Preregistration

Migration Experience Trajectories: A Three-Mode Principal Component Analysis

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Study Information

Title	Migration Experience Trajectories: A Three-Mode Principal Component Analysis
Description	**Shortened Description:** Recent reviews have called for more comprehensive assessment of human experiences and for more longitudinal real-life data, within the psychological sciences more broadly and in migration research in particular (e.g., **?????**). However, while generally speaking analytical methods for such, more complex, data have become more readily available (e.g., **?**), it remains unclear how we should identify key developmental patterns — especially across multiple variables at the same time. In this manuscript, we aim to assess the utility of a promising analysis technique for describing, summarizing, and understanding the initial developmental data patterns

— *three-mode principal component analysis* (3MPCA). We use 3MPCA specifically because recent studies have laid out the potential effectiveness of dimension reduction procedures, which can address the new forms of person-, variable-, and time point heterogeneity jointly (e.g., **?**). We analyse data from three experience sampling studies, which followed the migration experiences of recent migrants to the Netherlands. All three studies focus on the psychological adaptation of migrants (i.e., psychological acculturation). However, given that past investigations of psychological acculturation have underexplored the crucial aspect of motivational experiences (**?**), the three studies have placed a particular emphasis on the needs, goals, and motives of young migrants. To make full use of all three data sets and to guide future use of dimension reduction procedures with extensive psychological data, we will analyze the data in a descriptive and step wise manner, where we first consider the data jointly and will then assess potential differences between datasets, variables, and time scales.

Full Description:

Recent reviews have called for more comprehensive assessment of human experiences and for more longitudinal real-life data, within the psychological sciences more broadly and in migration research in particular (e.g., **?????**). However, while generally speaking analytical methods for such, more complex, data have become more readily available (e.g., **?**), it remains unclear how we should identify key developmental patterns — especially across multiple variables at the same time.

In essence, the novel extensive longitudinal datasets come with new forms of heterogeneity, where we have to consider differences between people, over time, and across variables. Yet, past analytical advances have almost exclusively pushed for inferential modeling procedures[1]. And while inferential model testing is certainly important, we still miss discussions of methods for the more fundamental task of describing, summarizing, and understanding the initial developmental data patterns.

[1]For example, stationary lagged regression models that assume stable means and variances over time (incl., vector autoregressive models, dynamic structural equation models, autoregressive integrated moving average models, and cross-lagged panel analyses) or basic trajectory models (e.g., mixed effects models, spline regression models, and latent growth curve modeling).

As an example, a recent review of migration experiences has pointed out that despite many complex and dynamic theories, investigations of migrant adaptation have undervalued developmental data — especially when it comes to the more internal experiences of motivations and emotions (**?**). Yet, understanding how people differ in their migration trajectories, can be crucial in understanding adaptive and maladaptive patterns. To identify which variables are most important in the adaptation of migrants over time, we need methods to break down the data heterogeneity into its core components (in terms of important variables and developments) and we need ways to identify how these core components relate to key adaptation markers (including, well-being, intergroup anxiety, outgroup trust, or societal participation). There is, thus, a clear need to assess the utility of analysis procedures focused on the description and understanding of complex dynamical data.

In this manuscript, we aim to assess the utility of one such promising analysis technique — *three-mode principal component analysis* (3MPCA). We use 3MPCA specifically because recent studies have laid out the potential effectiveness of dimension reduction procedures, which can address the new forms of person-, variable-, and time point heterogeneity jointly (e.g., **?**). We are among the first to apply this analysis to experience sampling data and, to the best of our knowledge, we are the first to decompose social psychological experiences. This stands in stark contrast, to a renewed recognition that social psychological phenomena unfold over time, a rapid increase of extensive longitudinal data collections, and a growing interest in understanding the co-development of multiple experience aspects (e.g., **?????**).

To untangle the heterogeneity in real-life migrant adaptations, we will analyse data from three experience sampling studies, which followed the migration experiences of recent migrants to the Netherlands. All three studies focus on the psychological adaptation of migrants (i.e., psychological acculturation). However, given that past investigations of psychological acculturation have underexplored the crucial aspect of motivational experiences (**?**), the three studies have placed a particular emphasis on the needs, goals, and motives of young migrants. To make full use of all three data sets and to guide future use of dimension reduction procedures with extensive psychological data, we will analyze the data in a descriptive and step wise manner, where we first consider the data jointly and will then assess potential differences between datasets, variables, and time scales.

