Preregistration Protocol: Smartphone Sensing Panel Study – Cognitive Abilities in the Wild

This preregistration protocol deals with specific research questions and is completed before any preprocessing of data. We denote that as this study is based on secondary data analysis, we do have access to the raw logging data. Study procedures and further background information are described in the corresponding basic protocol (Schoedel & Oldemeier, 2020). This template is inspired by the OSF Prereg Challenge template (https://osf.io/).

Working Title
Cognitive Abilities in the Wild: Predicting Fluid Intelligence from Digital Footprints of Everyday Smartphone Usage

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Background

Background Information (Optional; Short description of the theoretical background/introduction to research question)
Individual differences in cognitive abilities are known to predict various important life outcomes (e.g., educational attainment, job performance, income, mental health, longevity; Brown et al., 2021; Deary et al., 2021), making their study a critical area of interest for practitioners and researchers alike. While most research studied cognitive abilities within laboratory or achievement contexts, different lines of research investigated their role in everyday life, repeatedly linking them to our everyday

behavior (e.g., Alexander & Ryan, 2020; Gordon, 1997; Gottfredson, 1997). However, as this work mainly relied on reported behavior or simulated tasks, the relationship between cognitive abilities and objective behavior in everyday life remains unclear.

The recent adaption of smartphone sensing and computational methods in psychology has demonstrated the potential of studying individual differences in real-world settings (e.g., Stachl et al., 2020). In this fashion, the present study leverages digital footprints from everyday smartphone usage to investigate how fluid intelligence, one of the most central cognitive abilities within the Cattell-Horn-Carroll Theory (CHC; McGrew, 2009), is related to objective behavior in everyday life. More specifically, by means of a machine learning approach, we investigate (1) to what extent behavioral patterns in everyday smartphone usage predict fluid intelligence and (2) which behavioral patterns are most important for these predictions.

For this purpose, we drew on existing literature to derive a comprehensive overview of behavioral correlates of fluid intelligence in everyday life capturable via logs of everyday smartphone usage. These behavioral indicators can be clustered into four theoretically interrelated but distinguishable behavioral categories: (1) Performance in basic cognitive tasks, (2) dealing with complexity, (3) acquisition of skills and knowledge, and (4) preference for cognitive stimulation. Translating these findings into features of multimodal smartphone usage data (e.g., phone usage duration, app installations, music/podcast consumption, typing patterns), we created a list of sensing features that correspond to the theory-based behavioral correlates and are described in this preregistration protocol (see Table A1-A3). Using cross-validation, we will train linear and non-linear machine learning models (e.g., Elastic Net, Random Forest) based on these features and determine their predictiveness for participants' composite scores of a fluid intelligence test (Schuhfried, 2019). By means of interpretable machine learning techniques, we will examine which single features and feature groups contribute most to the predictive performance of these models.

The present study pushes forward efforts to understand cognitive abilities in the real world and takes first steps towards predicting fluid intelligence from digital footprints of everyday behavior (i.e., smartphone usage). Insights can inspire future research on the mechanisms of identified relationships (e.g., cross-lagged longitudinal analyses), inform research on effects of cognitive abilities on differential life outcomes (e.g., potential behavioral differences), and more generally demonstrate the potential of smartphone sensing and machine learning for intelligence research. Furthermore, they can build a basis for improving interventions in fields where individuals' fluid intelligence as well as related behavioral patterns play an eminent role (e.g., cognitive aging, psychotherapy, professional re-training), and inform regulators towards evidence-based policy making (e.g., data privacy).

Research question(s)

Can individual differences in fluid intelligence be predicted from behavioral patterns in everyday smartphone usage?

What behavioral patterns in everyday smartphone usage are most important in predicting fluid intelligence?

Hypotheses
Please provide hypothesis for predicted results. If multiple hypotheses, uniquely number them (e.g. H1, H2a, H2b,) and refer to them the same way at other points in the registration document and in the manuscript.

As this study uses an exploratory machine learning approach, we have not formulated specific hypotheses.

Variables

Which variables will be used? (see Variables in the basic protocol for an extensive overview of all available variables)
This section shall be used to unambiguously clarify which variables are used to operationalize the specified hypotheses. Please (a) list all variables that will be used in this study and (b) explicitly state the functional role of each variable (i.e., independent variable, dependent variable, covariate, mediator, moderator). It is important to (c) specify for each hypothesis how it is operationalized, i.e., which variables will be used to test the respective hypothesis and how the hypothesis will be operationally defined in terms of these variables. This section is closely related to the statistical models used to test the hypotheses.

All data used in this study is retrieved from the Smartphone Sensing Panel Study (SSPS; Schoedel & Oldemeier, 2020). The SSPS is a six-month German panel study conducted by researchers at Ludwig-Maximilian-Universität München (LMU) in cooperation with Leibniz-Institut für Psychologie (ZPID) from May until November

2020. Using a specially developed smartphone sensing application (PhoneStudy app) developed at LMU, a multi-modal dataset was collected comprising six monthly surveys, two experience sampling waves, as well as continuous smartphone logging during the complete study period. The collection procedures were approved by the ethics board at LMU. For more details about the study procedure, please see the study protocol provided by Schoedel and Oldemeier (2020).

Features

We will aggregate raw logging data from different sensing modalities (e.g., screen status, app usage, keyboard usage, audio consumption) into theory-based sensing features. These features can be grouped into four behavioral categories:

1. Performance in basic cognitive tasks (e.g., speed or output rate in relatively basic tasks of information processing)
2. Dealing with complexity in everyday Life (e.g., completing tasks involving novel information processing or problem solving, compensatory behavior to cope with complexity)
3. Acquisition of knowledge and skills (e.g., Rate of acquiring new skills and knowledge, propensity for activities associated with complex or extensive knowledge)
4. Preference for cognitive stimulation (e.g., engaging in learning opportunities and activities of effortful cognition, preference for complex aesthetic stimuli)

An exhaustive list of all features as well as corresponding theoretical and empirical support of behavioral differences are provided in detail in Table A2 of the appendix.

Target variable

Fluid intelligence was assessed in month five of the SSPS with a short version of the Inventory for Testing Cognitive Abilities (INT; Schuhfried, 2019). The INT is a test based on CHC-theory, specifically designed and validated for the assessment of cognitive abilities via smartphones. In this study, participants completed three subtests of different content facets of fluid reasoning ability (i.e., figural, numeric, verbal; Schneider & McGrew, 2018) on their smartphone. Following the test manual of the INT, we compute a fluid reasoning ability composite score based on the Rasch person parameters from each subtest, using structural equation modeling. The obtained composite scores of fluid intelligence constitute the target variable of this study.

Analysis Plan

Preprocessing

Inclusion criteria (e.g., criteria for including (1) participants (e.g., Do you only use a subsample?, (2) study days (e.g., only weekdays, certain number of study days), (3) any other criteria concerning data quality (e.g., only days with at least x% of logging data) etc. *If you cannot specify these aspects now, please state why.*

We will use all available sensing data (i.e., up to six months) from each participant. To ensure quality of the analyzed data, we define the following exclusion criteria on participant level. We exclude participants who
• have sensing data for less than four weeks (i.e., 28 days)
• have not completed all items of the fluid intelligence test or whose data is marked as careless test taking. Here, we declare test data as careless test taking, if participants
    o used repeating answering patterns (i.e., choosing the same option, alternating between two options, choosing options in ascending/descending order)
    o completed the test in unrealistic time (i.e., less than 30 seconds)
    o have significant person misfit parameters (α = .05) in all three subtests
 	
Due to technical logging-errors, single observations (e.g., maximum duration of a phone session) can reach extreme values unrelated to participants' behavior. Thus, distributions of features will be examined and in case of extremely imbalanced data, outliers will be excluded prior to predictive modeling. As extreme behavior shall not be excluded from this study (e.g., long sessions due to heavy gaming), outliers are defined as values exceeding four standard deviations from the sample estimate of central tendency.

