Abstract

Increased geographical mobility motivates dialectologists to consider the exposure of survey participants to linguistic variation. Changing mobility patterns (e.g. longer-distance commuting; easier relocation to distant places for work, study or marriage) have caused linguistic connections to become much more diverse, contributing to an acceleration of dialect change. To assess the impact of individual mobility on this change, we propose the *Linguistic Mobility Index* (LMI) framework, which estimates long-term exposure to dialectal variation based on episodes of linguistic biography. An LMI of a survey participant comprises combinations of influencing factors, such as dialects of parents, long-term partners, places lived, place of work and education. The linguistic effects of these factors are represented by linguistic distances to the survey participant in question, and the effects are cumulated into an LMI in a weighted manner, according to the relationship the factor embodies and the intensity of the participant's exposure to the factor. LMI is conceptualised and evaluated based on 500 speakers from 125 localities in the Swiss German Dialects Across Time and Space (SDATS) corpus. Four LMI prototypes are constructed, employing different theoretical considerations and combinations of influencing factors to simulate the availability of metadata in other studies, thereby assessing the generalisability of the framework. Using mixed-effects modelling, we evaluate the utility of the LMI prototypes as predictors of dialect change between historic and contemporary linguistic data of Swiss German. The LMI prototypes successfully show that higher exposure to dialectal variation contributes to more dialect change and that its effect is stronger than some of those sociodemographic variables often tested for similar effects (e.g. sex and educational background). The success of the four prototypes justifies the potential implementation of the LMI framework in other studies, including those with a limited amount of metadata, for which we also provide further guidance in the contribution.

Introduction

In this paper, we argue that quantifying exposure to other dialects at the speaker level may provide researchers with a new tool for investigating language variation and change. Increased mobility jeopardises the validity of region being the primary determinant of linguistic variation [1], due to mobility-induced dialect change. Mobility leads to a potential increase in contact, exposing individuals to linguistic variation, and the intensity of this exposure plays a key role in language change [2]. Due to this increasing exposure to linguistic variation, it is indispensable to address the mobility of participants in linguistic surveys [3,4]. This paper introduces the framework of the *Linguistic Mobility Index* (LMI), a tool to estimate individuals' exposure to potential linguistic influences through examining long-term mobility patterns in their linguistic biographies. Our focus is on dialectology and sociolinguistics, but we also encourage the application of the linguistic mobility framework in other fields within linguistics.

Mobile behaviour results in potential contact with peers in different localities and long-term exposure to linguistic variation (e.g. through regular contact, such as via commuting or relocation). Previous dialectological and sociolinguistic studies have researched mobility and exposure to contact in relation to different linguistic aspects (e.g. [1–3,5–9]). We view linguistic mobility as reflecting the combined potential effects of the places visited or contacts made (i.e. contact with peers from these places) on an individual's dialect. Thus, a linguistically mobile person is characterised by activities that bring them into contact with linguistically different localities, such as multiple relocations throughout their lives, routinely commuting for study, work or other regular activities, or having familiar ties in such localities. In contrast, a linguistically non-mobile person would gain most of their linguistic influences from the inhabitants of the locality in which they grew up.

The constant increase in geographical mobility over the last century has strengthened the potential of diverse linguistic contacts to impact dialects [10–12]. This linguistic change caused by the intensification of dialect contact among speakers from a larger number of places has been framed in dialectology as a function of the general mobility patterns of the population, conceptualised, for example, as the wave model of language change [13] and the linguistic gravity model [9]. However, little quantitative research has been conducted on the effects of mobility at the speaker level, partly because surveys traditionally focused on capturing variation elicited from NORMs and NORFs, cf. [14]. Of the available studies on geographical mobility of individuals, Chambers [1] tested his *Regionality Index* (RI) on three Canadian city-wide lexical databases, Beaman [5] studied the role of relocation in the attrition of Swabian German through observing dialect change within the lifespan of individuals, while Bowie [6] and Regan [8] observed the retention of phonological forms and, respectively, change in the perceived socioeconomic status of words, based on the number of years spent away from a reference locality. Moreover, Chambers' RI [1] was applied in studies to account for the extent to which individuals could represent local communities [15–17].

In terms of quantifying exposure to the linguistic effects of contact, research has focused on the relation between language change and the most important linguistic influences in individuals' lives. An individual's linguistic inheritance is viewed as coming from the dialects of their parents and primary caregivers, who have a foundational influence on their dialect, especially in early childhood before large-scale exposure to older peers (e.g. [18–21]). These foundations are then strongly shaped by other intense contacts, including relatives; peers during childhood and adolescence [21], such as at school [22,23];

partners [24,25]; and contacts within the workplace and other communities as adults [7,26]. These factors are important to take into consideration when studying linguistic mobility.

To date, quantitative measures of the linguistic exposure of individuals to other dialects have not been determined based on aggregating biographical information and other influential factors from survey metadata; instead, quantification of linguistic mobility has been rather elementary, such as focusing on flat rates of time spent away from a reference locality [5,6,8]. The LMI framework addresses this research gap by systematically constructing an index from multiple linguistically influential factors that can be extracted from survey metadata. Thus, LMI integrates linguistic biography data into a single value representing exposure to linguistic variation.

In this paper we implement the LMI framework using data from 500 survey participants recorded in the SDATS corpus (*Swiss German Dialects Across Time and Space* [27]). Four LMI prototypes are constructed which simulate the availability of metadata in other dialect surveys, thereby testing the generalisability and flexibility of the LMI framework.

We evaluate the usefulness of the implemented LMI by testing its relation to dialect change and controlling for variation in sociodemographic variables frequently used to assess language change. Other studies have included in such tasks, depending on the design of the linguistic survey, for instance, gender (e.g. [28,29]), educational background (e.g. [30]), and urbanity and social networks (e.g. [31–35]). Our evaluation tests the performance of the four LMI prototypes as predictors in mixed-effects models. A dialect change rate is calculated based on ten lexical variables, using historical linguistic data from the SDS (*Sprachatlas der deutschen Schweiz* [36]) and contemporary data from the SDATS project. We expect the model results to confirm that linguistically mobile speakers have higher rates of dialect change, while non-mobile speakers have lower rates.

The remainder of this paper is structured as follows. After outlining the general construction of LMI, we present the implementation of LMI for the SDATS corpus and evaluate the four LMI prototypes in mixed-effects models. In addition, we briefly address the question of regionality and urbanity regarding the effects of mobility. After presenting and discussing the results of the models, we indicate the limitations of LMI and provide recommendations for the application of LMI in other studies.

Methods

Introducing the Linguistic Mobility Index

The core concept of LMI is the aggregation of the linguistic effects of linguistic connections in a participant's biography. These linguistic connections (henceforth referred to as 'factors') may be people and groups that the participant has been exposed to, and which have had linguistic effects on them. LMI estimates a summary of these linguistic effects accumulated throughout the life of the participant, and the effects are weighted according to the intensity of the contact and the participant's relation to the factor. Linguistic surveys with a controlled selection of participants usually elicit some metadata about their participants and the influential factors in question. Usually, surveys assign each participant to a reference locality or linguistic variety, and a location could also be assigned to the factors. The potential linguistic effect is determined based on these assigned locations through the calculation of linguistic distance. The intensity of the participant's exposure to these locations, and their relation, is expressed based on information elicited from survey questionnaires or other metadata (e.g. through what kind of personal relation they were exposed to the location, or how much time they spent there). In comparison to RI, which is used for measuring the extent to which an individual has been exposed to a reference locality, LMI measures the potential effect of the linguistic variation pertaining to places encountered by the participant outside the reference locality.

A generic solution to calculate the exposure of an individual to one linguistically influential factor is based on the following steps.

- **Calculating linguistic distance**: The basis of LMI is linguistic distance, which is a quantitative estimate of the difference between the linguistic variety pertaining to the factor and the participant's own variety.
- **Weighting based on the intensity of the exposure**: Fine-tuning the estimation of the factor's effect based on the available metadata in the linguistic biography (e.g. age at the time of contact, duration and frequency of the contact).
- **Weighting based on the relationship to the factor**: Estimating the possible role of the factor in the individual's life and thereby its long-term influence, in a categorical manner.

LMI is then created as an aggregation of the exposure to the factors considered. The larger the resulting LMI, the more long-term exposure the participant had to dialectal variation.

Implementing the LMI framework on Swiss German dialect data

Before embarking on the implementation of the LMI framework, it is important to take note of the specific linguistic situation of Swiss German dialects. In the diglossic context of Switzerland, dialects enjoy high prestige compared to Standard

German (e.g. [37,38]) and do not have a strong orientation to social class. Swiss German speakers (practically all German speakers born or raised in Switzerland) use their own dialects colloquially, with the lingua franca between speakers of various dialects rarely being the standard language, although 'levelling' is occurring in Swiss German dialects [19,39]. Use of Standard German is expected only in a few official situations, but Swiss German speakers are constantly exposed to Standard German from an early age, such as in school and via the media. The diverse topography and the (historical) administrative structure of Switzerland cause specific mobility flows and cultural orientations, contributing to the regional diversity of the dialects. Thus, spatial patterns in linguistic mobility and, correspondingly, in dialect change are expected.