Hypotheses We do not have hypotheses in the traditional sense. Our analysis plan is based on the aim of describing, summarizing, and understanding a complex set of extensive longitudinal data. We propose that the dimension reduction procedure we employ will identify meaningful patterns and developments within the data, which are useful to migration researchers and practitioners. An additional aim is to test the feasibility and utility of simultaneous dimension reduction procedures in experience sampling data.

Design Plan

Study type **Observational Study**. Data is collected from study subjects that are not randomly assigned to a treatment. This includes surveys, natural experiments, and regression discontinuity designs.

Blinding No participant blinding is involved in this study.

Study design All three studies used an extensive longitudinal design. Using a daily diary format, for at least 30 days participants received a short survey twice per day (at around 12pm and 7pm). We additionally included a longer pre- and post measurement survey the days before and after the extensive longitudinal data collection.

Randomization No randomization is involved in this study.

Sampling Plan

Existing data **Registration following analysis of the data**: As of the date of submission, you have accessed and analyzed some of the data relevant to the research plan. This includes preliminary analysis of variables, calculation of descriptive statistics, and observation of data distributions. Please see cos.io/prereg for more information.

Explanation of existing data	The data was collected as part of a larger collaboration on daily intergroup relations. A sub-sample of variables has recently been accessed by the research team for an unrelated analysis (**?**). Additionally, several of the variables were prepared for a graphical presentation of the dataset. Thus far, none of the proposed analyses have been conducted and none of the previous analyses have been related to dimension reductions or time-series modeling.
Data collection procedures	We collected three experience sampling studies, following the daily migration experiences of young migrants, who had recently arrived in the Netherlands (median time in the Netherlands = 3 Months). For all three studies, the data was collected in a three-step procedure: 1. Entry Survey: A pre-measurement questionnaire (appr. 25 minutes) including demographic information, and relations to the Dutch majority (payment: 2 Euros). 2. Experience Recaps: At least 30 days of short reflection surveys (appr. 3—5 minutes) on intergroup interactions twice a day (payment: 1 Euro per Recap; up to 2 Euros per day). 3. Conclusion Survey: On the last day, we conclude with a post-measurement questionnaire (appr. 25 minutes) with some questions on habits and reflections on the study (payment: 2 Euros). For the third study, participants had the option of continuing the study for an unspecified amount of time. After the initial 30 day duration, participants were offered the possibility to continue participating in the study either with payment if daily diary measures were missed during the initial study phase or without payment after a total of 60 daily diary measurements were completed. After the initial 30-day period, participants receive automated feedback visualizing the development of their own well-being, attitudes, and motive responses as an additional initiative and to give participants access to their own data and to compensate study participation.
Sample size	For Study 1 (initial preliminary study) our target sample size is a sum of 1,000 daily diary measurements. As we expected a completion rate of around 80% we aimed to recruite 20 participants (20 participants X 50 measurements). We further

over-sampled slightly to compensate for potential drop outs given the length and intensity of the study. The total collected sample size of Study 1 was thus 1,225 survey responses from 23 participants.

For Studies 2 and 3, our target sample size was a sum of 4,000 daily diary measurements each. With 100% completion rate that would be archived with 67 participants (60 daily diary responses each). Given that we expect some incomplete daily diary measurements, we again over-sampled in both studies. In Study 2, we were ultimately able to collect 4,965 survey responses from 113 participants. In Study 3 we collected 4,107 survey responses from 71 participants.

Sample size rationale

The targeted sample size depended on a combination of different factors. Different analyses were planned as part of the collaboration and budgeting was a practical constraint. Some analyses were planned based on (1) the pre- to post measurements, (2) the dynamic developments over the daily diary measurements, or (3) the contemporary effects within the daily diary measurements.

Power considerations of mixed effects model such as with extensive longitudinal data are difficult to estimate because of the complex covariance structures. Simulation studies based on the first sample indicated that with well-distributed scales, and small to medium effect sizes, 70-80 participants with at least seven daily diary measurements and a simple pre–post survey were sufficiently powerful (power = .8, alpha = .05) to answer most of the key research questions of the collaboration.

