Vernieuwingsimpuls
Innovational Research Incentives Scheme
Grant application form 2018
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Research proposal

2a1 and 2a2. Description of the proposed research

2a1. Overall aim and key objectives

The aim of this project is to develop innovative tools for *network-based adaptive assessment* (NAA). This is done in in three steps, by (I) creating a system that personalizes questionnaires by automatically selecting the most informative item to administer (reducing strain and allowing tests to be shortened), (II) developing methodology to estimate network models from incomplete data, and (III) inventing techniques to update time-varying networks in real time as new data become available. While all projects taken together form the starting point for a network-based adaptive assessment framework, each project individually improves upon state-of-the-art methods independent of the other projects (see 2b).

Scientific relevance and challenges

Relevance. The *network perspective* on psychology conceptualizes observed variables (e.g., attitudes, symptoms, and moods) as causal agents in a complex interplay of psychological, biological, sociological and other components [5,**8**,22]. The field of *network psychometrics* aims to estimate network models from psychological datasets in an attempt to map out this complex interplay [**35**]. These network models visualize observed variables as nodes and the strength of conditional association between two variables after controlling for all other variables as links [**31**].

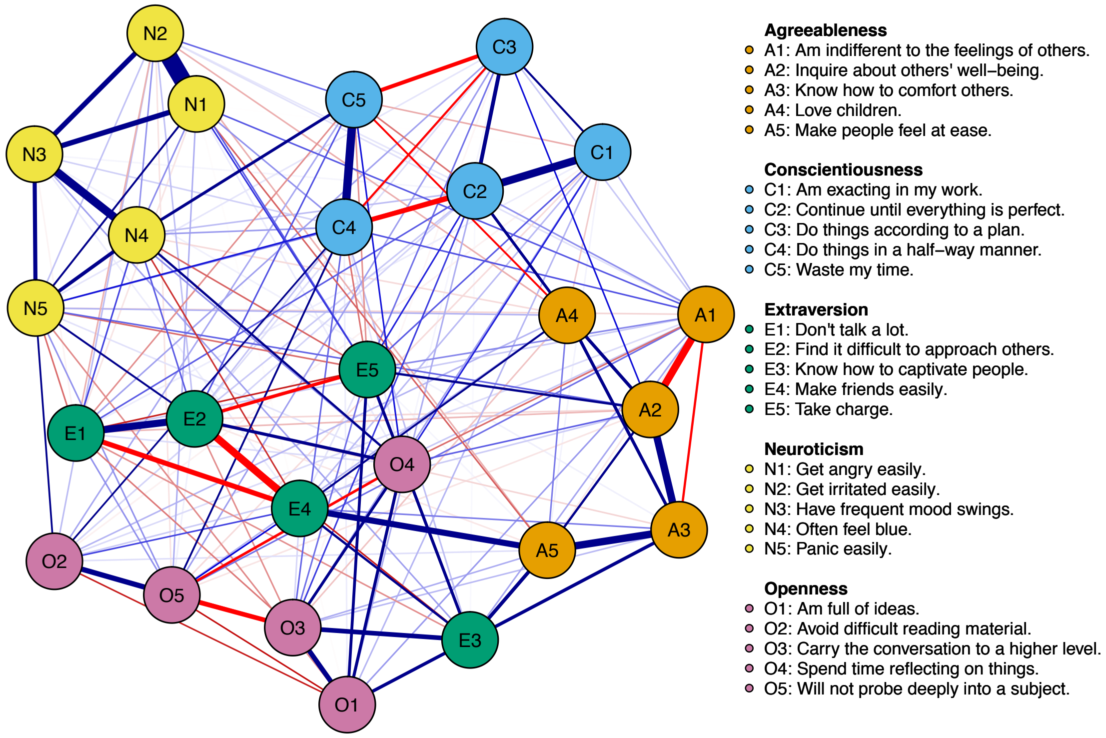

Figure 1. Estimated non-dynamical network structure ([**28**], chapter 1). Blue (red) links indicate positive (negative) partial correlations. Subgoals of this proposal are to shorten the questionnaire by adaptively selecting informative items (I-A) and to estimate such models from data with severe missingness (II).