The LMI framework was implemented using information elicited in the SDATS metadata about various long-term linguistic influences. SDATS speakers were recorded in 2020–2021 across 125 localities in German-speaking Switzerland, which form a subset of the SDS survey localities [40]. From each of these reference localities, we used data from four participants: two older (65+ years old) and two younger speakers (20–35 years old), with one male and one female speaker in both age cohorts. For every speaker, one parent came from the region of the reference locality, and the speakers themselves grew up in and lived most of their lives there. Further, their daily travel time was required to not exceed the Swiss average of approximately two hours. After a dialect interview, the speakers filled out an unsupervised online metadata questionnaire consisting of over 300 items (cf. [41] for details). The SDATS participants were properly instructed and indicated their consent to participate by signing an appropriate consent form, approved by the Legal Services Office of the University of Bern. The participants explicitly consented to the anonymous analysis of the data they provided and were informed about the applicability of the Data Privacy Act of the Canton of Berne (Datenschutzgesetz des Kantons Bern – KDSG; BSG 152.04, from 19.02.1986). This procedure of collecting and analysing anonymous user data conforms to the regulations of the Bern cantonal ethics committee (https://www.gsi.be.ch/de/start/ueber-uns/kommissionen-gsi/ethikkommission.html) and the accompanying federal act on research involving human beings in Switzerland (https://www.fedlex.admin.ch/eli/cc/2013/617/en). For this reason, we did not seek further ethical approval from cantonal or federal institutional bodies.

Through the example of Speaker A, we will demonstrate the construction of LMI based on SDATS metadata. Figure 1 also illustrates the steps followed in constructing LMI. Information on the data preparation, construction of LMI and data modelling can be accessed in the Supplementary Material, along with the corresponding R source code in **S1_Appendix** and **S2_Appendix**, at https://osf.io/hfbpk/.

Implementing the LMI framework started by determining the relevant linguistically influential factors that could be retrieved based on the speakers' biographical data. We constructed the following factors: mother, father, long-term partner (henceforth: partner), residence where a speaker has lived outside the reference locality (henceforth: external residence), place of ongoing education and current workplace. Each factor contributes to LMI, in the manner detailed below.

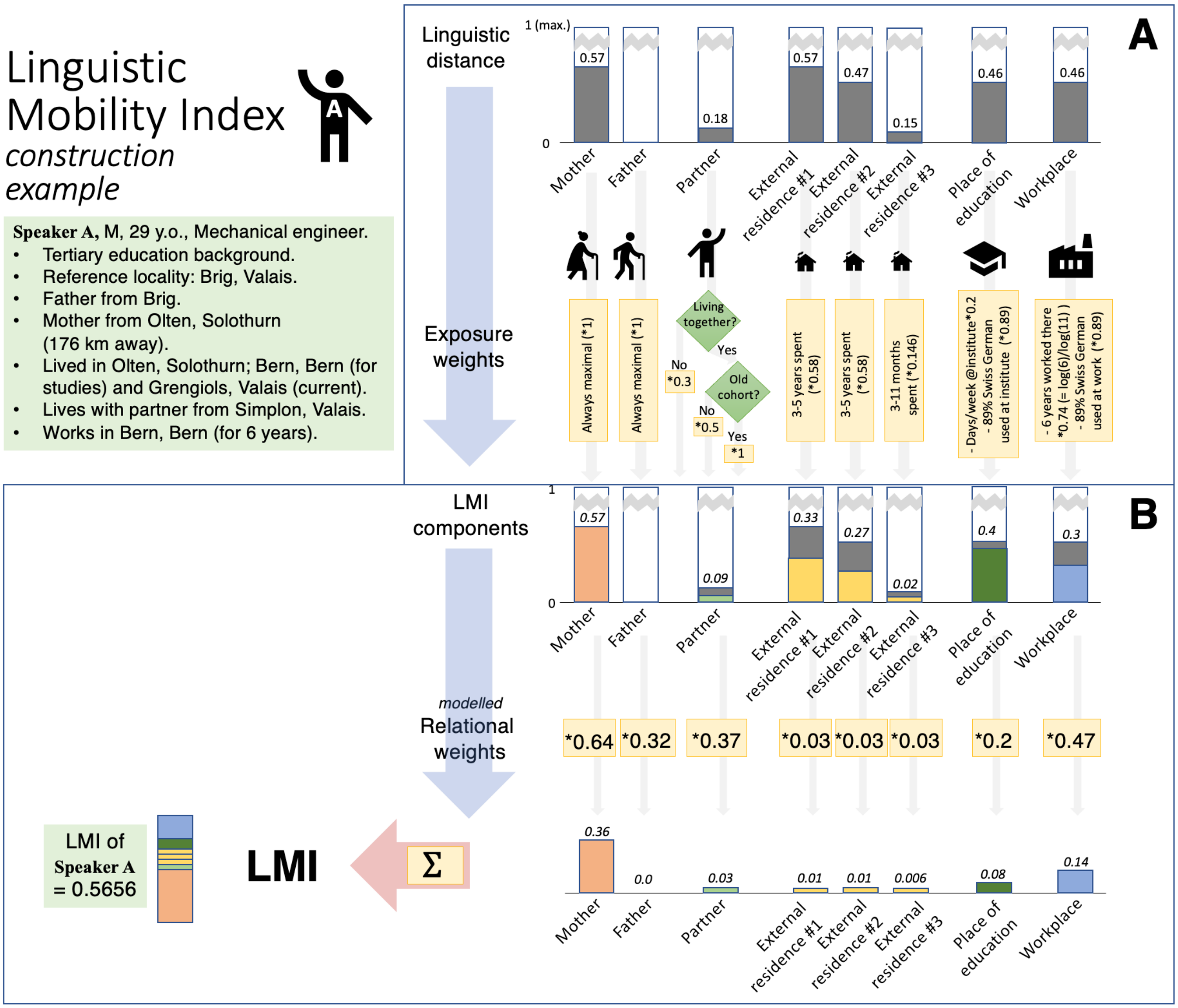


Figure 1 **Example calculation of LMI components, demonstrating the three main steps of the process: linguistic distance calculation, exposure weights and relational weights.** The linguistic distance values are multiplied by the exposure weights and by the relational weights, and then the results are summed.

Linguistic distance

The potential linguistic effect of a factor on a speaker is quantified by calculating a linguistic distance. As the first step in this quantification, a locality is assigned to the factor through geocoding. A linguistic distance is then calculated between the reference locality of the speaker and the locality assigned to the factor.

We assigned an SDS survey locality (n=565) to each factor in the following way. In R [42] (version 4.0.4.), the locality names associated with the factors, as recorded in the metadata questionnaire, were matched to geographical coordinates by means of geocoding, using the *tidygeocoder* package [43] (version 1.0.3.). Then, solving point-in-polygon problems using the Voronoi polygons of SDS localities, the closest SDS survey locality was assigned to the factor with the help of the *sf* package [44] (version 1.0-2.). Speaker A named Bern as the locality of his workplace. Geocoding returned the geographic coordinates of the capital city, Bern. The point-in-polygon routine then determined that the coordinates are found in the Voronoi polygon of the SDS locality 'Bern'.

As the next step, linguistic distances were determined between the assigned locality and the reference locality of the speaker. These linguistic distances were calculated based on Goebl's Relative Identity Value RIV_{jk} [45], using a portion of the SDS variables (289 linguistic variables: 107 phonetic, 118 morphosyntactic and 64 lexical variables), which were digitised by Scherrer and his colleagues [46], and spanning from 0 to 1 (i.e. 0=linguistically identical and 1=total linguistic discrepancy). Based on this data, a linguistic distance matrix was set up, consisting of linguistic distances for each pair of SDS localities, calculated as follows [47]. For each linguistic variable, variant categories were constructed based on phonetic similarity. Within these variant categories, a further distinction was made between subvariants. The linguistic distance between a locality pair is the proportion of variables (among those n variables that had data for both localities) that differ regarding the variant categories. If the variant categories match for a variable, but the subvariants differ, the linguistic distance still grows by a smaller amount. At variable level this can be written as

$$D_{ij}^{ling} = \frac{\Sigma D_Q}{n}$$

where D_Q is the number of differing variables regarding localities i and j. For the workplace of Speaker A, the linguistic distance between Bern and Brig (the reference locality of Speaker A) amounts to 0.46, which means that about half of the linguistic features considered are different across the two localities.

The linguistic effect of the reference locality received a flat rate of 0 because it is known that the speakers grew up in the reference locality and, lacking additional information, we infer the peer effect to be local in the first 10–20 years of language acquisition. The same is the case for places that are officially not German speaking, as we do not consider their linguistic impact on the speaker's dialect. Places in Germany and Austria, representing Standard German, received a flat rate of 0.5 as linguistic distance, regardless of possible local dialectal influence. As a matter of fact, there are fewer than 200 places in Austria and Germany among the 3000+ places geolocated.