Definition of variables based on smartphone sensing. Please specify your degrees of freedom in variable extraction procedures, e.g., • *time information (e.g., what does night, daily, weekend exactly mean?)* • *Aggregation measures (e.g., measures of central tendency/dispersion).* *If you cannot specify these aspects now, please state why.*

To extract psychologically meaningful features from the raw sensing data, we will aggregate the data by participant, applying different (robust) estimators that reflect a participant's behavior in terms of

- propensity (e.g., relative frequency)
- central tendency (e.g., Huber's *M*; Huber, 1981)
- dispersion (e.g., Q_n; Croux & Rousseeuw, 1992)
- clustering (e.g., k-means clusters)
- trajectory (e.g., parameters of hyperbolic growth curve)
- routineness (e.g., IV-irregularity; Williams et al., 2012)

Additionally, the extracted features will describe a participant's behavior on different levels of temporal aggregation such as

- logging event (e.g., minimum time between two in-app events)
- usage (e.g., maximum duration of an app usage)
- session (e.g., average number of different apps used in one phone session)
- day (e.g., day-level routineness of app usage)
- participation period (e.g., total number of app usages)

A detailed description of all features as well as relevant key terms is provided in Table A1-A3 of the appendix of this preregistration protocol.

Further preprocessing steps (e.g., transformation of data, handling of missing data/outliers etc.)

To avoid overestimation of the model's predictive performance, all further preprocessing steps will be incorporated in the resampling scheme. Within each resampling iteration, the following preprocessing steps will be performed:

- Exclusion of data: Features with more than 90% missing values, zero or near-zero variance (10% cut-off), or strong correlations with other features ($r > .90$) will be removed, following recommendations by Kuhn and Johnson (2013).
- Handling of missing data: We will compute missing value indicators (i.e., dummy variable indicating a missing value) for each numeric feature comprising missing values. Additionally, we will impute missing values using out of range imputation (i.e., add a "missing" factor level) for factorial features

and histogram imputation (i.e., sampling values out of frequency histogram) for numeric features, respectively.

- Transformation of data: For Elastic Net models, data needs to be standardized to perform regularization during model training. Here, we will use the default methods of the glmnet function (Friedman et al., 2023) which comprises re-coding into dummy variables for factorial features and z-standardization for numeric features, respectively.

Data Analysis

Statistical models
Please specify the statistical model (e.g. t-test, ANOVA, LMM) or algorithms that will be used to test each of your hypotheses. Give all necessary information about model specification (e.g., variables, interactions, planned contrasts) and follow-up analyses. Include model selection criteria (e.g., fit indices), corrections for multiple testing, and tests for statistical violations, if applicable. Please also indicate Inference Criteria (e.g., p-values, effect sizes, performance measures etc.).

Framed as a regression problem, we will train different machine learning models on the extracted sensing features to predict participants' composite score of fluid intelligence.

We plan to compare the predictive performance of linear (e.g., Elastic Net), non-linear (e.g., Random Forest), and featureless baseline (e.g., predicting sample mean) models in a benchmark experiment applying a 10x10 nested cross validation scheme.

In the main analyses of this study, our models will be trained without additional hyperparameter tuning beyond the default settings in the mlr3 package (Lang et al., 2019), which constitutes our machine learning framework we will use in R.

Performance of each model will be evaluated on how "accurate" unseen cases can be predicted. Here, we will draw on related work and use the typical performance measures Spearman correlation (r_s), coefficient of determination (R^2), and mean absolute error (*MAE*). We aim to run variance- and multiple-testing corrected tests to determine, whether fluid intelligence scores could be predicted significantly above chance.

In case of prediction success (i.e., performance measures of the linear or non-linear models are better than the baseline model), we plan to use interpretable machine learning methods and compute variable importance measures of single features as well as feature groups. This will allow us to investigate which theory-based features are most important for predicting fluid intelligence.

Optional exploratory analysis
As part of our optional analysis, we aim to investigate the predictiveness of our features for each content facet assessed with our fluid intelligence (i.e., figural, numeric, verbal) similar to the analyses described above. Additionally, we may investigate different extensions of our analyses by adding more exploratory features to our models, performing nested hyperparameter tuning, or applying more data-driven modeling strategies (e.g., sequence modeling).

References

Alexander, R. M., & Reynolds, M. R. (2020). Intelligence and Adaptive Behavior: A Meta-Analysis. *School Psychology Review*, *49*(2), 85–110. https://doi.org/10.1080/2372966X.2020.1717374

Brown, M. I., Wai, J., & Chabris, C. F. (2021). Can You Ever Be Too Smart for Your Own Good? Comparing Linear and Nonlinear Effects of Cognitive Ability on Life Outcomes. *Perspectives on Psychological Science*, *16*(6), 1337–1359. https://doi.org/10.1177/1745691620964122

Croux, C., & Rousseeuw, P., J. (1992). Time-Efficient Algorithms for Two Highly Robust Estimators of Scale. In *Computational Statistics* (pp. 411–428). Physica-Verlag HD.

Deary, I. J., Hill, W. D., & Gale, C. R. (2021). Intelligence, health and death. *Nature Human Behaviour*, *5*(4), Article 4. https://doi.org/10.1038/s41562-021-01078-9

Gordon, R. A. (1997). Everyday life as an intelligence test: Effects of intelligence and intelligence context. *Special Issue Intelligence and Social Policy*, *24*(1), 203–320. https://doi.org/10.1016/S0160-2896(97)90017-9

Gottfredson, L. S. (1997). Why g matters: The complexity of everyday life. *Intelligence*, *24*(1), 79–132. https://doi.org/10.1016/S0160-2896(97)90014-3

Huber, P., J. (1981). *Robust Statistics.* John Wiley & Sons.

McGrew, K. S. (2009). CHC theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research. *Intelligence*, *37*(1), 1–10. https://doi.org/10.1016/j.intell.2008.08.004

Schneider, W. J., & McGrew, K. S. (2018). The Cattell–Horn–Carroll theory of cognitive abilities. In *Contemporary intellectual assessment: Theories, tests, and issues, 4th ed* (pp. 73–163). The Guilford Press.

Schoedel, R., & Oldemeier, M. (2020). *Basic Protocol: Smartphone Sensing Panel Study*. https://doi.org/10.23668/PSYCHARCHIVES.2901

Schoedel, R., Oldemeier, M., Bonauer, L., & Sust, L. (2022). *Systematic Categorisation of 3,091 Smartphone Applications From a Large-Scale Smartphone Sensing Dataset* (1). *10*(1), Article 1. https://doi.org/10.5334/jopd.59

Schuhfried. (2019). *Manual Inventar zur Testung kognitiver Fähigkeiten* (52nd-Revision 2nd ed.). SCHUHFRIED GmbH.