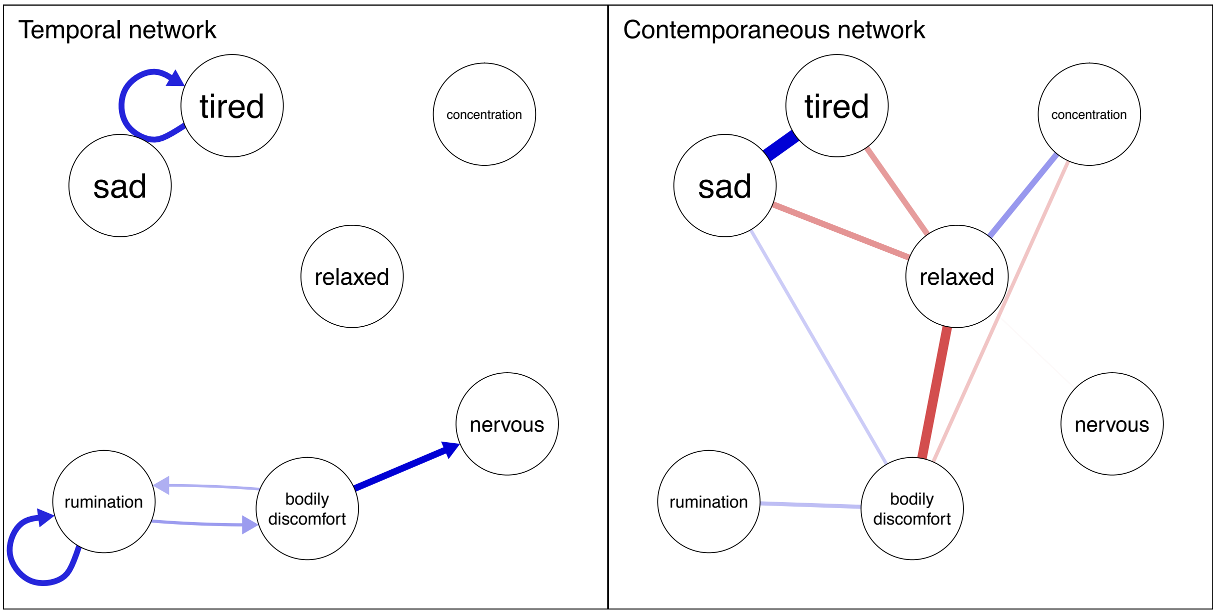

Figure 2. Estimated dynamical network structures from time-series data of a patient in clinical practice [**38**]. Temporal effects are now added describing how well an item-response predicts an item-response in the *next* window of measurement. Subgoals of this proposal are to reduce strain on participants (I-B), estimate these models from data with severe missingness (II) and update time-varying models as new data becomes available (III).

Non-dynamical networks (Figure 1) may be estimated from individual differences data [**30**,**34**,**39**,**81**], and *dynamical networks* (Figure 2)—showing intra-individual variation over time—may be estimated from time-series data [14,**38**,**39**]. Network models are powerful tools to discover psychological dynamics, map out multicollinearity and predictive effects [**39**], approximate the joint likelihood of observed variables [**35**,67], and to extend latent variable modeling [**37**,**49**,74]. Several software packages have been developed to facilitate research in estimating these models, assessing their accuracy and visualizing the results [**32**,**31**,**26**,**27**,**33**,51,**89**]. Network psychometrics is now applied in several fields of research (see 2b).

The outlined projects aim to move towards a fully *adaptive* form of network psychometrics. In adaptive item-administration (known as *computer adaptive testing;* CAT; [16,85]), the most appropriate item to administer is automatically selected during testing. In adaptive model estimation, a statistical model is updated as new data becomes available. A prime example of a testing environment that implements both forms of adaptivity is the *Math Garden* [62], in which children are administered items in a game-like environment chosen to be not too easy but also not too difficult. After each response the underlying statistical model of the math garden is updated to in turn improve item-administration. Combining these two forms of adaptive testing leads to a powerful framework in which children are only administered appropriate items and large datasets can be obtained to study development over time [15,58,57,75].

Challenges.

Network Psychometrics. Currently, gathering and analyzing data in network psychometrics is *static*: large datasets are first collected before network models are estimated and interpreted. This puts considerable strain on participants, who are required to answer lengthy questionnaires once or respond daily/several times per day to a sizable questionnaire. Such strain makes participant dropout more likely. Adaptive forms of assessment that require fewer items to be administered are a promising way to alleviate this problem. Another severe challenge in network psychometrics is proper handling of missing responses ([**28**], chapter 12). For example, prior work aimed to estimate networks based on large-scale epidemiological studies in which many responses were missing by design [7,10,22,42,76]. The employed imputation strategy, however, has recently been demonstrated to yield severely biased estimated network structures [**9**]. Moreover, network estimation currently cannot be updated from prior information, nor can time-varying dynamical networks [11,50] be continuously estimated as data are collected.