Exposure weights

Using *exposure weights*, which quantify the intensity of the speaker's contact with the factors, we fine-tuned the degree to which the effect of a factor is considered in LMI. The factors may have various associated parameters in the metadata, which can be compiled into weights to quantify the factors' linguistic influence on the speaker. For each factor, linguistic distance is multiplied by the exposure weight value (ranging from 0 to 1). For Speaker A's workplace, for example, the exposure weighting involves the proportion of Swiss German and Standard German used at work, and the years he has been working there, and was implemented as a multiplication (Figure 1). Exposure to Standard German among the calculation of exposure weights also used the flat rate of 0.5. Exposure weights are specific to the kinds of factors included and regulate the effect of these factors across speakers. The calculation of the exposure weights for each factor are explained in detail in **S1_Appendix**.

Relational weights

Linguistic exposure also depends on the nature of the relation an individual has to the locality (e.g. through a certain contact person or life situation). We can assume more intensive contact with the local variety through a person that is most likely from the locality in question (e.g. a partner) than through a factor more vaguely connected to the locality (e.g. studies, workplace) through which the speaker potentially meets a more mixed linguistic community.

Relational weights are independent of metadata items and of the possibility to calculate exposure weights. For a specific factor, every speaker receives the same relational weight as a multiplier to differentiate the assumed effect, for example, of the workplace from the effect of other factors, such as parents. In the case of Speaker A, after multiplying the linguistic distance pertaining to his workplace with the exposure weight as the quantifier of the intensity of his contact with the workplace (Figure 1A), this was also multiplied by the relational weight associated with workplace as a factor, 0.47 (Figure 1B).

To assign objective weights for the current study, we implemented a modelling procedure. We set up four mixed-effects models for estimating relational weights for specific factors, using their corresponding β-coefficients as relational weights:

- Relational weight of 'place of education' for those currently in education (n=119);
- Relational weight of 'partner' for those with a partner identified in the metadata (n=351);
- Relational weight of 'workplace' for those that indicated a workplace (n=306); and
- Relational weights of 'mother', 'father' and 'external residence' in a general model (n=500).

The models use the unweighted linguistic distances as fixed effects alongside the control variables age, sex and educational background, all of which were considered in the participant selection of the SDATS survey (henceforth: survey design variables). The models predict a dialect change rate based on ten lexical variables (also used for the evaluation of LMI, thus detailed further). Speaker identifier and the linguistic variable are used as random intercepts in the models. In terms of the missing values we used bootstrapped regression imputation to impute values for the partner's and the workplace's linguistic distance, with the help of the *mice* package [48] (version 3.14.0). For the details of this modelling procedure, see **S1_Appendix**. The resulting relational weights are highlighted in Figure 1B.

Setting up the LMI prototypes

We constructed four LMI prototypes based on the factors, exposure weights and relational weights. The prototypes are related to different theoretical considerations and simulate possible scenarios of metadata availability. We assigned a name and an abbreviation to each prototype. Table 1 presents the components involved in each LMI prototype along with the weights associated with the factors involved.

Minimal prototype (LMI^A)

The minimal prototype simulates a survey where only a little background information is available about the speakers. We included the origin of the father and the origin of the mother as factors, considering that many surveys include this information to account for authenticity. The factors are weighted only by relational weights.

Cumulative prototype (LMI^B)

Surveys often elicit various pieces of background information (e.g. origin of parents, partners and peers, former places of residence, places of education and work) without gathering detailed information about the possible effect of these localities (e.g. [49]). The cumulative prototype sums up the linguistic distances from all factors in a linear manner, disregarding exposure weights and using only the relational weights. Maximising the effect of each factor (i.e. each locality) considered, this prototype basically cumulates influential factors in a linguistic biography, assigning dialectal locations to them.

Comprehensive prototype (LMI^C)

All the aforementioned factors' effects (i.e. mother, father, partner, external residence, workplace and place of ongoing education) are included in LMI^C, using exposure weights and the relational weights associated with them. The parameters of this prototype correspond to a scenario where a larger range of metadata is elicited from which one could estimate exposure weights for some of the components.

Cohort-based prototype (LMI^D)

The cohort-based prototype is tailored for the specific situation in SDATS. It accounts for the increased mobility of the last 50 years through assessing the history of potential exposure in the two age cohorts differently. The younger SDATS cohort (20–35 y.o. in 2020) has grown up in different circumstances regarding dialect acquisition and change compared to the older cohort (60–80 y.o. in 2020) [19]. With societal changes, the increasing likelihood of geographical mobility and the access to a wider variety of media, the younger cohort has potentially more intense exposure to other dialects and to the standard language than the older cohort did at the same age. As we will show later, age is the strongest design variable in our survey to explain language change: younger speakers tend to show more dialect change. This is also because more time has elapsed between the SDS and the younger speakers' dialect acquisition, allowing more time for dialects to change. That is, the younger cohort has a different baseline against which their dialect might change over their lifespan [21]. Although dialect-related identities and attitudes may also change, in the case of Swiss German, the SDATS data shows that the strength of identity is maintained [50].

The relational weights are constant across the LMI prototypes. For LMI^D , however, we have implemented age-cohort-based relational weights for the 'workplace' and 'external residence' factors (**S1 and S2_Appendix**), incorporating information that age provides about the speakers and overcoming the difference in the metadata available about the two cohorts. This allows the younger cohort to gain higher LMI values than in the other LMI prototypes.

Table 1 Composition of the four LMI prototypes.

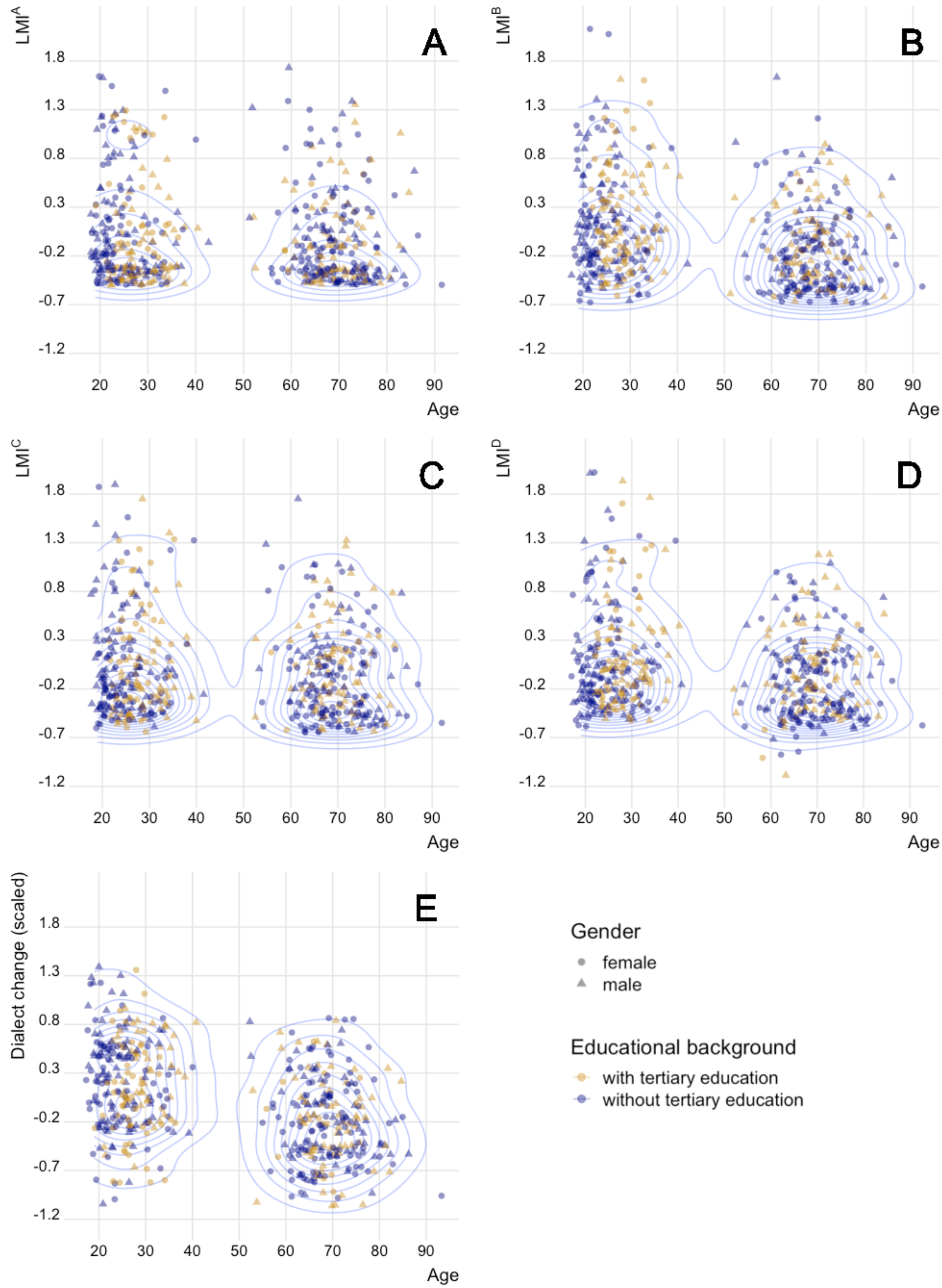
Factor	LMI^A	LMI^B	LMI^C	LMI^D
Mother's origin	Ling. Dist.* 0.6351	Ling. Dist. * 0.6351	Ling. Dist. * 0.6351	Ling. Dist. * 0.6351
Father's origin	Ling. Dist. * 0.317	Ling. Dist. * 0.317	Ling. Dist. * 0.317	Ling. Dist. * 0.317
Partner's origin	-	Ling. Dist. * 0.3461	Ling. Dist. * $weight_{exposure}$ * 0.3461	Ling. Dist. * $weight_{exposure}$ * 0.3461
External residence	-	Σ Ling. Dist. * 0.0319	Σ Ling. Dist. * $weight_{exposure}$ * 0.0319	Older cohort: Σ Ling. Dist. * $weight_{exposure}$ * 0.0206 Younger cohort: Σ Ling. Dist. * $weight_{exposure}$ * 0.1663
Workplace	-	Ling. Dist. * 0.4728	Ling. Dist. * $weight_{exposure}$ * 0.4728	Older cohort: Ling. Dist. * $weight_{exposure}$ * -0.8728 Younger cohort: Ling. Dist. * $weight_{exposure}$ * 0.6061
Place of education	-	Ling. Dist. * 0.2023	Ling. Dist. * $weight_{exposure}$ * 0.2023	Ling. Dist. * $weight_{exposure}$ * 0.2023

Relational weights are indicated numerically.

