Preregistration

Migration Experience Trajectories: A Three Mode Principle Component Analysis

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Study Information

Title	Migration Experience Trajectories: A Three Mode Principle Component Analysis

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., Kreienkamp et al., 2022b; MacInnis and Page-Gould, 2015; McKeown and Dixon, 2017; Pettigrew and Tropp, 2011; Ward and Szabo, 2019). However, while generally speaking analytical methods for such, more complex, data have become more readily available (e.g., O'Donnell et al., 2021), 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 top-down 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 developmental data patterns.

As an example, little data has thus far investigated the development of migration experiences and no research has assessed the co-development of multiple experience aspects. Yet, understanding how people differ in their migration trajectories, can be crucial in understanding adaptive and maladaptive patterns. [c1][c2]To identify which variables are most important in the adaptation of migrants [c3]over time, we need methods to [c4]break down the data heterogeneity into its core components (in terms of important variables and developments) and we need [c5]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 for the use of social psychological experience sampling data. 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 (i.e., three-mode principle component analyses, 3MPCA; e.g., Monden et al., 2015).

[c6]To this aim, we will analyse the data from three experience sampling studies, which followed the migration experiences of recent migrants to the Netherlands. [c7]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

[1] For example, stationary lagged regression models that assume stable means and variances over time (incl., vector [c1]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).

[c1] ~~We we need~~

[c2] ~~t~~

[c3] *Text added.*

[c4] ~~identify clusters of similar individuals and developments~~

[c5] ~~to assess whether such clusters differ in~~

[c6] ~~We will, particularly,~~

[c7] *Text added.*

(Kreienkamp et al., 2022b)[c8], the three studies have places a particular emphasis on the needs, goals, and motives of young migrants.

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 data 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.

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. [c1]

Blinding No participant blinding is involved in this study.

Study design All three studies[c2] 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

[c8] *Text added.*

[c1] Note: This is part of the OSF dropdown answer and we can't change the description.

[c2] Note: I now extended the introduction of the three studies in the end of the description section. So I hope this doesn't come out of the blue as much anymore.

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 (Kreienkamp et al., 2022a). 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 [c1]nor have any of the past analyses analysed the longitudinal nature of the data.

Data collection procedures

[c2]We collected three experience sampling studies, following the daily migration experiences of young migrants, who had recently arrived in the Netherlands. 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.

[c1] ~~or longitudinal trajectories~~

[c2] *Text added.*

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. [c1]The total collected sample size was thus 23 participants. We then used several key relationships (relevant to the broader research team) to estimate sufficient power for a range of different analyses (i.e., using power simulations). Based on these power simulations, for Studies 2 and 3, our target sample size was a sum of 4,000 daily diary measurements. 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 aimed to recruit 80 participants. For [c2]Studies 2 and 3, we again aimed to over-sampled slightly to account for expected drop outs. [c3]We were ultimately able to recruited a total of 113 particpants for Study 2 and 71 participants for Study 3.
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 within this project 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

[c1] *Text added.*
[c2] ~~both studies~~
[c3] *Text added.*

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: 'VariableSelectionDaily.xlsx' and 'VariableSelectionPrePost.xlsx'.

Key variables

[c1]While most of the variables are identical across all studies, [c2] 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)

[c1] *Text added.*

[c2] ~~however~~

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.

Interpretation correlation variables

To interpret the [c1]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 'VariableSelectionDaily.xlsx' and 'VariableSelectionPrePost.xlsx'), we provide a few examples of the targeted categories below.

1. demographic variables

    a. age
    b. gender
    c. ...

2. societal participation

[c1] *Text added.*

   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 Monden et al. (2015), and include any pre-, post-, or daily dairy variables that are significantly ($p < .01$) and meaningfully ($r > .3$) correlated with either the key variables or missingness on the key variables. For an overview of the variables that qualify as auxiliary variables see the enclosed data sheets (see 'VariableSelectionDaily.xlsx' and 'VariableSelectionPrePost.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 (Pettigrew and Tropp, 2006, p. 766). Similar to past studies we thus hope to build a global indicator (e.g., see Pettigrew and Tropp, 2006). As with other indices we will ensure that the individual items indeed relate to a common latent construct and are meaningfully combine[c1]d 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

[c1] *Text added.*

   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 the accompanying validation literature:

[c1] Added:

> **Note.**
> We have a group of six variables that are consistent across all three studies. Additionally, we have a number of variables that are either only relevant to a single study or a subset of the studies. If we agree on the study consolidation procedure as it is described below, I would suggest that we focus on the variables we have in all studies, and will include the other variables in the follow-up analyses and report only significant correlations (after alpha correction). I would also suggest that we add the list below to one of the variable selection files (Excel) instead of listing them all here (to avoid unnecessary confusion).