Stachl, C., Au, Q., Schoedel, R., Gosling, S. D., Harari, G. M., Buschek, D., Völkel, S. T., Schuwerk, T., Oldemeier, M., Ullmann, T., Hussmann, H., Bischl, B., & Bühner, M. (2020). Predicting personality from patterns of behavior collected with smartphones. *Proceedings of the National Academy of Sciences*, *117*(30), 17680–17687. https://doi.org/10.1073/pnas.1920484117

Williams, M. J., Whitaker, R. M., & Allen, S. M. (2012). Measuring Individual Regularity in Human Visiting Patterns. *2012 International Conference on Privacy, Security, Risk and Trust and 2012 International Confernece on Social Computing*, 117–122. https://doi.org/10.1109/SocialCom-PASSAT.2012.93

Appendix

Table A1

Name and Specification of Key Terms Used in the Feature Description

Key Term	Specification
Features	
phone session	Sequence of logging events between a screen unlock and screen lock event
app usage	Sequence of logging events between opening and closing an app.
app session	All app usages from the same app that occurred during one phone session
new app	An app that was not on a user's phone at the beginning of the sensing period and then installed during study participation
new app category	An app category that was not present on the user's phone at the beginning of the sensing period and then installed during study participation
in-app event	Events logged during an app usage which indicate that an app's user interface is moved to the background and another user interface is moved to the foreground of the screen. For example, this can occur when a user is navigating between levels of an app's menu structure (e.g., from a messenger's home menu to the chat with a specific contact).
weekday	Monday, 00:00 - Friday, 23:59
weekend	Saturday, 00:00 - Sunday, 23:59
Estimators	
min	Measure of “lowest” values in a distribution, e.g., 5% percentile
max	Measure of “highest” values in a distribution, e.g., 95% percentile
sum	Measure of the total sum of all values, e.g., following Stachl et al. (2020) the sum is calculated by multiplying the Huber's M with the number of observations.
avg	Measure of central tendency, e.g., Huber's *M* (Huber, 1981)
var	Measure of variation, e.g., *Qn*; Croux & Rousseeuw, 1992)
skew	Measure for asymmetry of probability distribution of values
kurt	Measure of tailedness of a probability distribution of values
m1, m2, break	Estimates of different clustering algorithms with *m1* and *m2* as cluster centers of a k-means clustering (k = 2) and *break* as the natural breakpoint between two clusters using the Fisher-Jenks algorithm (Fisher, 1958; Slocum et al., 2022). Following prior work (e.g., Gordon et al., 2019) we apply these to user’s log-transformed app usage durations.
IV-irregularity	Function measuring repeated routine over time following Willams et al. (2012)
entr	Measure of even distributions of instances across categories, e.g., Shannon entropy (Shannon, 1948)
intercept, slope	Estimates of a hyperbolic growth function fitted to a user's longitudinal app usage data (i.e., duration, number of in-app events) by instance of observation (i.e., app usage, app sessions).

Table A2

Behavioral Differences, Empirical Evidence, and Corresponding Sensing Features by Related Theory-Based Behavioral Category

Behavioral Difference	Feature	Estimator	Sensing Modality
	Category 1: Performance in Basic Cognitive Tasks Cattell-Horn-Carroll Theory of Cognitive Abilities (Schneider & McGrew, 2018)		
Higher speed in tasks of basic information processing.	• time between start of an app usage and the first in-app event	min, max, avg, var, skew, kurt	app
+ Speed in simple and choice reactions (Deary et al., 2001)	• time between start of an app usage of [app category] and the first in-app event[1]	min, max, avg, var, skew, kurt	app
	• time between in-app events	min, max, avg, var, skew, kurt	app
- Variability of speed in simple and choice reactions (Doebler et al., 2016)	• time between in-app events in [app category] apps[1]	min, max, avg, var, skew, kurt	app
	• time between last in-app event and end of an app usage	min, max, avg, var, skew, kurt	app
	• time between last in-app event and end of an app usage of [app category][1]	min, max, avg, var, skew, kurt	app
+ Speed in long-term memory retrieval tasks (Wang et al., 2017)	• time between end of an app usage and start of an app usage	min, max, avg, var, skew, kurt	app
	• time between end of an app usage and start of an app usage of [app category] apps[1]	min, max, avg, var, skew, kurt	app
+ Speed switching between apps during phone usage (Gordon et al., 2019)	• time between end of an app usage of [app category] apps and start of an app usage[1]	min, max, avg, var, skew, kurt	app
Higher output rate in relatively basic tasks of information processing.	• typing rate	min, max, avg, var, skew, kurt	keyboard
+ Completion rate of simple cognitive tasks (Sheppard & Vernon, 2008)	• typing rate in [app category] apps[1]	min, max, avg, var, skew, kurt	app, keyboard
	• typing rate searching	min, max, avg, var, skew, kurt	keyboard
	• typing rate commenting	min, max, avg, var, skew, kurt	keyboard
+ Ideational fluency (Batey et al., 2009)	• typing rate posting	min, max, avg, var, skew, kurt	keyboard
	• typing rate messaging	min, max, avg, var, skew, kurt	keyboard
	• typing rate filling forms	min, max, avg, var, skew, kurt	keyboard
+ Rate of text production and editing; Hayes & Chenoweth, 2006)	• typing rate in other keyboard uses	min, max, avg, var, skew, kurt	keyboard

Category 2: Dealing with Complexity in Everyday Life

Cognitive Load Theory (Chandler & Sweller, 1991), Extended Mind Theory (Clark & Calmers, 1998)

Higher efficiency in tasks that involve novel information processing and problem solving.

+ Complex problem solving (Stadler et al., 2015)

+ Efficiency in web searches (Allen, 1992; Sharit et al., 2008; Trewin et al., 2012)

+ Efficiency in completing everyday tasks (e.g., banking, using maps and transportation schedules; Alexander & Reynolds, 2019; Gottfredson, 1997)

+ Comprehending complex texts (e.g., interpreting news articles; Gottfredson, 1997; Peng et al., 2019)

• duration of first app session of new apps	min, max, avg, var, skew, kurt	app, screen
• duration of first app session of new apps of a new category	min, max, avg, var, skew, kurt	app, screen
• duration of first app session of new [app category] apps 1	min, max, avg, var, skew, kurt	app, screen
• duration of first app session of new [app category] apps as a new category[1]	min, max, avg, var, skew, kurt	app, screen
• duration of first app session of [new single app][1]	min, max, avg, var, skew, kurt	app, screen
• duration of first app usage of new apps	min, max, avg, var, skew, kurt	apps
• duration of first app usage of new apps of a new category	min, max, avg, var, skew, kurt	apps
• duration of first app usage of new [app category] apps[1]	min, max, avg, var, skew, kurt	apps
• duration of first app usage of new [app category] apps as a new category[1]	min, max, avg, var, skew, kurt	apps
• duration of first app usage of [new single app][1]	min, max, avg, var, skew, kurt	apps
• number of in app-events in first app session of new apps	min, max, avg, var, skew, kurt	app, screen
• number of in app-events in first app session of new apps of a new category	min, max, avg, var, skew, kurt	app, screen
• number of in app-events in first app session of new apps of [app category] apps[1]	min, max, avg, var, skew, kurt	app, screen
• number of in app-events in first app session of new [app category] apps as a new category[1]	min, max, avg, var, skew, kurt	app, screen
• number of in-app events in first app session of [new single app][1]	min, max, avg, var, skew, kurt	app, screen
• number of in-app events in first app usage of new apps	min, max, avg, var, skew, kurt	apps
• number of in-app events in first app usage of new apps of a new category	min, max, avg, var, skew, kurt	apps
• number of in-app events in first app usage of new [app category] apps[1]	min, max, avg, var, skew, kurt	apps
• number of in-app events in first app usage of new [app category] apps as a new category[1]	min, max, avg, var, skew, kurt	apps
• number of in-app events in first app usage of [new single app][1]	min, max, avg, var, skew, kurt	apps
• duration of an app usage of Internet apps with search engine usage	min, max, avg, var, skew, kurt	app, keyboard
• duration of an app usage of Internet apps without search engine usage	min, max, avg, var, skew, kurt	app, keyboard