CAT. CAT systems often critically rely on latent variable modelling, aiming to measure one latent trait per person. However, many applications aim to assess people at the item-level instead [6]. For example, symptoms of depression are known to be very heterogeneous and fit one-dimensional models poorly, making it important to diagnose *which* symptoms a person suffers from rather than merely assessing a person's score on an unrealistically hypothesized unidimensional trait [47,44,46]. Although multidimensional versions of CAT exist, as do adaptive procedures not based on a latent variable model, they often aim to assess several latent traits [66], latent class membership [40,84] or the total test score [92]. What is missing is a psychometric theory on how to best handle item-level CAT. In addition, adaptive testing in time-series of intra-individual measurements has not yet gathered much attention. <u>The current proposal aims to tackle these listed challenges to network psychometrics and CAT.</u>

Originality and innovative character

An innovative application of network models is to help predict a subject's future responses (unanswered items in the current administration, or the next time a questionnaire is administered), based on their already given responses [53,68]. A response is predicted by responses of directly connected variables in the network. Combining this predictive information with base rates (intercepts), the network model describes for each variable (1) how uncertain our current prediction on the response is and (2) how much knowing one variable helps predicting other variables. This information can be used in an original adaptive item-administration application. The best question to ask is the question that, when answered, will aid prediction of remaining unanswered questions as well as possible (Figure 3). This process can be repeated until all remaining unanswered questions can adequately be predicted (low conditional entropy). Adaptive systems allow questionnaires to be substantially shortened. This decreases participant burden by collecting only the most relevant data, and may also prevent asking inappropriate items.

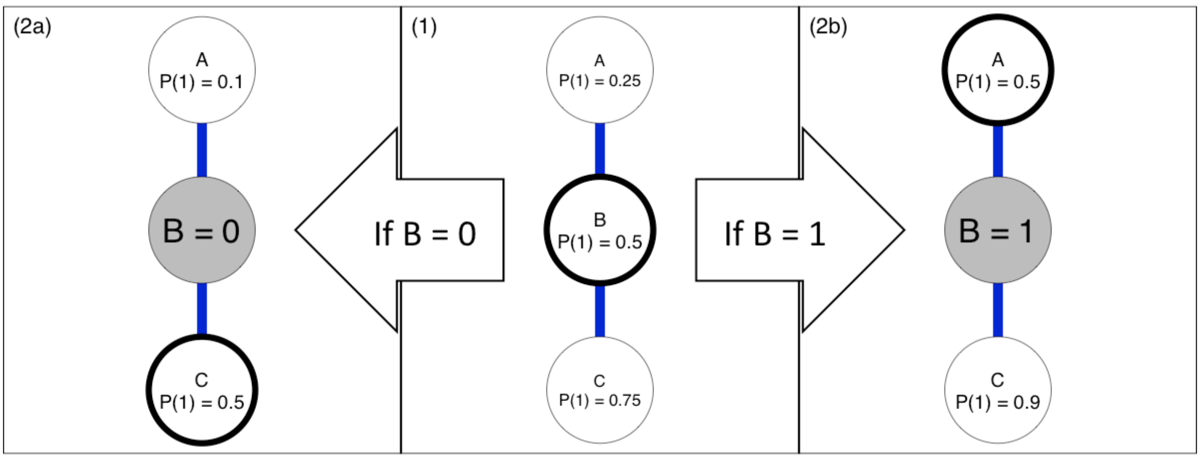

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Figure 3. Hypothetical example of network-based adaptive assessment of three (A, B, C) binary variables ("0" or "1"). A gray box indicates a response is known and a thick border indicates the variable that should be asked next. The label (P(1) = …) indicates the probability that a person will endorse an item (score a "1"). Before any responses (1), B should be administered as (a) it is highly informative of A and C, and (b) its response is poorly predictable. If a person endorses B (2b), the probability of endorsing A and C go up. Now, A is the most informative next variable to administer, as we can already predict C to be 1 with high probability. If, instead, a person does not endorse B (2a), all probabilities go down, and C becomes the most informative variable to administer next.

Methods and techniques

The project will work towards the development of an online item administration platform, which may be used to administer items (once for non-dynamical studies or several times for dynamical studies) in an optimal order and possibly shortened. The goal is for the underlying network model to subsequently be updated and improved as new data becomes available, thus further improving the adaptive system (Figure 4). <u>Two projects focus on adaptive item-administration (I-A and I-B) and two projects focus on adaptive model estimation (II and III).</u> The proposed projects will study both non-dynamical and dynamical networks (Figure 5).