Study 1 only:

1. Acculturation, Habits, and Interests Multicultural Scale for Adolescents (AHIMSA; S1)
2. Vancouver Index of Acculturation (VIA; S1)
3. Situational Self Awareness Scale (SAS; S1)

Study 3 only:

[c1] *Text added.*

1. Outgroup Trust
2. Work Group Inclusion
3. Meaningful Life Scale
4. Big Five Personality Questionnaire
5. Attachment Styles Scale
6. Paranoia Scale

Studies 1 and 2:

1. Self Determination Theory Scale (SDT; S1, S2)
2. Interpersonal Support Evaluation List (ISEL; S1, S2)
3. Perceived Stress Scale (PSS; S1, S2)
4. Negative Life Events Scale (NLES; S1, S2)

Studies 2 and 3:

1. Social Identification Scale (S2, S3)
2. Multidimensional Mood State Questionnaire (MDMQ; S2, S3)
3. Homesickness Scale (S2, S3)

All Studies:

1. Intergroup Anxiety Scale (IAS)
2. The Satisfaction with Life Scale (SWL)
3. Rosenberg Self-Esteem Scale (SES)
4. Everyday Discrimination Scale
5. Language Proficiency
6. Association Participation

Analysis Plan

Statistical models For our analysis, we adapt the procedures outlined by Monden et al. (2015):

Main Data Splits:

1. **Three studies (S1, S2, S3)**
   (a) Combined for most power in correlations (including, correlation with study indicator)
   (b) Separate in follow up analysis to ensure that we do not have a simpson's paradox
   (c) Explore additional ideosyncratic variables in separated follow up
2. **Two question types (interaction, no interaction)**:
   (a) Combined for most power in correlations (including, correlation with interaction indicator)
   (b) Separate in subgroup follow up analysis to ensure that we do not have a simpson's paradox
3. **Three time scales (half-day, day, week)**
   (a) If all variables clearly show single most variance on the same time-scale, single analysis only
   (b) If multiple time-scales are possible within single analysis, single analysis only (see question box below)
   (c) If variance split across multiple time scales for substantial number of variables ($> 1/4$ of all variables), multiple analyses for the different time scales
4. **Multiple Imputation (20 imputations)**
   (a) Test stability
   (b) Split-half analysis
   (c) Combine after analysis

1. **Sample Selection.** [c1]For our sample selection [c2]we address both the selec-

[c1] *Text added.*
[c2] ~~consists of three main steps. We (a) aggregate the key variables over time to archive a rea-~~

tion of time points and participants. Given that multiple imputation procedures even work well with large proportions of missing data [assuming missingness at random; Madley-Dowd et al. (2019)], 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 [c3] select the time points for which we have \change{responses from 55% of the participants}{less than 45% missingness} and [c4] select participants who have \change{responded to at least 55% of the surveys}{less than 45% missingness} across the selected time range. [c5]Because the studies are comparable but not identical in their sampling strategy, question selection, and question wording, we also have to consider, whether to combine the samples.

2. **Time point aggregation:** [c1]We then 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 Ram et al., 2014). This is to say that we create multi-level unconditional means models (without predictors) that include possible nested time scales as levels. [c2]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 ideal time scale for each of the key variables.

~~sonably interpretable number of time points and the remove a first proportion of missing data.~~

[c3] ~~(b)~~
[c4] ~~(c)~~
[c5] *Text added.*
[c1] *Text added.*
[c2] ~~We, for example, assess the explained variances for measurements nested in days, nested in weeks, nested in months.~~

Note: I talked about the individual time scales with Rei. And one issue that came up was that although the time points do not have to be equidistal between measurement ocasions, each variable needs to have data at each measured time point and the time scales should be equal across variables. This would mean that we will need to have the same time scale (e.g., daily) for all variables. Given that we have now only three time scales (i.e., bi-daily, daily, weekly) we could run the 3MPCA for all three time scales and assess differences (in a multi-verse style analysis).

Question: I am not entirely sure I fully understand yet why it is not possible to aggregate items across different time windows as long as data is available for all time points. For example, if energy levels are kept at bi-daily measurements but for well-being we calculate a daily average, we could then replace both daily time points of well-being with the daily average. I understand that this sounds a bit silly because we give up the morning/afternoon variance but it might still be useful in terms of missingess reduction. Here my confused thoughts: Does this mean that 3MPCA cannot deal with variables that change at different speeds? Is this because the time components are estimated across all variables and might be mis-specified if we have different time scales? This seems counter my current understanding of the core array (i.e., interactions between the components) where time components could interact with variable components.

Long story short: Maybe we can discuss this issue again, I feel like I might have misunderstood something somewhere :-D

Sorry...

3. **Multiple Imputation.** We then create 20 imputed datasets to perform the analyses on. As outlined by Monden et al. (2015), 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 interdependence of the three modes.

5. **Data preprocessing.** For the [c1]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 [c2]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 [c3]core array (the full 3MPCA array, which [c4]specifies all combinations of the three mode components). A Joint Orthomax orthogonal rotation and standard weights [c5] 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

[c1] ~~three mode~~

[c2] *Text added.*

[c3] ~~array core~~

[c4] ~~holds the weights of all combinations of the three modes~~

[c5] ~~(when necessary)~~

these fit metrices 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.

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[c1] 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 Monden et al. (2015).

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

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

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

Inference criteria

Many of the proposed procedures are descriptive rather then 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

[c1] ~~k ($k = 1, ..., K$)~~

whether the correlation and regression coefficients are statistically significant. [c2]We will use appropriate multiple-comparison corrections whenever multiple tests are performed. We will place particular emphasis on effect sizes [c3](e.g., correlations) in our interpretations of the results wherever [c4]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.

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[c2] *Text added.*
[c3] *Text added.*
[c4] ~~necessary~~

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