• number of in-app events in an app usage of Internet apps with search engine usage	min, max, avg, var, skew, kurt	app, keyboard
• number of in-app events in an app usage of Internet apps without search engine usage	min, max, avg, var, skew, kurt	app, keyboard
• number of keyboard usages in an app usage of Internet apps with search engine usage	min, max, avg, var, skew, kurt	app, keyboard
• number of keyboard usages in an app usage of Internet apps without search engine usage	min, max, avg, var, skew, kurt	app, keyboard
• duration of an app usage	min, max, avg, var, skew, kurt, m1, m2, break	app
• duration of an app usage of [app category] apps[1a]	min, max, avg, var, skew, kurt, m1, m2, break	app
• duration of an app usage of [single app of app category][1a]	min, max, avg, var, skew, kurt, m1, m2, break	app
• duration of an app usage of new apps	min, max, avg, var, skew, kurt, m1, m2, break	app
• duration of an app usage of new apps of a new app category	min, max, avg, var, skew, kurt, m1, m2, break	app
• duration of an app usage of new [app category] apps[1a]	min, max, avg, var, skew, kurt, m1, m2, break	app
• duration of an app usage of new [app category] apps as a new category[1a]	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage of [app category] apps[1a]	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage of [single app of app category][1a]	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage of new apps	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage of new apps from new app category	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage of new [app category] apps[1a]	min, max, avg, var, skew, kurt	app
• number of in-app events in an app usage of new [app category] apps as a new category[1a]	min, max, avg, var, skew, kurt	app
• duration of a phone session	min, max, avg, var, skew, kurt, m1, m2, break	screen
• duration of all app usages per phone session	min, max, avg, var, skew, kurt	app, screen
• number of app usages per phone session	min, max, avg, var, skew, kurt	app, screen
• number of apps used per phone session	min, max, avg, var, skew, kurt	app, screen

	• number of app categories used per phone session	min, max, avg, var, skew, kurt	app, screen
Relying less on compensatory behavior to deal with complexity of everyday life.			
	• total number of phone sessions	sum	screen
	• total duration of phone sessions	sum	screen
- Overall phone and internet usage (Barr et al., 2015)	• total number of app usages	sum	app
	• total number of app usages of [app category][1b]	sum	app
	• total number of app usages of [single app of app category][1b]	sum	app
- Routine seeking (Moutafi et al., 2004; Stanek & Ones, 2023)	• total number of browser usages with search engine use	sum	app, keyboard
	• total number of browser usages without search engine use	sum	app, keyboard
	• total duration of app usages	sum	app
	• total duration of app usages of [app category][1b]	sum	app
	• total duration of app usages of [single app of app category][1b]	sum	app
	• total duration of browser usages with search engine use	sum	app, keyboard
	• total duration of browser usages without search engine use	sum	app, keyboard
	• total text length of searches in browser usages with search engine use	sum	app, keyboard
	• day-level routineness of phone sessions	IV irregularity	screen
	• day-level routineness of app usage	IV irregularity	app
	• day-level routineness of app usage of [app category][1]	IV irregularity	app
	• day-level routineness of phone sessions on weekdays	IV irregularity	screen
	• day-level routineness of app usage on weekdays	IV irregularity	app
	• day-level routineness of app usage of [app category] on weekdays[1]	IV irregularity	app
	• day-level routineness of phone sessions on weekends	IV irregularity	screen
	• day-level routineness of app usage on weekends	IV irregularity	app
	• day-level routineness of app usage of [app category] on weekends[1]	IV irregularity	app

Category 3: Acquisition of Knowledge and Skills

Investment Theory (Cattell, 1987), Mutualism Model (Van der Maas et al., 2006)

Faster acquisition of skills and knowledge.			
	• duration-based learning for app sessions of new apps	intercept, slope	app, screen
+ Rate of acquiring skills and knowledge in occupational context (Hunter & Schmidt, 1996)	• duration-based learning for app sessions of new apps of a new app category	intercept, slope	app, screen
	• duration-based learning for app sessions of new [app category] apps[1]	intercept, slope	app, screen

+ Rate of acquiring skills and knowledge in learning contexts (Primi et al., 2010, Lechner et al., 2019)	• duration-based learning for app sessions of new [app category] apps as a new category[1]	intercept, slope	app, screen
	• duration-based learning for app sessions of [new single app][1]	intercept, slope	app, screen
	• duration-based learning rate for app sessions per new app across all new apps	min, max, avg, entr	app, screen
	• duration-based learning for app usages of new apps	intercept, slope	app
	• duration-based learning for app usages of new apps of a new app category	intercept, slope	app
	• duration-based learning for app usages of new [app category] apps[1]	intercept, slope	app
	• duration-based learning for app usages of new [app category] apps as a new category[1]	intercept, slope	app
	• duration-based learning for app usages of [new single app][1]	intercept, slope	app
	• duration-based learning rate for app usages per new app across all new apps	min, max, avg, entr	app
	• in-app-event-based learning for app sessions of new apps	intercept, slope	app, screen
	• in-app-event-based learning for app sessions of new apps of a new app category	intercept, slope	app, screen
	• in-app-event-based learning for app sessions of new [app category] apps[1]	intercept, slope	app, screen
	• in-app-event-based learning for app sessions of new [app category] apps as a new category[1]	intercept, slope	app, screen
	• in-app-event-based learning for app sessions of [new single app][1]	intercept, slope	app, screen
	• in-app-event-based learning rate for app sessions per new app across all new apps	min, max, avg, entr	app, screen
	• in-app-event-based learning for app usages of new apps	intercept, slope	app
	• in-app-event-based learning for app usages of new apps of a new app category	intercept, slope	app
	• in-app-event-based learning for app usages of new [app category] apps[1]	intercept, slope	app
	• in-app-event-based learning for app usages of new [app category] apps as a new category[1]	intercept, slope	app
	• in-app-event-based learning for app usages [new single app][1]	intercept, slope	app
	• in-app-event-based learning rate for app usages per new app all new apps	min, max, avg, var, skew, kurt	app
Higher propensity for engaging in activities associated with complex or extensive knowledge.	• total number of [app category] apps[1c]	sum	app
	• total number of app usages of [app category][1c]	sum	app
	• total number of app usages of [single app of app category][1c]	sum	app