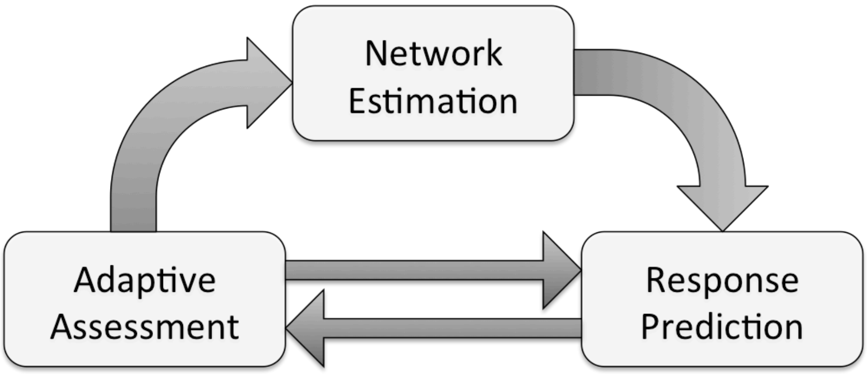


Figure 4. Adaptive testing in which a network model is used in choosing the most informative item to administer, and new responses are subsequently used to update the network model.

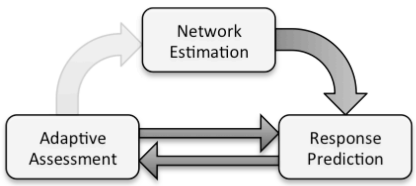
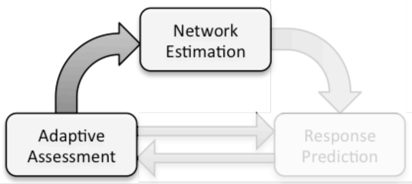
	Non-dynamical	**Dynamical**	
Item-selection	Project I-A	Project I-B	
Model estimation	Project II	Projects II and III	

Figure 5. Separation of projects.

Project I-A. Network-based Adaptive Assessment. The goal of this project is to set up a methodology that adaptively administers informative items given a known network structure (e.g., diagnosing which symptoms of the DSM [1] a patient endorses). A possible selection mechanism would be to choose the variable that has the highest mutual information with all unanswered variables [20], and a possible stopping criterion is to reduce conditional entropy in the set of not administered items to some threshold. The project will first consider binary data, for which *Ising models* may be used to model the dependency between items [**35**,**81**]. Afterwards, the methodology can be extended to multicategory responses using *mixed graphical models* [52] and polytomous responses using polychoric Gaussian graphical models [**34**]. The methodology will be validated using a large dataset of the UnderCovers app (see 2b).

Project I-B. Intra-individual Adaptive Assessment. The goal of this project is to extend results of I-A to dynamical studies. When item-responses are expected to change over time (e.g., today's mood is not the same as tomorrow's mood), the methodology of I-A needs to also consider when to administer an item *again.* Such time-series datasets are used to estimate dynamical networks, or to monitor patients in their symptomatology over time. Network models may be extended with temporal effects (Figure 2) to estimate how well a variable predicts other variables in the next measurement occasion [**38**,**39**]. While I-A focuses on a large item-set (e.g., 100+) administered once, I-B focuses on a smaller set (e.g., 10-30) administered many times. The project assumes the network structure to be known and will investigate adaptive item selection in a time-series analysis. The procedure will be validated using iLab data (see 2b).

Project II. Network Estimation with Severely Missing Data. The goal of this project is to estimate network structures based on data with severe missingness. The goal of projects I-A and I-B is to administer questionnaires more efficiently, possibly by not administering items that are not informative. Such systems will lead to data with many missing values, which presents, as discussed above, a known challenge to network psychometrics ([**28**], chapter 12). Bayesian estimation methods are promising in this regard [79], and novel Bayesian procedures offer a possible solution for the problem of model selection [54,91]. Other options are multiple imputation [**61**], approximate models [68], and full information maximum likelihood estimation. This project will implement these methods in accessible software and compare their performance in simulation studies. The methods will be validated using large epidemiological datasets (NCS-R [59] & NSMHWB [80]; see 2e) and data from the Math Garden application [62]. This project will partly be performed while visiting Virginia Commonwealth University (VCU).