Table 1 summarises the components included in the four LMI prototypes and the corresponding weighting.

Evaluating LMI as a predictor of dialect change

We will evaluate LMI by testing the performance of the four prototypes as predictors of dialect change. Figure 2A–D shows the relation of the four LMI prototypes to age, with the shape of the symbols representing sex and colours representing educational background. Speakers without tertiary education appear to be less mobile, while a number of younger speakers with no or ongoing higher-level education form a cluster on the left side of Figure 2A–D. For comparison, Figure 2E presents the relation of age, sex, educational background and the dialect change rate used for the evaluation. All panels in Figure 2 show that younger speakers have, on average, a slightly higher LMI and dialect change rate, respectively.



A
B
C
D
E
LMI^A
LMI^B
LMI^C
LMI^D
Dialect change (scaled)
1.8
1.3
0.8
0.3
-0.2
-0.7
-1.2
20
30
40
50
60
70
80
90
Age
Gender
female
male
Educational background
with tertiary education
without tertiary education

Figure 2 ***Distribution of LMI and dialect change with regards to age.*** *In Panels (A)-(D) the distribution of standardised* LMI^A, LMI^B, LMI^C *and* LMI^D *values are shown (y-axes) against the age of the speakers (x-axes). Panel (E) shows the distribution of standardised dialect change rates, against the age of the speakers. Each point represents a speaker (n=500). Point colour represents educational level and shape represents sex. The blue concentrical lines show the density of speakers.*

To test the utility of LMI as a predictor of language change, the four LMI prototypes were modelled as fixed effects in logistic mixed-effects regression models. We expect the model results to confirm, while controlling for the survey design variables, that linguistically mobile speakers have higher rates of dialect change and less mobile speakers have lower rates. The outcome variable explained in the models is change rate in lexical variables, calculated based on ten items (Table 2) recorded at 125 survey localities which were included in both SDS and in SDATS, approximately 70 years apart. The ten lexical items were chosen to represent maximal expected variation in terms of dialect change and different word frequencies. Lexical items, also including those investigated by [19], were chosen specifically to capture substantial dialect change as the lexical level changes faster compared to grammatical linguistic levels [51]. Table 2 shows the rates of change in the 500 speakers and the word frequency in Switzerland in 2019 based on Google Books Ngrams [52]. Most change occurred in the word 'freckles' (*Std. Germ.: 'Sommersprossen'*) followed by 'butterfly' (*Std. Germ.: 'Schmetterling'*), while other lexical items show a smaller, comparable rate of change. The goal of the modelling for this evaluation was neither to find the perfect model for predicting dialect change nor to explain language change at the level of individual SDATS speakers or linguistic items. The evaluation also tests whether LMI has validity for explaining dialect change that may not have happened within the lifetime of the speakers, but which is partly hereditary.

Table 2 The ten lexical items used in the evaluation study.

SDS map number	**Standard German**	**Dialectal variants**	**English**	**Proportion of change from SDS**	**Frequency in Switzerland in 2019**
V 179	Butter	Butter, Schmalz, Anke etc.	butter	33.2%	0.001'425%
VI 237	Schmetterling	Summervogel, Fifolter, Schmätterling etc.	butterfly	48.4%	0.000'316%
V 212	Bonbon	Zuckerli, Täfeli, Tröpsli, Bombom, Guetsch etc.	(hard) candy	29%	0.000'073%
IV 17	Wange	Wang, Wang(j)i, Backe (with or without fricative second consonant)	cheek	36.4%	0.003'38%

IV 43	Sommersprossen	Laubfläcke, Summersprosse, Merzetupf, Merzedräck etc.	freckles	72.8%	0.000’234%
IV 71	Schluckauf	Hitzgi, Gluggsi, Hixer, Hösch etc.	hiccup	41.8%	0.000’065%
V 21	Kuss	Kuss, Schmutz, Müntschi, Muntsi etc.	kiss	28%	0.004’093%
VI 179	Zwiebel	Zibele, Zwible, Bele, Böl(l)e etc.	onion	28%	0.000’55%
VI 40	Pfütze	Glunte, Gumpe, Gülle, Gudle, Glungge, Lache, Pütze etc.	puddle	42%	0.000’231%
V 139, V 140	Taschentuch	Nastuech, Naselumpe, Schnupftuech, Fazeneetli etc.	tissue (hanky)	28.2%	0.000’787%

The data on word frequency in Switzerland in 2019 comes from Google Books Ngrams, based on the Standard German version of the words.

Predictors of dialect change

Dialect change rates show differences with regard to age, sex and educational background. We test these empirical observations, often used in sociolinguistics for dialect change modelling, in simple linear regression models and we control for them in the mixed-effect models of the evaluation. Due to the differing baselines of dialect change, we expect that any predictor of language change would deliver more noisy results for the younger cohort, which makes it crucial to control for age cohort in our study. The baseline for dialect change would also be expected to vary in space, making the spatial origin of individuals an important predictor of dialect change. However, in this evaluation, we avoided including spatial variation directly in the modelling due to the following reasons. On the one hand, accounting for spatial variation in Switzerland may not bring additional value to establishing LMI as a *general* framework for language change studies, which may include scenarios where spatial variation in the speaker sample is irrelevant. On the other hand, four speakers in 125 survey localities is not an optimal number for accounting for categorical effects in tests that assume normality. To characterise the spatial distribution of the dialect change rate and linguistic mobility, we tested the similarity of localities with regard to the values (using the Kruskal-Wallis test) and the clustering of values in space (measuring the spatial autocorrelation using Moran’s I). Additionally, we tested the effect of urbanity, operationalised based on the population of the SDATS survey sites in 2018.

Mixed-effects modelling

The mixed-effects modelling was implemented in *R* using the *lme4* package [53] (version 1.1-27.1). Each observation in the dataset represents a combination of a speaker (*n*=500) and an item (*n*=10), amounting to 4983 observations after removing invalid or missing answers. As fixed effects, each model includes one of the four LMI prototypes, together with the survey design variables (Table 3). All fixed effects were z-standardised (Equation 2) to facilitate the interpretation of the model results [54].

[Equation 2 about here]

$$\frac{x-\mu_x}{2\sigma_x}$$

Binary fixed effects were contrast coded to zeroes and ones in the order of expected dialect change (z-standardised to -0.5 and 0.5). The standardised LMI values range between -1.62 and 2.14. Due to the presence of pseudoreplication (all speakers answered each of the ten questions), we included speaker and item as random effects in the mixed-effects models. This also controlled for the differences in the frequency with which words occur, as more frequent forms are expected to be more resistant to change [55]. Collinearity was tested through the analysis of variance inflation factors (VIFs), using the *car* package [56] (version 3.0-10.), resulting in values only slightly larger than 1; thus, collinearity problems were not expected. For more details, consult S2_Appendix.

Table 3 The variables entered in the mixed-effects models of the evaluation

Outcome variable	
Dialect change in item	Change (1), or no change (0) in comparison to SDS data in the same locality
Fixed effects	
Linguistic Mobility Index (LMI)	Continuous variable – One of the four LMI prototypes, z-standardised (the four LMI prototypes LMI^A, LMI^B, LMI^C and LMI^D are used in separate models)
Age cohort	Binary variable – ‘older’ > 45 years (-0.5); ‘younger’ < 45 years old (0.5)
Sex	Binary variable – female (-0.5) and male (0.5)
Highest completed education	Binary variable – with tertiary education background (-0.5) or without (0.5)
Random effects	
Speaker	*n* = 500
Item	*n* = 10

Results

In this section we report the outputs of the mixed-effects models described above, in order to evaluate the LMI framework as a useful heuristic for language variation and change studies. In addition, to contextualise the correspondence of linguistic mobility and dialect change, we characterise the spatial patterns of dialect change rate and the LMI prototypes. First, however, we briefly explore simple linear regression models of the survey design variables, LMI prototypes and dialect change. Age cohorts and sex are statistically significant predictors of dialect change, while the difference relating to education is not (see also Figure 3). The younger cohort shows more change (μ = 47.03%, *SD* = 18.75%) than the older cohort (μ = 30.8%, *SD* = 17.18%), with slightly more change occurring among males (μ = 40.77%, *SD* = 20.16%) than among females (μ = 37.07%, *SD* = 19.13%). In terms of the four LMI prototypes (scaled and centred), although all four show significant predictive power, the correlation coefficients determine that LMI^{B} (the cumulative prototype, R^2 = 0.1073) and LMI^{D} (the cohort-based prototype, R^2 = 0.1014) are better as sole predictors of the dialect change rate than the other prototypes (Figure 4).

