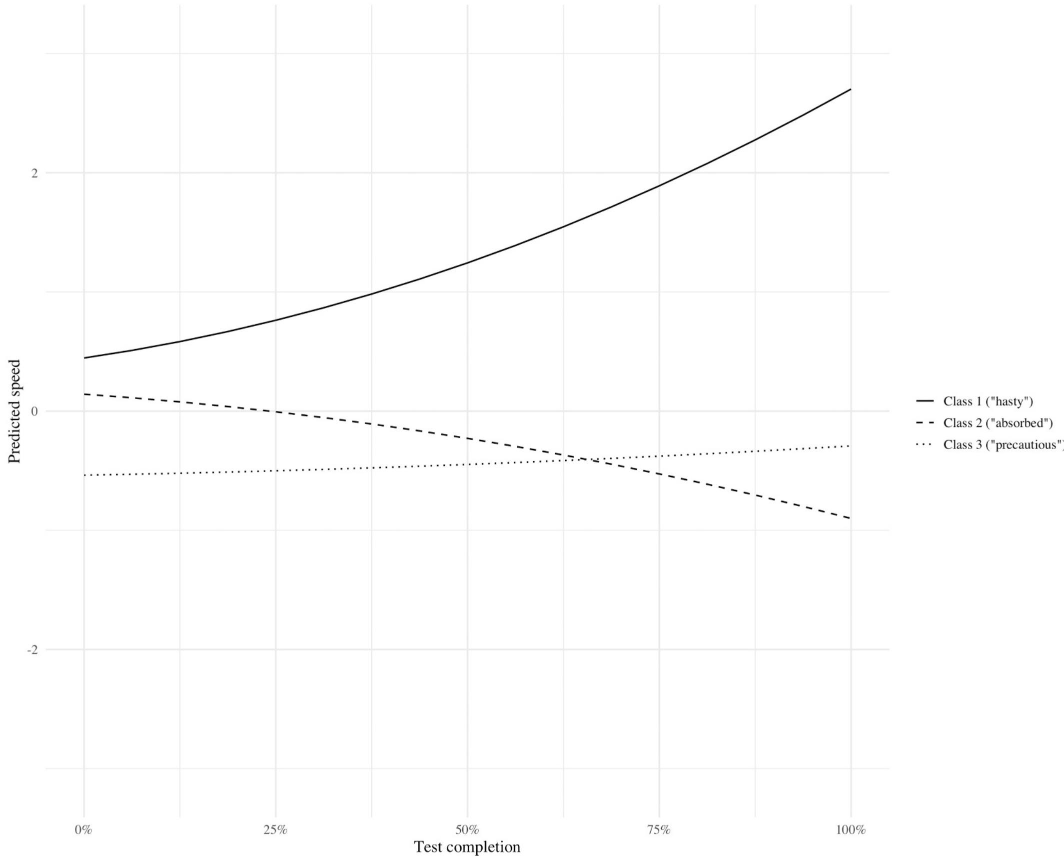

Fig. 4. Predicted speed trajectories of the classes identified with Latent Profile Analysis.

2.3. Analyses

2.3.1. Estimating individual latent speed trajectories

To estimate speed and ability, we used the dynamic speed joint hierarchical Item Response Theory model (Fox et al., 2007; van der Linden & Fox, 2016), implemented in the R library `LNIRT` (Fox et al., 2007). Responses were modeled using a 2-parameter normal ogive model.

For a given person *i* and item *j*, the lognormal variable speed model predicts log-response times $ln(T_{ij})$, as a function of 2 item parameters – time-discrimination ϕ_j, and time-intensity λ_j – and person speed. Person speed is modeled as a quadratic function of the item position X_{ij} and 3 person parameters – intercept (ζ_{i0}), linear (ζ_{i1}) and quadratic (ζ_{i2}) coefficients – see Eq. (1).

$$\begin{aligned} ln\left(T_{ij}\right) &= \lambda_j - \phi_j\left(\zeta_{i0} + \zeta_{i1}X_{ij} + \zeta_{i2}X_{ij}^2\right) + \varepsilon_{ij} \\ \varepsilon_{ij} &\sim \mathcal{N}\left(0, \sigma^2_{\varepsilon_{ij}}\right) \end{aligned} \tag{1}$$

`LNIRT` estimates the responses and response time models using a Bayesian Markov Chain Monte Carlo (MCMC) algorithm, with non-informative priors. MCMC estimation being a stochastic estimation process, like previous studies using this package (Myszkowski, 2019), we used several estimation chains (6) with different random seeds, to ensure that the parameters estimated from the estimation were stable across chains. Each estimation chain was comprised of 2000 iterations, and we discarded the 10% first iterations as burn-in.