+ Stock market participation (Christelis et al., 2010)	• total duration of app usages of [app category][1c]	sum	app
	• total duration of app usages of [single app of app category][1c]	sum	app
+ Domain knowledge in civics (e.g., economics) and science (e.g., math; Rusche & Ziegler, 2023)	• total number of distinct words used	sum	keyboard
	• total number of word usages per word across all distinct words	min, max, avg, entr	keyboard
	• commonness of a used word	min, max, avg, var, skew, kurt	keyboard
+ Breadth of word knowledge and verbal concepts (Kievit et al., 2017)	• commonness of the distinct words used	min, max, avg, var, skew, kurt	keyboard
	Category 4: Preference for Cognitive Stimulation *PPIK Model (Ackerman, 1996), OFCI Model (Ziegler et al., 2012)*		
Higher propensity for engaging in learning opportunities and effortful cognition.	• total number of apps	sum	app
+ Diversity of interests (Silvia & Sanders, 2010)	• total number of app categories	sum	app
	• total number of new apps installed	sum	app
	• total number of new app categories installed	sum	app
+ Propensity for interests associated with effortful cognition (e.g., investigative interests; Ackerman & Heggestad, 1997; Hyland et al., 2022)	• total number of new apps of a new app category installed	sum	app
	• total number of app usages of new apps	sum	app
	• total number of app usages of new apps of a new app category	sum	app
	• total number of app usages per app across all apps	min, max, avg, entr	app
	• total number of app usages per app category across all app categories	min, max, avg, entr	app
+ Engaging in intellectual/open activities and lifestyle (e.g., reading, calculating; Borgeest et al., 2020; Trapp et al., 2019)	• total number of app usages per new app across all new apps	min, max, avg, entr	app
	• total number of app usages per app category across all app categories of new apps	min, max, avg, entr	app
	• total number of songs per music genre across all music genres	min, max, avg, entr	audio
+ Voluntary learning and testing of knowledge (Fellman et al., 2020)	• total number of podcasts per podcast genre across all podcast genres	min, max, avg, entr	audio
	• total duration of app usages of new apps	sum	app
+ Engaging in cognitive demanding games (Unsworth et al., 2015)	• total duration of app usages of new apps of a new app category	sum	app
	• total duration of app usages per app across all apps	min, max, avg, entr	app
	• total duration of app usages per app category across all app categories	min, max, avg, entr	app

	• total duration of app usages per app across all new apps	min, max, avg, entr	app
	• total duration of app usages per app category across all app categories of new apps	min, max, avg, entr	app
	• total duration of songs per music genre across all music genres	min, max, avg, entr	audio
	• total duration of podcasts per podcast genre across all podcast genres	min, max, avg, entr	audio
	• total number of [app category] apps[1d]	sum	app
	• total number of new [app category] apps[1d]	sum	app
	• total number of app usages of [app category] apps[1d]	sum	app
	• total number of app usages of [single app of app category][1d]	sum	app
	• total number of app usages of new [app category] apps[1d]	sum	app
	• total number of app usages per app across all [app category] apps[1d]	min, max, avg, entr	app
	• total duration of app usages of [app category] apps[1d]	sum	app
	• total duration of app usages of [single app of app category][1d]	sum	app
	• total duration of app usages of new [app category] apps[1d]	sum	app
	• total duration of app usages per app across all [app category] apps[1d]	min, max, avg, entr	app
	• total number of podcasts	sum	audio
	• total number of [podcast genre] podcasts[2]	sum	audio
	• total duration of podcasts	Sum	audio
	• duration of a podcast	min, max, avg, var, skew, kurt	audio
	• total duration of [podcast genre] podcasts[2]	sum	audio
Higher preference for complex aesthetic stimuli. + Instrumental, reflective, intense, sophisticated, popular music - Conservative music (Racevska & Tadinac, 2019) + Reflective, complex, intense. rebellious music - Upbeat, conventional music (Rentfrow & Gosling, 2003) + Music in minor (Bonetti & Costa, 2016)	• total number of songs	sum	audio
	• total number of songs of [music genre][3]	sum	audio
	• total duration of songs	sum	audio
	• total duration of songs of [music genre][3]	sum	audio
	• level of [song characteristic] of a song[4]	min, max, avg, var, skew, kurt	audio

Note. PPIK framework = intelligence-as-Process, Personality, Interests, and intelligence-as-Knowledge framework, OFCI model = Openness-Fluid-Crystallized-Intelligence model;

All features describing a user's behavior on level of participation period (e.g., total number of app usages, total duration of songs) will be relativized by days of users' study participation. For instance, for *total number of app usages*, a user with 1000 app usages in 100 days of study participation will have a value of 1000/100 = 10. For new apps, feature values will be relativized by participation days after installation of the app;

Indices denote that the feature will be extracted for each
(1) app category that involves active usage (e.g., Communication, Tools Calculator, Finance Investing, Games Puzzle),
(1a) app category where patterns on level of single usages can be associated with completing everyday tasks that involve novel information processing or problem solving (e.g., Communication, Internet, Tools Documents, Weather),
(1b) app category where patterns on level of participation period can be associated with relying on support to deal with complexity in everyday life (e.g., Tools Calculator, Internet, Orientation Navigation),
(1c) app category where patterns on level of participation period can be associated with engagement in activities requiring complex domain knowledge (e.g., Finance Investing, Finance Tax),
(1d) app category where patterns on level of participation period can be associated with engagement in leisure activities (e.g., Games puzzle, Reading, Visual Entertainment),
(3) podacst genre (e.g., Science, Politics, Comedy),
(4) music genre (e.g., Jazz, Pop, Classical),
(5) song characteristic (e.g., Acousticness, Danceability, Tempo);

Features based on single apps will only be extracted for apps from the relevant app categories denoted by the indices (i.e.,1, 1a, 1b, 1c, 1d). Additionally, they will only be extracted for single apps (new single apps) if they were used (downloaded) at least by 1% of users;

App categories of the present study build on categorizations from Schoedel et al. (2022). A list of all app categories as well as their correspondence to features' indices (e.g., 1a, 1b, 1c, 1d) are provided in Table A3.
Heuristics for enrichment of the audio logs (i.e., podcast genre, music genre, song characteristic) will follow procedures suggested by Stachl et al. (2020).
Podcast genres are extracted from the iTunes podcast taxonomy (https://podcasts.apple.com/de/genre/podcasts/id26) with means of a web crawler (https://github.com/mdg/itunes-podcast-crawler).
Music genre and song characteristics are extracted using the Spotify API (https://developer.spotify.com/documentation/web-api/reference/#category-tracks).
Commonness of words will be extracted using the DeReWo (https://www.ids-mannheim.de/en/s/corpus-linguistics/projects/methods-of-analysis/corpus-based-lemma-and-word-form-lists/), a corpus-based word list of contemporary German.

Table A3

Name, Feature Index, and Definition of App Categories Used in Feature Extraction

App Category		Feature Index					Definition
Schoedel et al. (2022)	Present Study						
Audio Entertainment	Audio Entertainment	1	-	-	-	1d	*Audio Entertainment* describes apps serving acoustic-only entertainment. This category includes apps providing music, podcasts, audiobooks, or radio. The usage of *Audio Entertainment* apps can be seen as media consumption behavior limited to the auditory channel (i.e., excluding the visual channel)
Career	Career	1	1a	-	-	-	*Career* describes apps allowing users to promote their professional career. The category contains apps for job search, career-related networking, career planning, or counselling.
Communication	Communication	1	1a	-	-	-	*Communication* describes apps specifically designed for all sorts of communication behaviors. The category includes traditional calling and text messaging apps, but also apps for web-based instant messaging, email access or facetiming. While other apps may also contain communication functionalities as a secondary feature (e.g., *Social Media* or *Dating* apps), apps in the *Communication* category are only used for communicative purposes.
Creativity	Creativity	1	-	-	-	1d	*Creativity* describes apps that enable creative activities such as drawing, playing instruments, singing, recording sounds, or creative writing. This category explicitly excludes photography apps, which are contained in the category *Photo*.
Dating	Dating	1	-	-	-	1d	*Dating* describes apps specifically designed for dating activities ranging from browsing potential partners to communicating with them to arranging meetings. Thereby, the category excludes general *Communication*, which, of course, may also serve dating purposes.
Finance	Finance Banking	1	1a	-	1c	-	*Finance* describes apps related to financial and monetary issues. This category includes, for example, banking apps, apps for earning money, stock trading apps, apps for donating money, apps for comparing prices, or for checking currencies. From a behavioral perspective, the use of *Finance* apps indicates behaviors dealing with money, like making, spending, or monitoring money. • *Finance Banking*: Finance apps for banking tasks. • *Finance Gig Work*: Finance apps for gig working. • *Finance Investing*: Finance apps for investing. • *Finance Tax*: Finance apps for tax filing.
	Finance Gig Work	1	1a	-	-	-	
	Finance Investing	1	1a	-	1c	-	
	Finance Tax	1	1a	-	1c	-	
	Finance Other	1	1a	-	1c	-	