The ultimate sampling procedure decision was made as a practical balancing of the number of participants and the number of measurements provided by each participants.

Stopping rule

Participants were recruited until the targeted number of participant finished the pre-measurement. Invitations to complete additional daily diary measurements (in Study 3) were extended until participants chose to leave the study or at the most until two months (i.e., 64 days) after the initial entry survey (i.e., from the pre measurement survey).

Variables

Manipulated variables	Not applicable given that the study design is observational.
Measured variables	Given the circumstance that we utilize three independent experience sampling studies for our analyses, the variables are at times slightly different between studies. Additionally, given that the analysis we aim to undertake (i.e., 3MPCA) uses a large number of variables for the multiple imputations, dimension reduction, and correlational analyses, we will not list all items individually. Instead, we provide full variable information in the following data sheets in 'VariableSelectionAnalyses.xlsx'.

Key variables

While most of the variables are identical across all studies, some differ slightly in content or wording. However, for each study we aimed to collect the following types of variables.

1. Motivational variables
   a. core motive fulfillment (i.e., "*During your interaction with -X- (/this morning) your goal (-TEXT-) was fulfilled.*")
   b. goal importance ratings of 10 individual goals (e.g., "*career goals*", "*health / fitness goals*")
   c. self determination theory needs (i.e., autonomy, relatedness, competence)
2. Affective states
   a. experienced well-being (happiness, energy)
   b. general emotional state scale (e.g., "*How do you feel right now? not angry at all to very angry*")
3. Behavioral self-reports (Studies 2 and 3)
   a. pro-social behavior (e.g., "*Made demeaning, rude or derogatory remarks about someone.*")
   b. anti-social behavior (e.g., "*I was there to listen to someone's problems.*")
4. Cognitive measures

a. outgroup attitude ("*After the interaction, how favorably do you feel towards ... / At the moment, how favorably do you feel towards ... the Dutch.*")
b. Allport's contact condition perceptions (i.e., equal status, shared goal, cooperative, voluntary)
c. interaction quality ratings (e.g., "*Overall, the interaction was... Unpleasant to Pleasant*")

It should be noted, that we collected substantially more motivational and affecive variables, as they have been understudied in the past.

For the detailed variable selection of each analysis see 'VariableSelectionAnalyses.xlsx'.

Interpretation correlation variables

To interpret the person-mode components identified by the 3MPCA, we would like to correlate the component scores with a range of person- or time point specific variables. While the full list of variables is available in the accompanying data sheets (see 'VariableSelectionAnalyses.xlsx'), we provide a few examples of the targeted categories below.

1. demographic variables
   a. age
   b. gender
   c. ...
2. societal participation
   a. language comprehension and -use
   b. work inclusion
   c. ...
3. adaptation indicators
   a. social identification
   b. intergroup anxiety
   c. ...
4. everyday life obstacles

   a. discrimination experiences
   b. negative life events
   c. ...

5. individual differences
   a. big five personality scores
   b. attachment style
   c. ...

Auxiliary variables for multiple imputation

For the missing data imputation we follow the procedure reported by **?**, and include any pre-, post-, or daily dairy variables that are significantly correlated with either the key variables or missingness on the key variables (at $p < .01$). In case we encounter a convergence problem during the multiple imputation, we only include variable with a correlation larger than .3. For an overview of the variables that qualify as auxiliary variables see the enclosed data sheets (see 'VariableSelection-Analyses.xlsx'). Additional information about the multiple imputation procedure is also available at Statistical models 2.

We also provide an exemplary codebook (using Study 3 as an example; see 'Codebook_AOT-M_ItemsPerSection.xlsx'). The full survey files will be available as part of the main OSF repository connected to this preregistration.

Indices

1. Mean Allport's conditions. We create a mean-averaged index of Allport's conditions in response to past findings indicating that the conditions are best conceptualized jointly and as functioning together rather than as fully independent factors (**?**, p. 766). Similar to past studies we thus hope to build a global indicator (e.g., see **?**). As with other indices we will ensure that the individual items indeed relate to a common latent construct and are meaningfully combined in an index. If this is not possible we will create sub-indices and/or assess the impact of the conditions separately.
   a. The interaction with [name interaction partner] was on equal footing (same status)

b. [name interaction partner] shared your goal ([free-text entry interaction key need])
c. The interaction with [name interaction partner] was cooperative
d. The interaction with [name interaction partner] was voluntary

2. Mean belongingness during intergroup contact

    a. I shared information about myself.
    b. [name interaction partner] shared information about themselves.