The convergence across chains was examined using the Gelman-Rubin statistic, along with diagnostic plots (trace plots, autocorrelation plots and density plots) of the parameters, in order to ensure that the iterations were stationary and produced similar posterior distributions across chains.

Once convergence was ensured, we used the first MCMC chain to assess model fit (using person fit, item fit and residual tests provided in `LNIRT`) and to compute Expected A Posteriori (EAP) point estimates for the person parameters, used in subsequent analyses.

2.3.2. Identifying and interpreting speed trajectory classes

In order to identify speed trajectory profiles, we used Latent Profile Analysis (LPA) on the speed person estimates, using the package `tidyLPA` (Rosenberg et al., 2018). Models – which vary in the number of classes retained and the model constraints (equal/free variances and/or covariances) – were compared using their Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). We compared models with up to 10 latent classes, which, as confirmed by the fact that 3 classes were ultimately retained, was conservative. We plotted their speed trajectories, based on the average speed parameters in each class.

2.3.3. Comparing personality traits of the speed trajectory classes

We compared the Big Five personality traits of the different classes using One-Way Analyses Of Variance (ANOVA). When Levene's test indicated significant heterogeneity of variance, we used Robust (Welch's) One-Way ANOVAs. To assess if the classes differed in personality in general, we used a One-Way Multivariate Analysis Of Variance (MANOVA). As a secondary analysis, we also compared mean ability levels (in the matrix task) between classes using a One-Way ANOVA.

3. Results

3.1. Response time model convergence and fit

Gelman-Rubin statistics and their confidence interval upper bounds were all indistinguishable from 1, indicating satisfactory MCMC convergence across chains. Because of the large number of person and item parameters, we only present here the MCMC chains, density plots