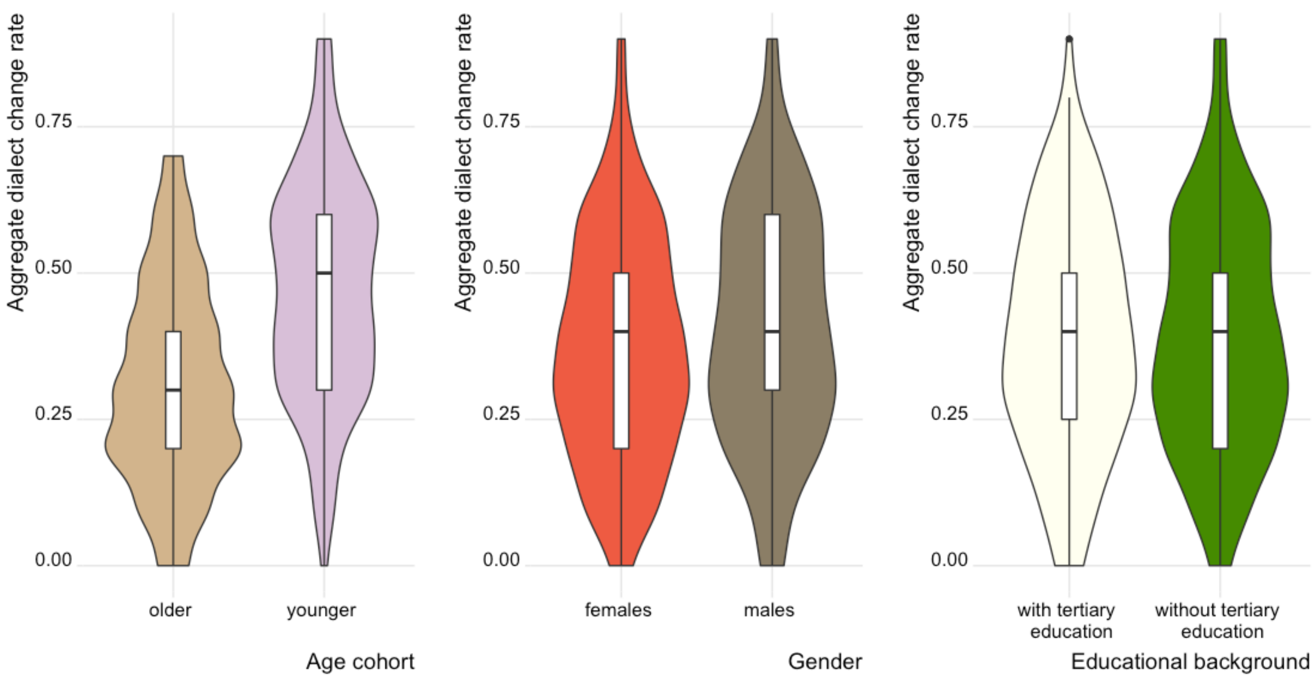


Figure 3 Dialect change rate for the ten lexical items by age cohort, sex and educational background

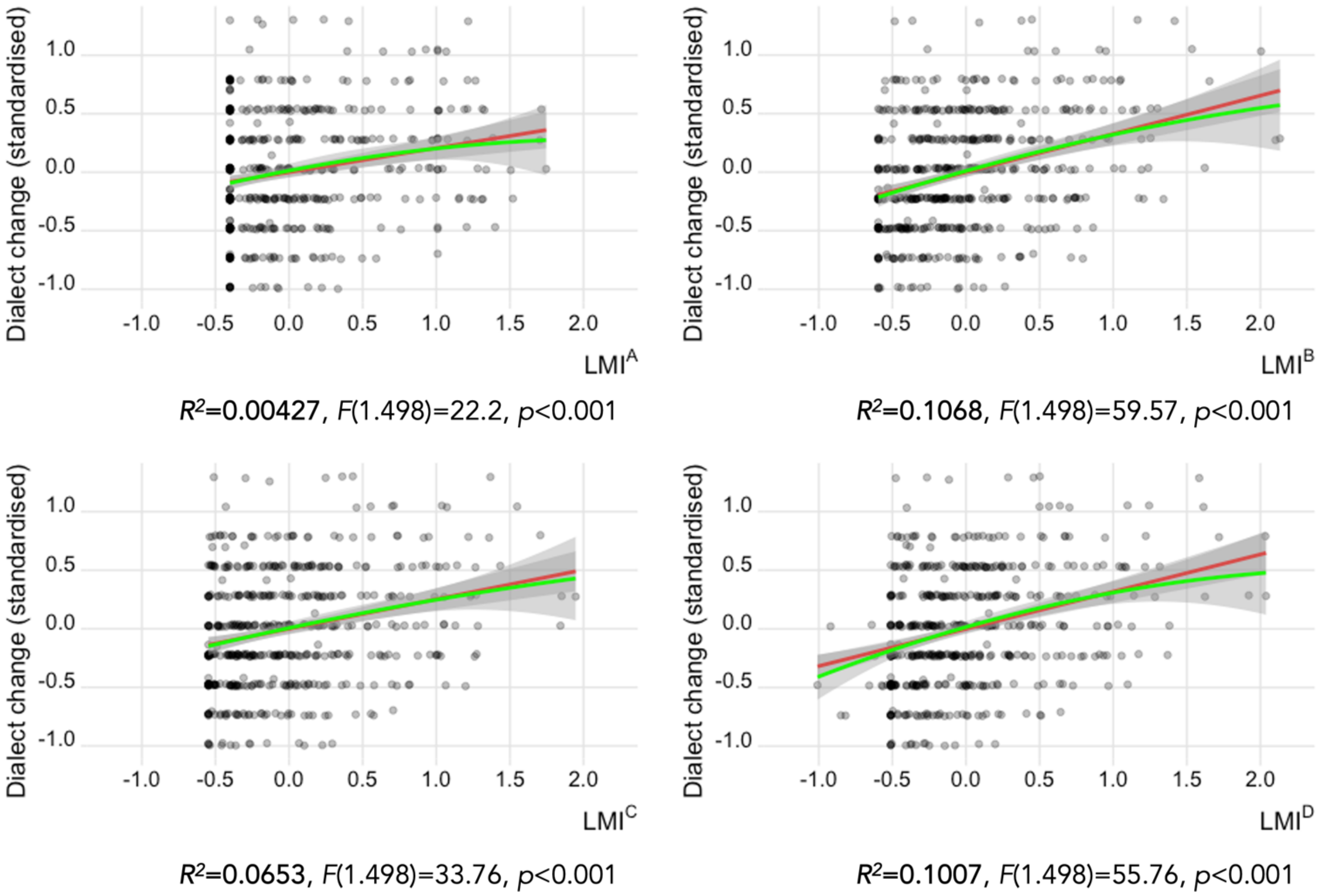


Figure 4 The relation of the four LMI prototypes to the dialect change rate. *LMI values and dialect change rates are standardised. The panels also show the numerical results of the linear regression models. Linear (red) and second-order polynomial regression lines (green) show the major trends. The slope of the lines shows the positive correlation.*

In the mixed-effects models, fixed effects prove to be significant predictors, except for educational background (Table 4). The LMI prototypes' predictive power in increasing order of their *z*-values is A (minimal), C (comprehensive), B (cumulative), D (cohort-based). Their highly significant effects are coupled with low standard error (*SE*). The smallest *AIC* (Akaike Information Criterion), characterising model quality, also belongs to LMI^{D}, which makes it the best model out of the four. Slope estimates and *SE* are on the log-odds scale and must be exponentiated for a more accessible interpretation. For example, two standard deviations of increase in LMI^{B}, $e^{0.4395} = 1.5519$ and the corresponding *SE*, $e^{0.0784} = 1.08155$ mean a 55.19% (± 8.15%) increase in odds for dialect change.

Table 4 Output of the mixed-effects models involving the survey design variables of the SDATS.