							• Finance Other: Other Finance apps.
Food	Food	1	1a	-	-	-	*Food* describes apps facilitating a range of behaviors related to food and eating. The category contains, for example, apps for ordering food or groceries online, for sharing food with others, for finding cooking recipes or for making meal plans. Apps related to diets (e.g., calorie counting apps) are excluded here and are featured in the *Health* category.
Gaming	Games Action	1	-	-	-	1d	*Gaming* describes apps for gaming behaviors ranging from playful strategy games to serious gambling or making bets. • *Games Action*: Gaming apps with the Google Play Store category Action • *Games Adventure*: Gaming apps with the Google Play Store category Adventure • *Games Arcade*: Gaming apps with the Google Play Store category Arcade • *Games Board*: Gaming apps with the Google Play Store category Board • *Games Card*: Gaming apps with the Google Play Store category Card • *Games Casino*: Gaming apps with the Google Play Store category Casino • *Games Casual*: Gaming apps with the Google Play Store category Casual • *Games Educational*: Gaming apps with the Google Play Store category Educational • *Games Music*: Gaming apps with the Google Play Store category Music • *Games Puzzle*: Gaming apps with the Google Play Store category Puzzle • *Games Racing*: Gaming apps with the Google Play Store category Racing • *Games Roleplaying*: Gaming apps with the Google Play Store category Roleplaying • *Games Simulation*: Gaming apps with the Google Play Store category Simulation • *Games Sports*: Gaming apps with the Google Play Store category Sports • *Games Strategy*: Gaming apps with the Google Play Store category Strategy • *Games Trivia*: Gaming apps with the Google Play Store category Trivia • *Games Word*: Gaming apps with the Google Play Store category Word
	Games Adventure	1	-	-	-	1d	
	Games Arcade	1	-	-	-	1d	
	Games Board	1	-	-	-	1d	
	Games Card	1	-	-	-	1d	
	Games Casino	1	-	-	-	1d	
	Games Casual	1	-	-	-	1d	
	Games Educational	1	-	-	-	1d	
	Games Music	1	-	-	-	1d	
	Games Puzzle	1	-	-	-	1d	
	Games Racing	1	-	-	-	1d	
	Games Roleplaying	1	-	-	-	1d	
	Games Simulation	1	-	-	-	1d	
	Games Sports	1	-	-	-	1d	
	Games Strategy	1	-	-	-	1d	
	Games Trivia	1	-	-	-	1d	
	Games Word	1	-	-	-	1d	

Health	Health	1	1a	-	-	-	*Health* describes apps related to the user's engagement with (their own) health. This category includes, for example, apps providing physical exercises, as well as apps for improving and/or monitoring physical and mental health, sleep, or diets.
Internet	Internet	1	1a	1b	-	-	*Internet* describes apps for browsing the internet, including search engines such as Google or Yahoo. Even though this category is unambiguously and narrowly defined, the behavioral implications of using *Internet* apps are various as surfing the web can fulfil a myriad of purposes.
Knowledge	Knowledge Info	1	1a	1b	-	-	*Knowledge* describes apps for the acquisition of knowledge or the seeking of specific information. This rather broad category includes apps providing general knowledge or specific information, as well as apps for learning new skills (e.g., languages). This category excludes general search engines and browser apps, which are featured in the category *Internet*. Furthermore, the *Knowledge* category does not contain apps related to the consumption of news, which are featured in the separate category *News*. • *Knowledge Info*: Knowledge apps for retrieving specific information. • *Knowledge Learning*: Knowledge apps for learning new skills.
	Knowledge Learning	1	-	-	-	1d	
News	News	1	1a	-	-	1d	*News* describes apps explicitly meant for the seeking of and consumption of daily news. These apps contain digital newspapers or news blogs. In contrast, the categories *Visual Entertainment* or *Social Media* may also contain news related content, which, however, cannot be determined without assessing the within usage behavior.
Orientation	Orientation Navigation	1	1a	1b	-	-	*Orientation* describes apps that help the user find their way in the surroundings. This rather narrow category includes, for example, apps with maps and for navigation. • *Orientation Navigation*: Orientation apps for active navigation assistance. • *Orientation Other*: Orientation apps without active navigation function.
	Orientation Other	1	1a	1b	-	-	
Photo	Photo	1	1a	-	-	1d	*Photo* describes apps for making, editing, or inspecting one's own photos and videos. This category does not include apps for posting or viewing posted photos or videos, which are featured in the category social media.
Reading	Reading	1	1a	-	-	1d	*Reading* refers to apps providing textual media sources like books, comics, magazines, or blog articles, whose consumption indicates reading behavior. This category explicitly excludes the consumption of news-related textual media (e.g., newspapers), which is featured in the separate category *News*.
Security	Security	1	-	-	-	-	*Security* describes apps that increase the user's security both online and offline, e.g., by concealing the user's identity when surfing the web via VPNs, by scanning websites for viruses or by tracking the user's way home. From a behavioral perspective, the use of *Security* apps can be interpreted as diligence.

Settings	Settings	-	-	-	-	-	*Settings* describe apps that are used to change the smartphone's settings, to monitor and optimise functions (e.g., monitoring the smartphone's usage time or battery consumption), or to personalise the smartphone. Unlike *System* apps, *Settings* apps involve active interactions (e.g., changes) made by the user. From a behavioral perspective, the usage of *Settings* apps may be seen as maintenance work done by the user.
Shopping	Shopping	1	1a	-	-	-	*Shopping* describes apps for buying and selling things both online and offline. This category includes, for example, apps of online shops, thrifting apps, apps providing brochures or membership apps for stores. The *Shopping* category explicitly excludes apps related to food shopping, which are featured in the category *Food*.
Social Media	Social Media	1	-	-	-	1d	*Social Media* describes apps for sharing, browsing & interacting (i.e., liking or commenting) with content (e.g., texts, pictures, videos) within an online community. This app category is rather heterogeneous, because social media apps often enable secondary functionalities like *Communication*, *Shopping* or *Dating*, and provide content from the categories *Visual Entertainment* (e.g., movie trailers), *Health* (e.g., food or fitness posts), *Knowledge* (e.g., science posts) or *News*. Nevertheless, all *Social Media* apps have content sharing as main functionality and their usage can be interpreted as social media usage behavior.
Spirituality	Spirituality	1	-	-	-	1d	*Spirituality* describes apps related to spiritual behaviors or beliefs ranging from religion to esotericism. This rather broad, but rare category contains, for example, apps for bible study, but also horoscope apps.
System	System	-	-	-	-	-	*System* describes apps that enable the basic functionality of the phone and its apps. *System* apps are not consciously accessed and actively interacted with. As they run in the background of the device, they have no informative power for behavioral analyses. Oftentimes, removing *System* apps facilitates further analyses of app usage.
Time	Time Planning	1	1a	-	-	-	*Time* describes apps with a time structuring function like clocks or timers or calendars. From a behavioral perspective, *Time* apps can fulfil different purposes ranging from planning (e.g., planning meetings) to monitoring actions (e.g., setting a timer for boiling eggs). • *Time Planning*: Time apps for planning behavior. • *Time Monitoring*: Time apps for monitoring behavior.
	Time Monitoring	1	1a	-	-	-	
Tools	Tools Calculator	1	1a	1b	-	-	*Tools* describe apps for the organisation of everyday life. This category is rather heterogeneous as it includes, for example, apps for creating notes or to-do lists, for managing files (e.g., scanning, printing, opening, editing,
	Tools Device	1	1a	-	-	-	