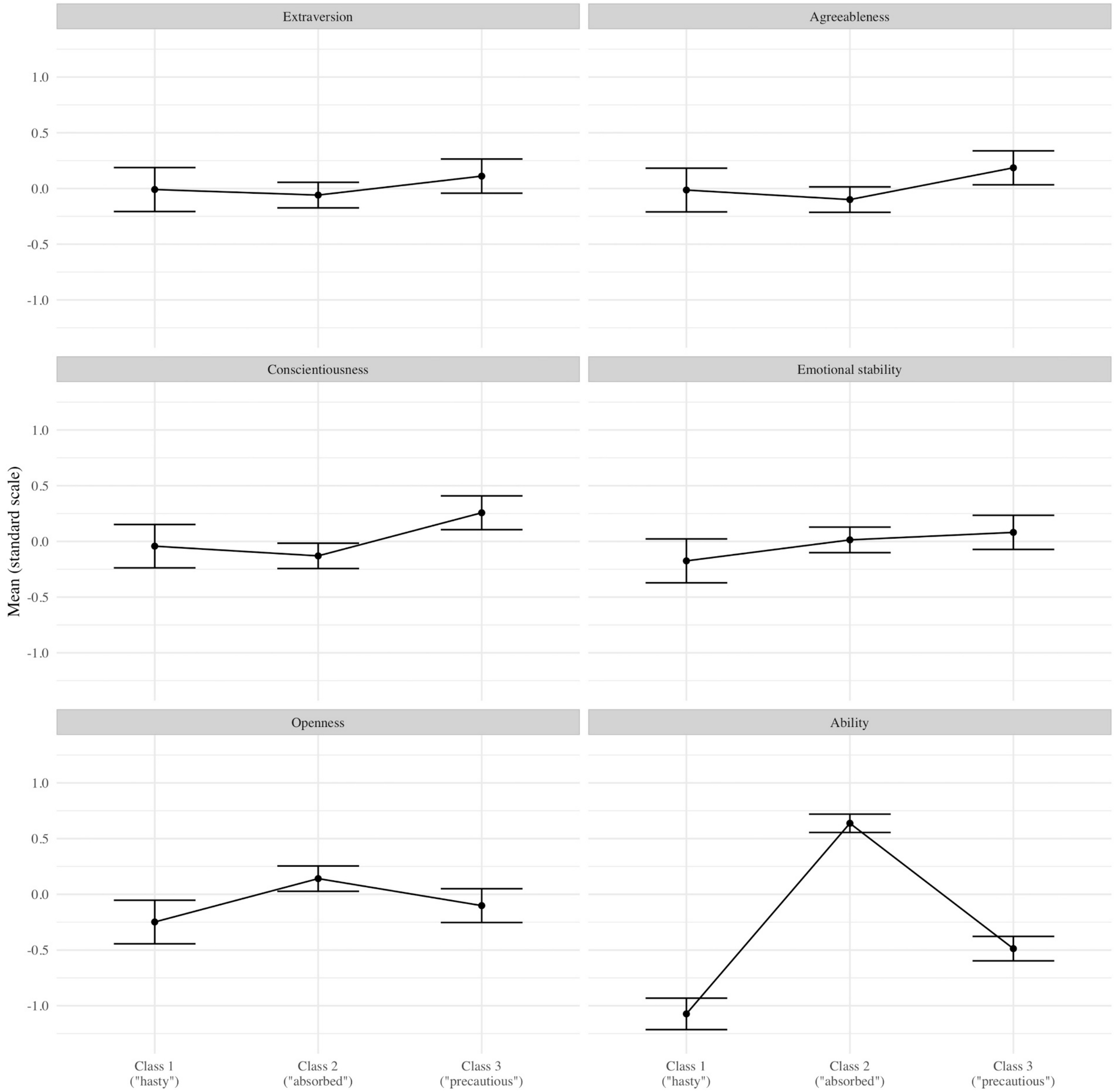

Fig. 5. Mean (with 95% confidence intervals) ability and personality estimates by class.

and auto-correlation plots for the parameters used in later analyses (person parameters), in, respectively Figs. 1, 2 and 3. It can be seen from these graphs that the 6 chains presented stationary iterations, and produced similar posterior parameter distributions. Similar findings were observed in the other parameters of the models, further confirming the satisfactory convergence of the models.

LNIRT reports various posterior probabilities, which can be used to detect misfit. Less than 0.01% of response time residuals were flagged as extreme with at least 95% posterior probability, and 10.8% of the examinees had significant (posterior probabilities of a more extreme person misfit below 0.05) misfit. As a consequence, model fit was considered acceptable.

3.2. Latent Profile Analysis of the speed estimates

Form the Analytic Hierarchy Process (AHP) implemented in TidyLPA, which uses various fit indices, such as the AIC and BIC (Akogul & Erisoglu, 2017), the best fitting model identified 3 latent classes. The model fit indices are reported as online supplementary material.

The speed trajectories of the 3 classes are represented in Fig. 4. Class 1 (17.8% cases) was characterized by high starting speed, and acceleration throughout the test: We refer to this class as the “hasty” class. Class 2 (526% cases) was characterized by average starting speed, and deceleration throughout the test. Since the test is of increasing difficulty, we labeled this class “absorbed”. Finally, class 3 (29.5% cases) was characterized by low starting speed remaining constant. We labeled it as the “precautious” class.

3.3. Speed trajectory classes and personality

Because of significant Levene's tests ($p<.05$), we used Welch's One-Way ANOVA for the comparison of extraversion and conscientiousness means, and Fisher's One-Way ANOVA for all other traits. The classes significantly differed on agreeableness – $F(2,552)=4.34$, $p=.014$ – conscientiousness – $F(2,552)=8.17$, $p<.001$ – and openness – $F(2,552)=6.94$, $p=.001$ – but not emotional stability – $F(2,552)=2.09$, $p=.125$ – nor extraversion – $F(2,552)=1.53$, $p=.218$. A One-Way MANOVA with all traits as outcomes indicated that classes overall significantly differed in personality – $F(10,1098)=4.57$, $p<.001$, Pillai's Trace = 0.08. Finally,