LMI^{A}	**Model quality**	*AIC* 6129.63	**Random effects**	$SD_{speaker}$ 0.4809	SD_{item} 0.6130
	Fixed effects	*estimate*	*SE*	*z-value*	*p*

	LMI	0.3486	0.0755	4.6152	<0.001
	Age cohort	0.7691	0.0771	9.9754	<0.001
	Sex	0.2022	0.0777	2.6025	0.0093
	Education	0.0901	0.0811	1.1105	0.2668
LMI^B	**Model quality**	*AIC* 6119.76	**Random effects**	$SD_{speaker}$ 0.4663	SD_{item} 0.6129
	Fixed effects	*estimate*	*SE*	*z-value*	*p*
	LMI	0.4395	0.0784	5.6041	<0.001
	Age cohort	0.6681	0.0789	8.4704	<0.001
	Sex	0.1919	0.0769	2.4942	0.0126
	Education	0.1374	0.0806	1.7055	0.0881
LMI^C	**Model quality**	*AIC* 6120.18	**Random effects**	$SD_{speaker}$ 0.4672	SD_{item} 0.613
	Fixed effects	*estimate*	*SE*	*z-value*	*p*
	LMI	0.4203	0.0755	5.5694	<0.001
	Age cohort	0.7596	0.0764	9.9386	<0.001
	Sex	0.1797	0.077	2.3325	0.0197
	Education	0.1228	0.0804	1.5264	0.1269
LMI^D	**Model quality**	*AIC* 6115.63	**Random effects**	$SD_{speaker}$ 0.4602	SD_{item} 0.6129
	Fixed effects	*estimate*	*SE*	*z-value*	*p*
	LMI	0.4602	0.077	5.9714	<0.001
	Age cohort	0.6934	0.0773	8.9693	<0.001
	Sex	0.1859	0.0766	2.4261	0.0153
	Education	0.1264	0.0801	1.5779	0.1146

For each model variant, containing one of LMI^A, LMI^B, LMI^C or LMI^D, fixed-effect coefficients are shown in yellow, while the standard deviations of random effects are shown in green and the AIC of the model in blue.

In the case of each LMI prototype, the predictive power of age cohort shows a decisive effect. They are significant, with estimates larger than LMI's estimates and a *SE* similar to LMI's *SE* values in each case. Age cohort reaches the highest estimate and z-value in the case of LMI^A and LMI^C where, in turn, LMI estimates are lower compared to LMI^B and LMI^D. The effects of sex are significant and show similar slope estimates across the prototypes. Relative to the slope estimates of age cohort and LMI, *SE* values of sex are higher. Educational background does not have a significant effect for any LMI prototype (although it is almost significant in LMI^B), and its *SE* values are high. Comparing the different predictors, LMI emerges as a better predictor than sex and education in every case. The effect of age cohort dominates over the other variables, while the effect of sex is larger than that of education.

A heuristic explanation of the importance of the random effects is provided by comparing their standard deviation (*SD*) to the estimate of a fixed effect. If the *SD* of the random effects is larger than the LMI prototypes' slope estimates, this means that the speaker and item effects are larger than the effect of LMI. Note that SD_{item} is practically the same for every model as the fixed effects are related to the speaker rather than the item.

Adding an interaction term between age cohorts and LMI means a small, but significant, increase for LMI^A (Table 5). This fact and the negative slope estimate indicate that the difference in LMI's effect is smaller than expected within the younger cohort compared to that in the older cohort. Not observing an interaction between these variables in the other models tells us that the effect of LMI does not depend on age cohort and therefore LMI is a predictor of similar worth in both age cohorts. Submodel ranking, using the *MuMIn* package [57] (version 1.43.17.), detailed in **S2_Appendix**, shows all fixed effects as significant contributors to the model quality.

Table 5 Addition of an interaction term between age cohort and the minimal LMI prototype.

LMI^A	**Model quality**	*AIC* 6125.35	**Random effects**	$SD_{speaker}$ 0.4710	SD_{item} 0.6132
	Fixed effects	*estimate*	*SE*	*z-value*	*p*
	LMI	0.3754	0.0756	4.9662	<0.001
	Age cohort	0.7716	0.0766	10.0723	<0.001
	Sex	0.1998	0.0772	2.5886	0.0096
	Education	0.0921	0.0806	1.1432	0.2529
	LMI*Age cohort	-0.3805	0.1509	-2.5206	0.0117

Table 6 Spatial characteristics of the dialect change rate and the LMI prototypes, using the Kruskal-Wallis test and measuring the spatial autocorrelation using Moran's I

	Dependence of distribution (Kruskal-Wallis test)			**Spatial autocorrelation (Moran's *I*)**			
	χ^2	*df*	*p*	*I*	$I_{expected}$	*SD*	*p*
Dialect change rate (10 variables)	266.82	124	< 0.001	-0.0223	-0.002	0.0012	< 0.001
Minimal (LMI^A)	141.17	124	0.1388	-0.004	-0.002	0.0012	0.0946
Cumulative (LMI^B)	155.14	124	0.0305	-0.005	-0.002	0.0012	0.0013
Comprehensive (LMI^C)	152.06	124	0.0442	-0.0053	-0.002	0.0012	0.0068
Cohort-based (LMI^D)	153.02	124	0.0394	-0.0055	-0.002	0.0012	0.0034

To contextualise linguistic mobility and dialect change with spatial processes, we provide our insights regarding the spatial distribution of dialect change and LMI. Although a Kruskal-Wallis test (Table 6) shows significant differences across our 125 localities with regard to the dialect change rate based on the ten lexical variables ($\chi^2 = 266.82$, $df = 124$, $p < 0.001$), these also stem from the different regional baselines regarding dialect change, i.e., there is also spatial variation in the lexical items in the SDS. Regarding LMI prototypes, we also find significant local differences using the Kruskal-Wallis test, except in the case of LMI^A.

Due to the aforementioned, potentially different, regional baselines of dialect change and the regional variation present in Swiss German dialects, we will address the expected correspondence of spatial patterns in the dialect change trends and linguistic mobility. In the polygons of the 125 SDATS survey sites, Figure 5A and 5C chart the dialect change rates, while Figure 5B and 5D show the LMI^D values, for the two age cohorts. Urban areas are traditionally associated with more dialect change [58]. Those SDATS localities that had more than 10,000 inhabitants in 2018, qualifying for the 'city' rank in Switzerland, are shown with magenta edges. It is visible from the maps in Figure 5A and C, however, that urban areas, especially in the cantons of Bern (BE) and Zurich (ZH), show the least dialect change in both age cohorts. Population of the survey localities shows a significant negative linear correlation with language change ($R^2 = 0.032$, $F(1,498) = 16.4824$, $p < 0.001$), meaning that the higher the population, the less language change can be expected. Dialect change in the non-urban areas below 10,000 inhabitants ($\mu = 40.06\%$, $SD = 19.12\%$) is almost significantly higher ($t = 1.9069$, $df = 498$, $p = 0.057$) than in the urban areas ($\mu = 36.47\%$, $SD = 20.78\%$). As the largest urban localities change remarkably less than rural areas do, and urbanity is a fluid category, this definition of 'urban' seems to influence the result of the test. Also, contrary to naive expectations, rural and mountainous areas, especially in the centre and south-east (e.g. cantons of Lucerne, Nidwalden, Obwalden, Uri and Valais – LU, NW, OW, UR, VS, respectively), show the most dialect change in the younger cohort. Moran's *I* analysis, however, shows significant negative spatial autocorrelation in dialect change rate ($I = -0.0223$, $SD = 0.0012$, $p < 0.001$). This means that there is a higher likelihood of finding different dialect change rates in nearby localities rather than similar ones. In other words, dialect change does not cluster in space.

Geographic patterns of LMI^D also show a negative spatial autocorrelation ($I = -0.0055$, $SD = 0.0012$, $p < 0.0034$) with little visual similarity across the age cohorts (Figure 5B and D) except in rural parts of BE and LU, and the generally suburban region of ZH. Regarding the spatial autocorrelation of the other LMI prototypes, Moran's I values are also negative, i.e., mobile or non-mobile speakers do not cluster in space. LMI, thus, cannot be safely interpreted as a function of geography in our sample. Although trends of slight correspondence were seen in Figure 4, visual inspection of Figure 5 does not reveal spatial correspondence between LMI^D and dialect change rates except for parts of BE and ZH being less mobile and showing less change. A table containing all 125 SDATS localities with their average dialect change rates and LMI values can be found in **S2_Appendix**.