3. Mean alternative interaction quality definition ("Overall, the interaction with [name interaction partner] was . . . ")

    a. Unpleasant to Pleasant
    b. Superficial to Meaningful
    c. Ineffective to Effective
    d. Unimportant to Important

4. Mood Subscales (MDMQ)

    a. alertness
    b. calmness
    c. valence

5. Mean anti-social behaviors

    a. Put someone down
    b. Show little attention in someones opinion
    c. Demeaning remarks
    d. Inappropriately addressing someone
    e. Ignored or excluded someone
    f. Doubt someones judgement
    g. Unwanted attempts of personal matters

6. Mean pro-social behaviors

    a. Listen to someones problems
    b. Cheer someone up
    c. Help someone get things done
    d. Help someone with responsibilities

Additionally, in the pre- and post-measurement surveys are several validated scales that we will combine into their sub-scales. Indices will be created in line with their respective validation literature. For a full list of all variables and indices see 'VariableSelectionAnalyses.xlsx'.

Analysis Plan

Statistical models

For our analysis, we adapt the procedures outlined by **?**:

1. **Sample Selection.** For our sample selection we address both the selection of time points and participants. Given that multiple imputation procedures even work well with large proportions of missing data [assuming missingness at random; **?**], we decided on a general criterion of less than 45% missingness to balance sample size retention and bias in the multiple imputation model. Thus, we then select the time points for which we have less than 45% missingness and select participants who have less than 45% missingness across the selected time range.
2. **Time point aggregation.** We aggregate the key variables over time to archive a reasonably interpretable number of time points and remove a first proportion of missing data. Given that little data is available on the meaningful time scales of the selected psychological variables, we chose to determine the appropriate time scales using variance decomposition (e.g., see **?**). This is to say that we create multi-level unconditional means models (without predictors) that include possible nested time scales as levels. We chose to select time scales that align with common human cycles. We thus compare the variances of bi-daily, daily, and weekly aggregations. Additional aggregations of two weeks or the full four weeks might be possible but would most likely reduce the variance too much for any meaningul further reduction during the 3MPCA. We then chose the time scales that have the most variance.
3. **Multiple Imputation.** We then create 20 imputed datasets to perform the analyses on. As outlined by **?**, we will use the key variables themself as well as auxiliary variables to impute missing values. Auxiliary variables are any pre-, post-, or daily dairy variables that are significantly ($p < .01$) and meaningfully ($r > .3$) correlated with (1) the key variables or (2) missingness on the key

variables.

4. **Three-way ANOVA*.** We assess the percentages of explained variance for the person-, variable-, and time aspects — which offers an indication of whether a 3MPCA is useful for the dataset. Based on the grand mean centered variables we conduct a fixed-effects three-way ANOVA of the person-, variable-, and time modes as well as their various interactions. We are particularly interested in the highest order interaction term Person * Variable * Time + error, as a large amount of variance in this effect would speak towards the possible interdependence of the three modes.
5. **Data preprocessing*.** For the 3MPCA, we center (across participants but within time point) and normalize (within variable but across time points) all key variables. The between-person centering, ensures that all variations are around the mean trend (which is removed by the centering). The normalization within variable are important for ensuring equal variances across variables, which ensures equal weighting of the variables in the 3MPCA. For methodological detail see Transformations.
6. **Selection of 3MPCA model complexity*.** We then run the 3MPCA. We use a generalized scree plot to select the appropriate number of components for each of the three modes (i.e., person, variable, time). To test the stability of the solution results are compared across the 20 imputed datasets and split-half stability is assessed.
7. **3MPCA model fitting*.** For the selected complexities we then extract simple component structures (i.e., for each mode individually) as well as the core array (the full 3MPCA array, which specifies all combinations of the three mode components). A Joint Orthomax orthogonal rotation and standard weights are used to extract human interpretable component scores. This procedure is done on all 20 imputed data sets.
8. **Generalized Procrustes rotation*.** In order to combine the three individual component structure from the 20 data sets, we use a generalized Procrustes rotation — calculating the average of each compontent and core array.
9. **Explained variance*.** As fit indices we then calculate (1) fit percentage of the estimated array for each imputed data set (i.e., explained variance around the removed general trend) as well as (2) an *overall* fit percentage of the estimated array (i.e., explained variance including the general trend).