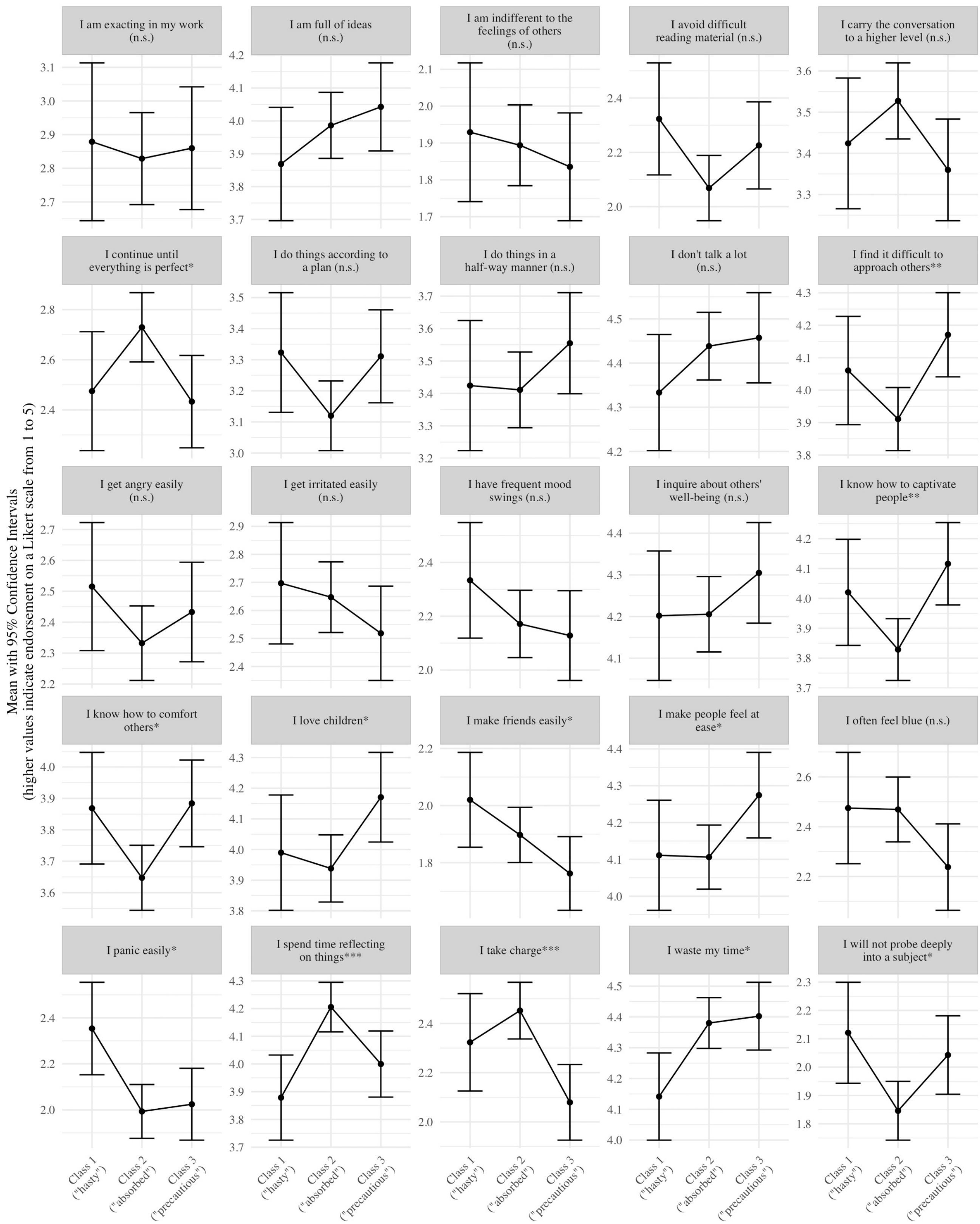

Fig. 6. Mean item responses by class.
Note: n.s.: $p>.05$, *: $p<.05$, **: $p<.01$, ***: $p<.001$.

as expected, the classes significantly differed in ability – $F(2,552)=265.52$, $p<.001$.

Measurement invariance comparisons across classes are reported as online supplementary material. Mixed results were found, depending on the criterion used to select models, although BICs supported strong invariance for all scales.

As showed in Fig. 5, the “hasty” class was characterized by having the lowest ability and openness. The “absorbed” class was characterized by having the highest mean ability and openness. Finally, the “precautious” class was characterized by having the highest agreeableness and conscientiousness. These results tend to confirm our hypotheses about the role of personality traits in speed trajectories. Item-level comparisons are presented in Fig. 6.

4. Discussion

Previous studies of the relations between personality and response speed in reasoning tests have assumed constant speed (Shaw et al., 2020). In contrast, we explored individual differences in speed trajectories and their relation with personality. We identified 3 trajectory profiles: “Hasty” (high initial speed and accelerating), “Absorbed” (average initial speed and decelerating), and “Precautious” (low constant speed). The trajectory classes significantly differed in personality overall, and they more specifically significantly differed on agreeableness, openness and conscientiousness.