Project III. Network Monitoring. The goal of this project is to update time-varying dynamical networks as new data becomes available. Adaptive network estimation of dynamical networks needs to be able to take into account that the network structure might be expected to change over time [50,71]. While methods have been developed trying to capture these changing dynamics [11,51], they estimate the network structure at any point of measurement by weighing past and future responses. When monitoring a person over time, one cannot rely on future responses. This project will investigate several ways in which dynamical network monitoring can be performed: (1) existing time-varying network estimation procedures [51] may be adapted to not weigh future responses when estimating the model at a certain time-point, (2) Bayesian updating rules may be valuable, and (3) heuristic algorithms to update a network structure may be developed that take into account how many data have recently been observed [62]. The procedure will be validated using iLab data (see 2b).

2a2. Research plan

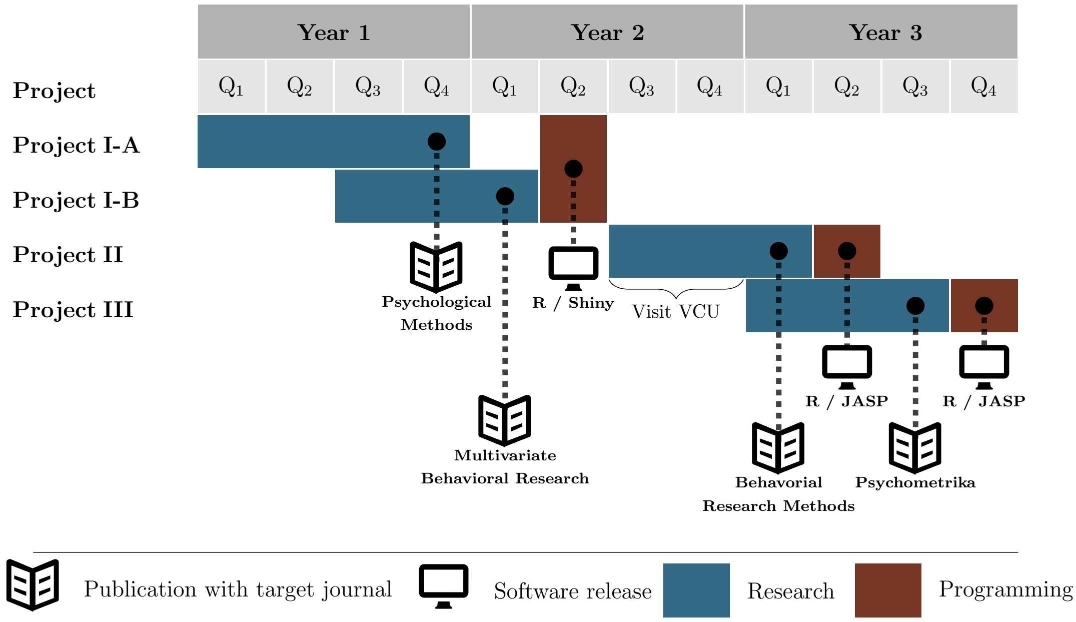
Practical timetable/timeline over the grant period. See work plan.

Local, national and international collaboration

The project will take place at the University of Amsterdam: Department of Psychological Methods, well known for its excellence in psychometrics and the development of new research methods. There, I will work closely with prof. Borsboom (expert in network psychometrics), prof. Van der Maas (expert in dynamical systems), dr. Waldorp (expert in multivariate statistics), and prof. Wagenmakers (expert in Bayesian statistics). I will collaborate both with the *Psychosystems* labgroup of prof. Borsboom (psychosystems.org) and the *JASP* labgroup of prof. Wagenmakers (jasp-stats.org). Beside the UvA, I have set up a large network of collaborators both national and international who have agreed to collaborate on the outlined projects (see work plan and 2b). Part of project II will take place at the Virginia Commonwealth University (VCU), which houses several excellent psychometricians, in collaboration with prof. Neale.

Work plan (see 2b and 2e on applications and datasets).