Both these fit metrics should give an indication of how much of the original variance the reduced component structure was able to capture.

10. **Component interpretation*.** To embed and interpret the resulting components (especially the person components), we calculate correlations of the component scores with key adaptation markers (including, well-being, anxiety, trust, or societal inclusion). If components remain unclear still we can additionally perform k-means clustering on the lower dimensional space to identify clearer groups, which can be compared on the adaptation markers if necessary.

***Step-wise Analysis Approach:**

I. **Studies (Study 1, Study 2, Study 3)**

- **Main Analysis:** All studies combined to have the most power.
- **Follow-up Analysis #01:** To make sure there is no Simpson's paradox, we also separate the three data sets in separate follow-up analyses.
- **Follow-up Analysis#02:** We add idiosyncratic variables (i.e., variables only available in a subset of studies) within the separated follow-up analyses. With these additional variables we explore whether our main analysis is robust to other psychological experiences or whether the additional variables might provide a qualitatively different understanding of migration processes.

II. **Response types (interaction, no interaction)**[2]

- **Main Analysis:** All available questions combined to have the most power.
- **Follow-up Analysis#03:** To make sure there is no Simpson's paradox, we separate the data into two subgroup follow-up analyses (i.e., responses following an interaction and responses without interactions). This analysis will again test the robustness of the main analysis and will explore whether the core dimensions are substantially different for interaction specific phenomena.

[2]Some questions were only available or had a slightly different focus depending on whether participants had an interaction or not.

III. **Time scales (half-day, day, week)**

- **Main Analysis:** For the main analysis, we will use the time scale that shows the most variance across the included items (e.g., daily; see *Time point aggregation* above).
- **Follow-up Analysis#04:** To explore the impact of time scales in (social) psychological data, we will also run the 3MPCA on the other time scale options (e.g., bi-daily, weekly).

Transformations

For three-mode PCA it is custom to center (across participants but within time point) and to normalize (within variable but across time points). This is done to create a meaningful zero value for each time point (to compare participants) and a variance of 1 across all time points of a variable (ensuring equal weightin of variables in the 3MPCA).

We provide the main equations of the procedure below, where individual i ($i = 1, ..., I$) reported variable x and its naturalized form z (where $[k = 1, ..., K]$ indexes all available variables) at time point t ($t = 1, ..., T$), so that I=number of persons, K=number of items, T=number of time points within the dataset. For further information as well as an example illustration see Supplemental Material 3 in **?**.

$$\overline{x}_{kt} = \sum_{i=1}^{I} x_{ikt} \tag{1}$$

$$\sigma_k = \sqrt{\sum_{i=1}^{I}\sum_{k=1}^{K}\frac{(x_{ikt} - \overline{x}_{kt})^2}{I * T}} \tag{2}$$

$$z_{ikt} = \frac{x_{ikt} - \overline{x}_{kt}}{\sigma_k} \tag{3}$$

Inference criteria

Many of the proposed procedures are descriptive rather than inferential. Importantly, we will use amounts of variances explained as our main fit indices. If we perform inferential analyses, we will use the standard p<.05 criteria for determining whether the correlation and regression coefficients are statistically significant. We will use appropriate multiple-comparison corrections whenever multiple tests are performed (such as Bonferroni correction). We will place particular emphasis on effect sizes (e.g., correlations) in our interpretations of the results wherever possible.

Data exclusion	No checks will be performed to determine eligibility for inclusion besides verification that each subject answered each of the variables of interest for a given analysis. Outliers will generally be included in analyses. However, we will use sensitivity analyses to assess the robustness of the results to outliers.
Missing data	The sample selection based on proportions of missing data and the multiple imputation procedures are described in Statistical models.
Exploratory analyses (optional)	A recent alternative for trajectory dimension reduction has been the use of LSTM auto encoders. The encoder decoder classification procedure has the advantage of being extremely flexible in the use of the data set and could be interpreted in a similar way as the 3MPCA (see Statistical models 9).

Other

Other (Optional)	Not applicable.