Open individuals were more often found in the “absorbed” class. This is in line with our hypothesis, according to which open individuals would be intellectually engaged in the test, leading to slower responses. Because they tend to take risks, they did not start slow, but they decreased in speed as the test became more challenging, and thus more intellectually engaging. Further, high conscientiousness and agreeableness, which are related to low risk taking, were found at higher levels in the “precautious” class, with constant slow speed.

The 3 classes differed in ability, with the “absorbed” group largely outperforming the others. This result is in line with previous studies (Goldhammer et al., 2015; Goldhammer & Klein Entink, 2011; Myszkowski, 2019) on the relations between speed – conceptualized similarly to the present study – and ability in cognitive tasks. The speed-accuracy trade-off appeared, however, more complex than previously described, as, interestingly, the “absorbed” class, which started faster than the “precautious” before decelerating, outperformed it in ability. In other words, the results presented here suggest that deceleration – more than low constant speed – predicts high accuracy (although this may be only observable in progressive tests). Overall, these results illustrate how studying speed as constant is an insufficient approach to understanding its relations with personality and ability.

4.1. Implications

The relations observed between personality traits and speed trajectories, along with the fact that a low-stakes test was used, suggest that there is an overlap between personality and performance in low-stakes tests. In line with the Typical Intellectual Engagement (Ackerman & Heggestad, 1997) approach, which predicts relations between one's typical engagement and one's typical performance, items that can be thought to represent typical engagement (e.g., “I spend time reflecting on things”, or “I continue until everything is perfect”) were items with significant differences between speed trajectory classes. Further, the fact that only intellectual engagement items from the openness scale were found to relate to speed trajectories is in line with recent studies (Rozgonjuk et al., 2021) showing the specificity of this particular aspect of openness when considering relations with intelligence in low-stakes – and e-assessment – contexts. The present study suggests that speed trajectories could be indicative of typical intellectual engagement, which in turn, is predictive of test performance.

Interestingly, classes differed more in speed at the end than the beginning of the test. In other words, based on our findings, and if they can be generalized, there could be a moderating effect of test length on the speed-accuracy trade-off, and on the effect of personality on speed. Thus, it could be that, shorter mental ability test lengths may, in some cases, be more desirable than longer ones, because longer ones would tend to be more influenced by personality. Our findings therefore suggest that the length of an intelligence test could have an impact on construct validity.

4.2. Limitations and future research

A first limitation of this study is the relative novelty of the joint hierarchical response-response time model, for which, notably, overall measures of fit are not yet available. The further development of fit indices would for example make it possible to determine whether the evolution of the speed at the time of the test is constant or variable. This would not only clarify our findings regarding the role of personality in explaining individual differences in test taking speed, but also clarify findings regarding the links between speed and performance.

Further, a limitation of this study is the sampling procedure. Notably, since the participants were already enrolled in an online assessment application, and were invited to participate on a voluntary basis, the sample cannot be considered a random sample of the general population, and is prone to self-selection bias. This is especially problematic in a study like this one, where intellectual engagement is particularly important.

A previous study – using, however, a constant speed model – has questioned the reproducibility of the speed-accuracy trade-off in high stakes contexts, because low-stakes contexts could accentuate the effect of individual engagement differences on test performance (Shaw et al., 2020). Strong relations between speed trajectories and ability were found in our study, but it would be interesting to replicate our study in a high stake context to investigate the generalizability of our findings. In any case, our findings remain relevant for the many low stakes situations (e.g., studies in which performance is not incentivized).

Further, our study was conducted with one test, with its characteristics – progressiveness, non-speededness, non-verbal content – which limits the generalizability of this study. The relations between personality traits and speed trajectories may vary from a test to the other, calling for replication with other tests.

Finally, our account of personality remains rudimentary: we used a relatively brief measure of the Big Five. More specific traits may be more relevant to investigate here. We think that risk-taking, prudence, perseverance, self-efficacy or typical intellectual engagement, would be especially relevant traits to investigate as predictors of speed trajectories in mental ability tests.

CRediT authorship contribution statement

Nils Myszkowski: Conceptualization, Methodology, Statistical Analysis, Writing; **Martin Storme**: Conceptualization, Methodology, Statistical Analysis, Writing; **Emeric Kubiak**: Conceptualization, Methodology, Data collection; **Simon Baron**: Conceptualization, Methodology, Data collection.

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Authors 3 and 4 hold positions in the company that owns the Computerized Adaptive Test (CAT) of intelligence used as external validity criterion for the IMaK-generated test.

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