	Tools Documents	1	1a	-	-	-	downloading), for calculating or programming, or for managing own devices. In addition, *Tools* include provider services (e.g., contract service, parcel service) unless they can be clearly assigned to one of the more content related categories (e.g., food delivery apps in the category *Food*). Due to the breadth of this category, *Tools* apps can have various behavioral meanings ranging from private organising behavior (e.g., making a shopping list) to more office related behaviors (e.g., working with documents).Tools Calculator: Tools apps for calculating. • *Tools Device*: Tools apps for interacting with another device (e.g., TV, smart home). • *Tools Documents*: Tools apps for viewing and editing documents. • *Tools Files*: Tools apps for managing file storage. • *Tools Notes/Lists*: Tools apps for taking notes or lists. • *Tools Provider*: Tools apps for accessing (product) services. • *Tools Scan*: Tools apps for scanning codes or documents. • *Tools Voice Audio*: Tools apps for voice recording or audio processing. • *Tools other*: Other Tools apps.
	Tools Files	1	1a	-	-	-	
	Tools Notes/Lists	1	1a	1b	-	-	
	Tools Provider	1	1a	-	-	-	
	Tools Scan	1	1a	-	-	-	
	Tools Voice Audio	1	1a	-	-	-	
	Tools Other	1	1a	-	-	-	
Transportation	Transportation Scheduled	1	1a	-	-	-	*Transportation* describes apps that assist the user with utilising or planning the use of different means of transport ranging from local and long-distance public transport to cars. This category includes, for example, apps for informing oneself about departure times of public transport, for doing research on best routes and for purchasing carsharing services. • *Transportation Scheduled*: Transportation apps for scheduled transportation systems. • *Transportation Other*: Transportation apps for other transportation services (e.g., taxicab, e-scooter)
	Transportation Other	1	1a	-	-	-	
Visual Entertainment	Visual Entertainment	1	-	-	-	1d	*Visual Entertainment* describes apps serving audiovisual entertainment. This category includes apps for viewing videos, for streaming movies or TV. Using *Visual Entertainment* apps can be interpreted as media consumption behavior including (but not exclusive to) the visual channel. In contrast to Social Media apps, apps in this category lack the sharing and community aspect.
Weather	Weather	1	1a	-	-	-	*Weather* describes apps for checking the local or international weather, including weather forecasts.

Note. App categories and descriptions are retrieved from Schoedel et al. (2022). Categories were refined for the present study, if necessary, and descriptions added in bullet points. For gaming apps, refinement was performed using the Google Play Store API. All other categories (i.e., Finance, Knowledge, Orientation, Time, Tools, Transportation) were refined manually based on app names and descriptions in the Google Play Store;

App categories (or single apps of that app category) were included in feature extraction by feature index, i.e., features with the same feature index (see Table A2) were extracted for the same set of app categories (or single apps of these categories). App categories were assigned to the corresponding features based on following rational:

(1) app category that involves active usage (e.g., Communication, Tools Calculator, Finance Investing, Games Puzzle),
(1a) app category where patterns on level of single usages can be associated with completing everyday tasks that involve novel information processing or problem solving (e.g., Communication, Internet, Tools Documents, Weather),
(1b) app category where patterns on level of participation period can be associated with relying on support to deal with complexity in everyday life (e.g., Tools Calculator, Internet, Orientation Navigation),
(1c) app category where patterns on level of participation period can be associated with engagement in activities requiring complex domain knowledge (e.g., Finance Investing, Finance Tax),
(1d) app category where patterns on level of participation period can be associated with engagement in leisure activities (e.g., Games Puzzle, Reading, Visual Entertainment).

References

Ackerman, P. L., & Heggestad, E. D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin*, *121*, 219–245. https://doi.org/10.1037/0033-2909.121.2.219

Alexander, R. M., & Reynolds, M. R. (2020). Intelligence and Adaptive Behavior: A Meta-Analysis. *School Psychology Review*, *49*(2), 85–110. https://doi.org/10.1080/2372966X.2020.1717374

Allen, B. (1992). Cognitive differences in end user searching of a CD-ROM index. *Proceedings of the 15th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 298–309. https://doi.org/10.1145/133160.133212

Barr, N., Pennycook, G., Stolz, J. A., & Fugelsang, J. A. (2015). The brain in your pocket: Evidence that Smartphones are used to supplant thinking. *Computers in Human Behavior*, *48*, 473–480. https://doi.org/10.1016/j.chb.2015.02.029

Batey, M., Chamorro-Premuzic, T., & Furnham, A. (2009). Intelligence and personality as predictors of divergent thinking: The role of general, fluid and crystallised intelligence. *Thinking Skills and Creativity*, *4*(1), 60–69. https://doi.org/10.1016/j.tsc.2009.01.002

Bonetti, L., & Costa, M. (2016). Intelligence and Musical Mode Preference. *Empirical Studies of the Arts*, *34*(2), 160–176. https://doi.org/10.1177/0276237416628907

Borgeest, G. S., Henson, R. N., Shafto, M., Samu, D., Cam-CAN, & Kievit, R. A. (2020). Greater lifestyle engagement is associated with better age-adjusted cognitive abilities. *PLOS ONE*, *15*(5), e0230077. https://doi.org/10.1371/journal.pone.0230077

Christelis, D., Jappelli, T., & Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, *54*(1), 18–38. https://doi.org/10.1016/j.euroecorev.2009.04.001

Croux, C., & Rousseeuw, P., J. (1992). Time-Efficient Algorithms for Two Highly Robust Estimators of Scale. In *Computational Statistics* (pp. 411–428). Physica-Verlag HD.