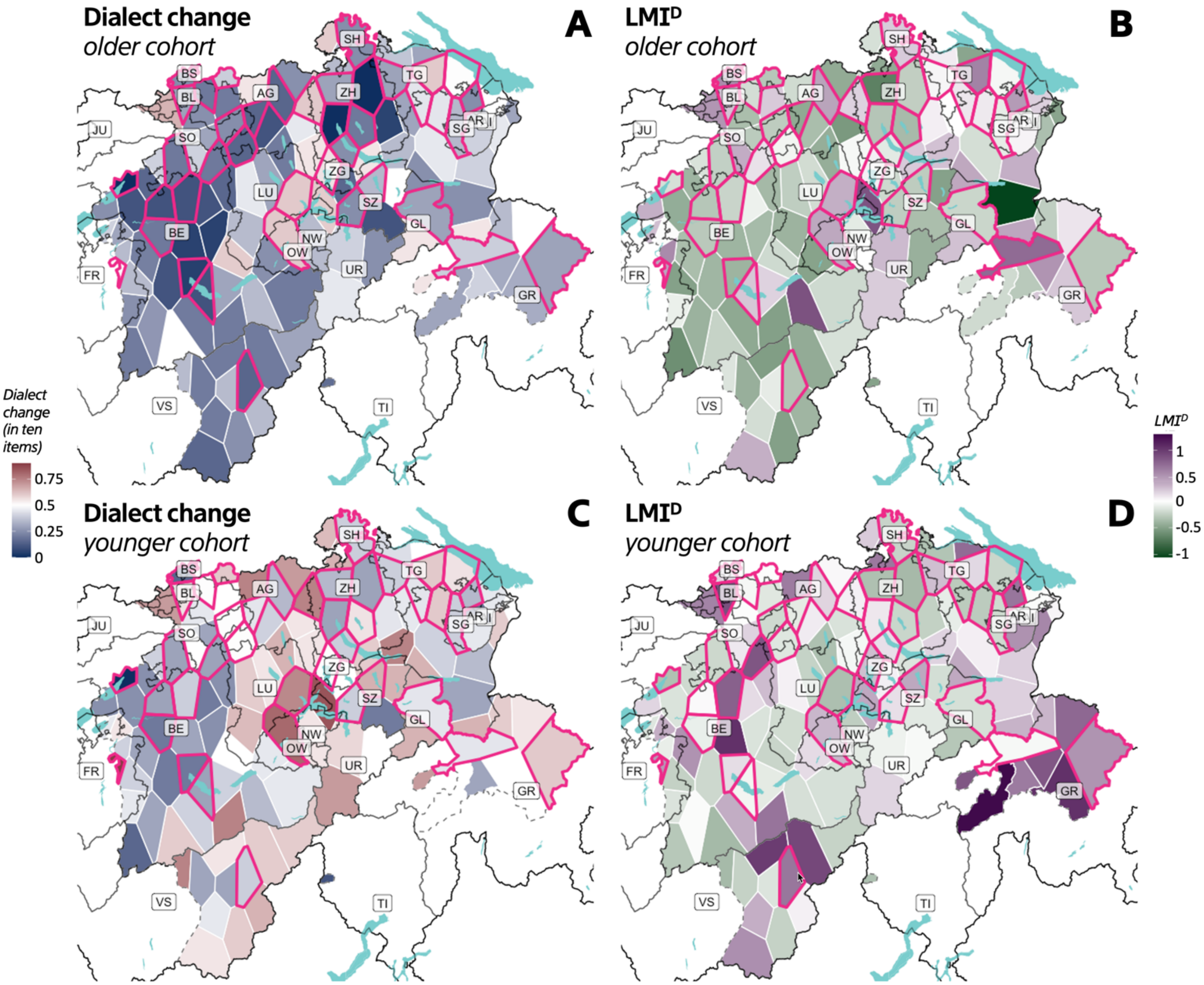


Figure 5 Spatial patterns of dialect change rates and LMI^D. Panels (A) and (C): the average rates of dialect change are shown (on a scale of 0 to 1) in the polygons representing SDATS localities. Panels (B) and (D): the standardised LMI^D values of each SDATS locality are shown with a different colour scale. The darker blue and green colours (respectively) mean a lower value, while the darker red and purple colours mean higher values. In each map, those SDATS survey localities qualifying for the city rank in Switzerland are highlighted with magenta edges.

Discussion

In this section we discuss LMI as a practical framework for researchers analysing language variation and change by reflecting on its composition and evaluation in our study. Following this, we present the limitations of LMI and its implementation, and make further suggestions about adapting the LMI framework for use in other studies.

LMI as a useful framework for language variation and change studies

With the growing (spatial) mobility of the modern world, any linguistic survey dealing with spatial variation must consider the mobility of its participants. To this end, many previous studies used an estimation for the 'localness' of a dialect by measuring the exposure of the participants to a reference locality, such as by applying the principles of the Regionality Index [1,15–17]. While RI shows the exposure to the reference dialect, LMI, in the form in which we implemented it, quantifies the exposure to variation outside the reference dialect. Without claiming its superiority in every scenario, if the availability of metadata allows, we suggest implementing LMI as a quantitative indicator of exposure for purposes similar to that of RI, for the following reasons.

Mobility has been shown to influence language change in several languages, including in theoretical work (e.g. [3,9,10]) and in studies on different linguistic levels [1,2,5,6,8], less complex from the point of view of metadata. Thus, we suggest that a more extensive quantitative explanatory factor aggregated from linguistic biography data would be successful for the task of elucidating the effect of mobility on language change. Our contribution shows the wider applicability of LMI by evaluating prototypes that simulate differences in metadata availability and theoretical considerations. In addition, our data features different baselines of dialect change (due to the different age cohorts in the data). Moreover, the LMI framework, consisting of setting up linguistic distances or judgements and weighting them by exposure and relational weights, is flexible as these steps can be tailored to the needs of the researcher and according to the available data. A further advantage of LMI is its cumulative nature, also enabling comparison across individuals when data is missing, which would otherwise affect statistical (e.g. mixed-effects) modelling.

Discussion of the findings specific to the application to SDATS data

The evaluation was conducted through modelling dialect change in Swiss German using the LMI prototypes and the SDATS survey design variables (age, sex, educational background). Our evaluation tested whether the patterns of linguistic mobility characterising speakers that acquired their dialect under different circumstances (due to age, education, residency etc.) are suitable predictors of language change patterns that might not be the direct consequences of the speakers' dialect acquisition.

This complex language change task makes the evaluation of the predictors difficult in terms of establishing causality, although the spatial diversity and covert prestige make Swiss German dialects an ideal environment for actual mobility-induced change to be present, as opposed to media- or prestige-induced change, for example. From the point of view of demonstrating the usefulness of LMI, the performance of the LMI prototypes beyond the fact that they are meaningful predictors is not of great importance.

In the Swiss German context, the results of the mixed-effects models can be interpreted in line with expectations: speakers with higher linguistic mobility (LMI) show more dialect change (Table 4). This corresponds to previous observations showing that being sedentary is a countereffect for dialect change in the Swiss German context (e.g. [19,39]). Each LMI prototype proved to be a significant predictor when controlling for the survey design variables (Table 4). Beside the mixed-effects model, we also showed the role of age and sex on dialect change in bivariate tests (visually in Figure 3), and linear regression models relating the LMI prototypes to language change (Figure 4) showed the cumulative LMI^{B} and cohort-based LMI^{D} as better sole predictors over the others. Regarding LMI, differences across the distribution of its prototypes also reflect the role of age (Figure 2A–D): no clear age-related pattern is present for LMI^{A}, but to a certain degree other prototypes show higher mobility for the younger cohort. The fact that younger speakers show more dialect change, which we expect LMI to predict, indicates that it is crucial to consider age when implementing LMI for SDATS.

Amongst the LMI prototypes, LMI^{D} holds the top position (based on *AIC* and *z*-values) as a predictor. We associate this success with LMI^{D} addressing the differences between the metadata availability of the two age cohorts, a fact that makes it more complex than LMI^{C}. Its top position is not so clear, however, which means that the inclusion of the design variables as fixed effects regulates the explanatory power of the LMI prototypes. That is, the composition of the LMI prototypes affected their explanatory power less when we controlled for the design variables in the model. As the cumulative prototype (LMI^{B}), not involving exposure weights, performed similarly to LMI^{D}, we can conclude that in our study, it was not the fine-grained details of the LMI implementation that were important but rather whether we successfully captured those mobility-related factors that impact dialect change. In comparison to other predictors, LMI has a stronger effect on dialect change than sex and educational background do (i.e. an increase of two standard deviations in the LMI values increases the odds of dialect change more than binary switches in sex and educational background do), which is an additional argument in support of the usefulness of LMI.

The high $SD_{speaker}$ value compared to the slope estimates means that random effects capture more variance in dialect change than LMI, sex and educational background do. Therefore, between-speaker variation, not accounted for by the LMI prototypes, is still very important for dialect change, which means that parts of the speakers' linguistic biographies that could not be included in LMI (such as contacts not present in the metadata, personality, dialect attitudes etc.) make a difference and that local baselines of dialect change also involved in personal variation (random speaker effect) still contain crucial effects.

Corroborated by the strong age effect on dialect change shown by the bivariate statistics (Figure 3), age cohorts maintain the highest estimate in each model, again showing that the manner of including an age effect in LMI is crucial when explaining language change. The significance of the interaction of age and LMI^A (Table 5) means that the minimalistic LMI^A is a weaker predictor in terms of the age effect. The negative slope estimate of the interaction of age with LMI^A tells us that the difference in LMI's effect is smaller than expected within the younger cohort than in the older cohort.

Sex being a significant predictor in the case of each LMI prototype means that more change is expected in the dialect of men compared to that of women, when keeping age cohort, educational background and linguistic mobility constant. Slope estimates of sex are very similar across the four models, which means that their effect is not influenced by the composition of the LMI prototypes. Indeed, the LMI prototypes do not comprise any dialectal exposure in a manner directly differentiated by sex.

Educational background is not significant in any of the models, with a large *SE* diminishing its worth as a predictor. The explanation for the lack of importance of educational background may partly be due to the varied educational backgrounds being suboptimally categorised into two groups (also recall that the dataset includes many young speakers attending higher education who are not yet eligible for the 'with tertiary education' label), and the fact that social stratification does not extensively influence dialectal differences in Switzerland.

The spatial analysis, showing that LMI values and dialect change rate do not cluster or correspond to each other in space, reveals that the trends within and correspondence between LMI and dialect change are independent from their spatial variation. Low mobility may not necessarily be the cause of little dialect change. Similarly, change may not occur even in very mobile speakers. Because of the restricted linguistic sample and since SDATS speakers are more sedentary than average, we can only speculate on a cause. Perhaps the pattern is an artefact of the selected lexical variables or, due to the levelling of Swiss German variation [19,39], locally there is no longer a more prestigious variant for them to adopt.