	Project I	Project II	Project III
Objective	Adaptive assessment: **I-A** Non-dynamical **I-B** Dynamical	Missing data analysis	Network Monitoring
Application / Data	UnderCovers iLab	NCS-R & NSMHWB Oefenweb	iLab
Collaborators - **Affiliation** - **Expertise**	**Dr. N. Smits** - University of Amsterdam - Adaptive testing **Prof. Dr. G. K. J. Maris** - ACT Next - Psychometrics	**Dr. M. T. Rhemtulla** - UC:Davis - Missing data **Prof. Dr. M. C. Neale** - Virginia Cmlth University - Psychometrics	**Dr. L. F. Bringmann** - University of Groningen - Dynamical Networks **Dr. C. J. Albers** - University of Groningen - Time-series analysis



2b. Knowledge utilization

Potential

Network Psychometrics. Network Psychometrics is utilized in different research fields [48], such as depression [12,**45**,82], post-traumatic stress [2,43,69,70], schizophrenia [3,56,55,72,88], comorbidity [4,10,77], autism [25,78], personality [**18**,19,21], attitude formation [23,24], intelligence research [60,86,87], health sciences [**63**,**65**], and clinical practice [**38**,41,64]. The proposed adaptive assessment platform may result in much data to be used in network estimation, as well as personalized assessment and network formation over time. In addition, the project will lead to better estimation of network models from incomplete data. As such, <u>all these fields directly benefit from the results.</u>

Diagnostic tools. A diagnostic tool that adaptively diagnoses which symptoms a person has from all symptoms present in the DSM [1] may offer a valuable addition to personalized care. In addition, many other online applications (apps) aim to provide personalized advice. For example, voting recommendation apps (e.g., stemwijzer.nl) aim to provide a personalized recommendation on which party to vote for, dating app (e.g., okcupid.com) aim to match people with similar interests, and learning environments (e.g., duolingo.com) aim to administer items that are challenging. In many such cases, the latent variable model and therefore existing CAT methods are not applicable. <u>NAA aims to overcome this problem, and therefore has great potential in improving item-administration in diagnostic tools and apps.</u>

Monitoring. NAA based on dynamical networks may be applied in monitoring symptom severity and personalized network structures over time, in addition to facilitating the gathering of large datasets by only administering relevant items. Furthermore, such a system may aid above-mentioned apps by selecting when to administer an item again.

<u>Each project is designed to have strong potential for utilization regardless of completion of other projects.</u> I-A may directly be applied in apps when a network model based on data without missingness is available. Likewise, I-B may directly be applied in patient monitoring when a network structure is available, for which large time-series analyses of multiple subjects [13,14,**39**] or prior information [**38**] may be used. II may directly be used to improve network estimation in light of severe missingness [**9**]. Finally, III may directly be used in patient monitoring over time without an adaptive system; all items could be administered at every measurement occasion as is now done in time-series analyses.

Implementation

Software. I have developed several extension packages for R to facilitate researchers in their work (e.g., [**29**,**32**,**36**,**31**,**26**,**33**,**73**]). Many of these packages now form a cornerstone in network psychometrics, and publications using my software have been very well cited. In addition, I have helped develop the open-source JASP program [**89**,**90**], an accessible point-and-click statistics program containing state-of-the-art analyses and developed at the prospected host department. All proposed projects have time allotted for the development and implementation of the methods in accessible software. Results from project I-A and I-B will be implemented in a new R package for adaptive testing as well as an interactive *shiny* interface [17]. Results from project II will be implemented in existing R packages [**31**,**33**,51,**83**], as well as the existing network module for JASP. Finally, results from project III will be implemented in a new R package and a new JASP module.

iLab (www.ilab-psychiatrie.nl) of the Psychiatry department of the University Medical Center Groningen focuses specifically on developing mobile technology and cutting-edge clinical and statistical procedures for time-series studies in individual psychiatric patients [64]. I have already extensively collaborated with iLab during the course of my PhD and ongoing projects [**38**]. I will work together with the iLab to implement results in their systems so they may be directly applied in clinical practice.

Oefenweb (www.trackandteach.com) is a sister organization of the prospected host department specialized in adaptive learning environments such as the *Math garden (used by about 2,000 primary schools)*. I have worked for Oefenweb as data scientist during my PhD project. Results of this project may be implemented in learning environments for which a latent variable model is not plausible (e.g., language learning tests). In addition, I will act as consultant for Oefenweb in setting up a series of adaptive testing environments for psychological questionnaires on the Oefenweb servers.

UnderCovers (www.undercoversapp.com) is an app designed to assess erotic interests of participants, and a prime example of an app in which adaptive assessment is required and in which a latent variable perspective is highly implausible. The developers of UnderCovers have agreed to collaborate with me on the proposed projects, allowing me to utilize data of over 200,000 users in validating the proposed systems. Upon completion, I will act as consultant for implementing the methods in the app.

2c. Number of words used

Section 2a: 1,834 (2a1) + 158 (2a2) = 1,992 (max. 2,000 words)

Section 2b: 750 (max. 750 words)

2d. Literature references

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