Deary, I. J., Der, G., & Ford, G. (2001). Reaction times and intelligence differences: A population-based cohort study. *Intelligence*, *29*(5), 389–399. https://doi.org/10.1016/S0160-2896(01)00062-9

Doebler, P., & Scheffler, B. (2016). The relationship of choice reaction time variability and intelligence: A meta-analysis. *Learning and Individual Differences*, *52*, 157–166. https://doi.org/10.1016/j.lindif.2015.02.009

Fellman, D., Lincke, A., & Jonsson, B. (2020). Do Individual Differences in Cognition and Personality Predict Retrieval Practice Activities on MOOCs? *Frontiers in Psychology*, *11*. https://www.frontiersin.org/articles/10.3389/fpsyg.2020.02076

Fisher, W. D. (1958). On Grouping for Maximum Homogeneity. *Journal of the American Statistical Association*, *53*(284), 789–798. https://doi.org/10.1080/01621459.1958.10501479

Gottfredson, L. S. (1997). Why g matters: The complexity of everyday life. *Intelligence*, *24*(1), 79–132. https://doi.org/10.1016/S0160-2896(97)90014-3

Gordon, M. L., Garys, L., Guestrin, C., Bigham, J. P., Trister, A., & Patel, K. (2019). App usage predicts cognitive ability in older adults. *Conference on Human Factors in Computing Systems - Proceedings*, 1–12. https://doi.org/10.1145/3290605.3300398

Hayes, J. R., & Chenoweth, N. A. (2006). Is Working Memory Involved in the Transcribing and Editing of Texts? *Written Communication*, *23*(2), 135–149. https://doi.org/10.1177/0741088306286283

Huber, P., J. (1981). *Robust Statistics.* John Wiley & Sons.

Hunter, J. E., & Schmidt, F. L. (1996). Intelligence and job performance: Economic and social implications. *Psychology, Public Policy, and Law*, *2*(3–4), 447–472. https://doi.org/10.1037/1076-8971.2.3-4.447

Hyland, W. E., Hoff, K. A., & Rounds, J. (2022). Interest–Ability Profiles: An Integrative Approach to Knowledge Acquisition. *Journal of Intelligence*, *10*(3), Article 3. https://doi.org/10.3390/jintelligence10030043

Jung, R. E., & Haier, R. J. (2007). The Parieto-Frontal Integration Theory (P-FIT) of intelligence: Converging neuroimaging evidence. *Behavioral and Brain Sciences*, *30*(2), 135–154. https://doi.org/10.1017/S0140525X07001185

Lechner, C. M., Miyamoto, A., & Knopf, T. (2019). Should students be smart, curious, or both? Fluid intelligence, openness, and interest co-shape the acquisition of reading and math competence. *Intelligence*, *76*, 101378. https://doi.org/10.1016/j.intell.2019.101378

Moutafi, J., Furnham, A., & Paltiel, L. (2004). Why is Conscientiousness negatively correlated with intelligence? *Personality and Individual Differences*, *37*(5), 1013–1022. https://doi.org/10.1016/j.paid.2003.11.010

Peng, P., Wang, T., Wang, C., & Lin, X. (2019). A meta-analysis on the relation between fluid intelligence and reading/mathematics: Effects of tasks, age, and social economics status. *Psychological Bulletin*, *145*, 189–236. https://doi.org/10.1037/bul0000182

Primi, R., Ferrão, M. E., & Almeida, L. S. (2010). Fluid intelligence as a predictor of learning: A longitudinal multilevel approach applied to math. *Learning and Individual Differences*, *20*(5), 446–451. https://doi.org/10.1016/j.lindif.2010.05.001

Racevska, E., & Tadinac, M. (2019). Intelligence, music preferences, and uses of music from the perspective of evolutionary psychology. *Evolutionary Behavioral Sciences*, *13*, 101–110. https://doi.org/10.1037/ebs0000124

Rentfrow, P. J., & Gosling, S. D. (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), 1236–1256. https://doi.org/10.1037/0022-3514.84.6.1236

Rusche, M. M., & Ziegler, M. (2023). Measuring Domain-Specific Knowledge: From Bach to Fibonacci. *Journal of Intelligence*, *11*(3), Article 3. https://doi.org/10.3390/jintelligence11030047

Schneider, W. J., & McGrew, K. S. (2018). The Cattell–Horn–Carroll theory of cognitive abilities. In *Contemporary intellectual assessment: Theories, tests, and issues, 4th ed* (pp. 73–163). The Guilford Press.

Schoedel, R., Oldemeier, M., Bonauer, L., & Sust, L. (2022). *Systematic Categorisation of 3,091 Smartphone Applications From a Large-Scale Smartphone Sensing Dataset* (1). *10*(1), Article 1. https://doi.org/10.5334/jopd.59

Sharit, J., Hernández, M. A., Czaja, S. J., & Pirolli, P. (2008). Investigating the Roles of Knowledge and Cognitive Abilities in Older Adult Information Seeking on the Web. *ACM Transactions on Computer-Human Interaction*, *15*(1), 3:1-3:25. https://doi.org/10.1145/1352782.1352785

Sheppard, L. D., & Vernon, P. A. (2008). Intelligence and speed of information-processing: A review of 50 years of research. *Personality and Individual Differences*, *44*(3), 535–551. https://doi.org/10.1016/j.paid.2007.09.015

Silvia, P. J., & Sanders, C. E. (2010). Why are smart people curious? Fluid intelligence, openness to experience, and interest. *Learning and Individual Differences*, *20*(3), 242–245. https://doi.org/10.1016/j.lindif.2010.01.006

Slocum, T. A., McMaster, R. B., Kessler, F. C., & Howard, H. H. (2022). *Thematic cartography and geovisualization* (4th ed.). CRC Press. https://doi.org/10.1201/9781003150527

Stachl, C., Au, Q., Schoedel, R., Gosling, S. D., Harari, G. M., Buschek, D., Völkel, S. T., Schuwerk, T., Oldemeier, M., Ullmann, T., Hussmann, H., Bischl, B., & Bühner, M. (2020). Predicting personality from patterns of behavior collected with smartphones. *Proceedings of the National Academy of Sciences*, *117*(30), 17680–17687. https://doi.org/10.1073/pnas.1920484117

Stadler, M., Becker, N., Gödker, M., Leutner, D., & Greiff, S. (2015). Complex problem solving and intelligence: A meta-analysis. *Intelligence*, *53*, 92–101. https://doi.org/10.1016/j.intell.2015.09.005

Stanek, K. C., & Ones, D. S. (2023). Meta-analytic relations between personality and cognitive ability. *Proceedings of the National Academy of Sciences*, *120*(23), e2212794120. https://doi.org/10.1073/pnas.2212794120

Trapp, S., Blömeke, S., & Ziegler, M. (2019). The openness-fluid-crystallized-intelligence (OFCI) model and the environmental enrichment hypothesis. *Intelligence*, *73*, 30–40. https://doi.org/10.1016/j.intell.2019.01.009

Trewin, S., Richards, J. T., Hanson, V. L., Sloan, D., John, B. E., Swart, C., & Thomas, J. C. (2012). Understanding the role of age and fluid intelligence in information search. *Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility*, 119–126. https://doi.org/10.1145/2384916.2384938

Unsworth, N., Redick, T. S., McMillan, B. D., Hambrick, D. Z., Kane, M. J., & Engle, R. W. (2015). Is Playing Video Games Related to Cognitive Abilities? *Psychological Science*, *26*(6), 759–774. https://doi.org/10.1177/0956797615570367

Van Der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842–861. https://doi.org/10.1037/0033-295X.113.4.842

Wang, T., Ren, X., & Schweizer, K. (2017). Learning and retrieval processes predict fluid intelligence over and above working memory. *Intelligence*, *61*, 29–36. https://doi.org/10.1016/j.intell.2016.12.005

Williams, M. J., Whitaker, R. M., & Allen, S. M. (2012). Measuring Individual Regularity in Human Visiting Patterns. *2012 International Conference on Privacy, Security, Risk and Trust and 2012 International Confernece on Social Computing*, 117–122. https://doi.org/10.1109/SocialCom-PASSAT.2012.93