Urban lifestyle is often associated with higher general mobility, but in our sample linguistic mobility does not correspond to this preconception (Figure 5B and D, magenta-edged polygons). Contrary to popular opinion, the population of SDATS survey localities shows a slightly negative correlation with dialect change rate across the ten items, which means that there is less dialect change in localities with a larger population. Correspondingly, rural areas in Figure 5A and C, represented by white polygon edges, show more change (white to redder hues) than cities (magenta edges), especially in the younger age cohorts. Considering the ongoing levelling, the rural population seems to align with the local urban varieties [59], although given that rural dialects often define their own identities by rejecting urban variants, this pattern might be an artefact of the linguistic sample. Intuitively, however, the spatial pattern of dialect change corresponds to the increasing geographical mobility, and thus is more difficult to unravel based on our restricted sample of linguistic items. In order to find true regional and geographic effects in dialect change, an explicit dialectometric study would be necessary, investigating a larger set of linguistic items.

Limitations

Beyond the default limitations and potential drawbacks associated with dialect surveys and their data elicitation practices, such as (socio)linguistic interviews and (unsupervised) metadata collection, the following limitations may also hinder other LMI implementations.

Owing to the limitations of the unsupervised metadata collection, inconsistent answers may always occur and some data may not be sufficient for inferences to be drawn on linguistic mobility. For example, geolocation problems arise due to the inconsistency or ambiguity of localities indicated by the speakers. The ongoing COVID-19 pandemic affected several SDATS questionnaire items directed at short-term mobility and social networks. Effects of short-term mobility were tested in two unpublished master theses in relation to dialect change [60,61], but no predictive effect was found. Additionally, questionnaire items regarding current linguistic connections do not necessarily characterise long-term contact.

Specific problems with metadata items which impact the composition of LMI include the availability of information. Information is available about the speakers' parents, their current most significant peer (the partner), place of education (if currently attending), and workplace. In addition, we can infer from different kinds of aggregate information on the reference locality, which (indirectly) indicates childhood and adolescent peer effects. There is, however, no information about the duration of contact between the speaker and the people elicited from their social networks, such as their flatmates and their closest personal and work-related peers. Regarding residence outside the reference locality, information is available about locations and the durations are recorded, but not the age at which the speaker lived there. Due to this, it was not possible to evaluate LMI by testing its predictive performance against mobility predictors based on the number of years spent away from the reference locality (cf. [6,8]). The discrepancy between the availability of information about the younger and the older cohort regarding their adolescence and other potential LMI components is also a limitation of our study. For instance, information is missing on pensioners' last workplace, as is the last place of education of those not attending any education at the time of the survey. Due to their age, the older cohort's baseline regarding dialect change is closer to the SDS, whereas for the younger cohort there is a higher probability of dialect change being inherited. This makes the older cohort more optimal subjects for assessing whether linguistic mobility impacts dialect change directly, as dialect change may have happened during their lives that was actually caused by some of the factors included in LMI.

Given that older linguistic material was used as the basis for calculating linguistic distance, estimates of exposure may be biased. In our study, the linguistic distance values based on 70-year-old data are somewhat conservative, as due to patterns of dialect change [19,39], linguistic distance values on the Swiss Plateau (Ger.: *Schweizer Mittelland*) have probably decreased more since the 1950s than they did in mountainous, more isolated areas.

Recommendations for applying the LMI framework in other studies

In this section, we will summarise a few issues to consider in order to facilitate the adoption of LMI in other studies, organised according to the steps outlined for the implementation of the LMI framework. Following this, we provide a few scenarios where we see the implementation of LMI is warranted.

Most importantly, a researcher must fine-tune the framework for their own goals. There is no single best LMI implementation for any study, since any composition will have a certain degree of subjectivity and its predictive power will depend on the speakers in the dataset, and on the linguistic scenario of the research. Prior to implementing LMI, crucial factors that impact the outcome variable in the specific study should also be determined. Such factors may include, beside those tested in the present study (age, sex, educational background, spatial variation), the role of the standard language, the strength of local identity (e.g. [62]) and the power relationship between urban and rural dialects [59,63], boosting or countering the effects of mobility. By the same token, an inclination or reluctance towards dialect change may also be associated with personality and identity, for example, openness, extraversion or pride in one's dialect [41]. In terms of language change studies, age and the time elapsed between points of comparison may be crucial as change accumulates over time, meaning that younger speakers would typically show more dialect change. This is exemplified by the emergence of the age-cohort-based LMI^D as the best predictor in our study. In order to determine the items of metadata to include in the composition of LMI, we advise testing metadata items as single predictors of the phenomenon investigated and also as aggregates, similarly to our relational weight model, to detect those that affect the outcome variable. Studies may also benefit from a similar spatial analysis to that presented here to determine whether the linguistic phenomenon investigated is governed by regional processes rather than the mobility of individuals.

Determining the linguistic distance between the speaker and the factor's locality is a possible way to estimate potential linguistic effects despite the exact effects of the factor being unknown. If the calculation of linguistic distances is not possible, other judgements could be made, including using proxies like geographical distance or travel time (e.g. [5,47]), since linguistic variation is, to a great extent, spatially autocorrelated [64]. Regarding the mismatch between growing linguistic and geographic distances, however, caution should be exercised.

Flat rates essentially address the general unfeasibility of quantifying the actual impact of people encountered. By utilising such average values, a certain dialect variety or place can be assigned to factors, and available data about the relationship to places (through specific people encountered) can be quantitatively used. Linguistic distances between pairs of localities are flat rates in our implementation, but other studies may choose other estimations of linguistic differences; however, any composition should be kept universal enough to be a valid, comparable measure for all speakers in a certain sample.

Exposure weights, also flat rates in our study, will be specific to available metadata, research questions, language and culture, beside practical and theoretical considerations, while relational weights can be estimated through the researchers' own assessment, beyond our models that are based on influential factors. Since significant effects are confirmed with our LMI prototypes featuring different components, the global meaningfulness of LMI may not depend heavily on the minor details of its construction but whether it successfully captures long-term exposure to dialectal variation from (often noisy) data. Using a double-weighting system similar to our study is, however, not the only way to operationalise individuals' relations and exposure to influencing factors. The determination of relational weights, beyond flat rates, is especially challenging given the vast between-speaker variation regarding contact with the factors, which could be hardly quantified without very specific metadata elicitation.

LMI can also be implemented with little metadata collected. Naturally, the implementation of LMI has better possibilities when a larger abundance of factors is collected, such as information on peers, especially before and around adolescence [21], or a comprehensive collection of metadata that allows researchers to assess the duration, intensity and temporal sequence of linguistic effects on an individual. Nevertheless, the significant performance of LMI^A, despite its minimalistic composition, means that implementing LMI should be possible for most linguistic survey data, since at least some information is usually available regarding survey design variables. LMI^A's different effects in the two age cohorts, however, raise caution for implementations using little metadata. Through the success of the cumulative strategy not using exposure weights (LMI^B), an LMI adding up influential factors in the metadata may also be a possibility for other studies. In certain cases, especially for studies with a smaller number of speakers, setting LMI or components of it manually may also be reasonable, e.g. based on qualitative or anecdotal information available, but comparability should be maintained in correspondence studies.

Beyond similar language change studies to the one presented in this paper, the suitability of LMI seems also to be affirmed for lifespan studies (e.g. [65]), investigating real-time effects of mobility and exposure to variation, rather than apparent-time ones in points recorded in different surveys. Similarly to studies finding that women [27], people with a higher level of education [28], people displaying extraversion [49], or social centrality [34] show more proneness to language change, LMI may also be useful for contributing to research on sociodemographic characteristics that make people more likely to adopt innovations. Further studies, thus, may find that the linguistically mobile (i.e. those with a higher exposure to varied dialects or languages, and in the case of most languages, exposure to the standard) are more likely to be linguistic innovators, while the non-mobile are the laggards resistant to change.

Dialectological research mostly references their participants to a single survey locality which they represent. The LMI framework could be a step towards the goal of addressing the phenomenon of mobility causing dialect change, achieved by measuring separately the degree to which an individual is exposed to different localities and varieties, in a multifaceted localisation. Beyond calculating one universal value, linguistic mobility could be implemented as a spatially directed predictor based on the general mobility network of the population, in correspondence with Trudgill's theory of linguistic gravity [9], rather than being focused on individuals. For example, based on (historic) commuting and relocation patterns, it could be investigated whether the linguistic mobility patterns or language change patterns of an individual conform to the strongest spatial streams. In addition, the term 'mobility' may represent the linguistic effects of exposure not only to other regions but other, social factors (e.g. social classes, other social groups or networks) as well.

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Supporting information

S1 Appendix LMI setup - R Markdown report in html format. The report describes with code the construction of LMI components from the SDATS survey metadata.

S2 Appendix Mixed models - R Markdown report in html format. The report presents the composition of the four LMI prototypes evaluated in this article, conducting the statistical tests and modelling reported here including their summary results. The reproducible code for both reports can be accessed at https://osf.io/hfbpk/