Why Has the Gender Gap in Life Satisfaction Grown Among Adolescents in Leipzig?

Julia M. Rohrer[1], Richard McElreath[2], & Gregor Kachel[3]

The city of Leipzig in Germany conducts large-scale school surveys of adolescents in secondary education schools. Following the regular surveys in 2010 and 2015, the 2020 survey had to be rescheduled to 2023 due to the COVID-19 pandemic. In this latest survey wave, the gender gap in general life satisfaction has significantly grown. While in 2010 and 2015 girls were somewhat less satisfied than boys (0.26 to 0.33 SD), in 2023 this gender gap had doubled (with girls 0.57 SD less satisfied). Why? Here, we probe various explanations, aiming to provide a template for researchers who are asking reverse causal questions ("What caused this?"). First, we find that the widening of the gender gap is much more pronounced among students with a migration background. This could plausibly be explained by a shift in the composition of the underlying population, with a strong increase of Syrian students, and a relative decrease of Vietnamese ones. Second, among students without a migration background, part of the increasing gender gap could potentially be attributed to survey mode: In 2023, for the first time, the survey was conducted on tablets—and unexpectedly, girls (but not boys) reported significantly lower satisfaction when surveyed on tablet rather than on paper. Third, beyond these two patterns, we still find significantly widening gender gaps in satisfaction with leisure time activities and relationships to friends. Thus, there may be a substantive increase in the gender gap in satisfaction in those two domains that is not readily attributable to changes in population and survey mode.

---

1 Wilhelm Wundt Institute for Psychology, Leipzig University, Leipzig, Germany

2 Department of Human Behavior, Ecology, and Culture, Max Planck Institute for Evolutionary Anthropology, Leipzig, Germany.

3 Institute for Psychology in Education, Leuphana University, Lüneburg, Germany.

We would like to thank Taym Alsalti, Saloni Dattani, Jens Lange, and Jan-Paul Ries who provided helpful input on this project in a colloquium; Stefan C. Schmukle provided extensive feedback on a draft of this manuscript. At the city of Leipzig, we would like to thank Katharina Hemming, Andrea Schultz and Martin Waschipky for their advice and feedback.

All analysis code can be found on the companion website (https://j-rohrer.github.io/Jugendstudienanalysen/). Due to legal and data protection requirements, the underlying data are only available upon request from the data holder (City of Leipzig).

Why Has the Gender Gap in Life Satisfaction Grown Among Adolescents in Leipzig?

There have been widespread—and controversially debated—concerns that mental health may be declining on a large scale among young people in particular. These concerns predate the COVID-19 pandemic of the early 2020s but may have been further aggravated by it. Since then, one particular narrative—highlighted in books such as Jonathan Haidt's "The Anxious Generation" (2024) and Donna Hackson Nakazawa's "Girls on the Brink" (2022) —has been gaining public attention: Mental health has deteriorated in girls and young women in particular, and social media is often invoked as major part of the explanation.

Against this backdrop, at the end of 2023, the city of Leipzig published a summary of their 2023 survey among students of all school tracks and types in the German secondary education system (Abel et al., 2023). The press release issued by the city highlighted that life satisfaction in adolescence had strongly declined since the last survey of the same age group. While in 2015, 72% of the youths reported to be satisfied or even very satisfied, that number decreased to 61% in 2023 (*Jugendstudie 2023: Lebenszufriedenheit der Schüler sinkt deutlich [Youth Survey 2023: Life satisfaction of students declines markedly]*, 2023). Furthermore, the decline was reportedly much more pronounced in girls (minus 14 percentage points) than in boys (minus 7 percentage points).

Generally, this local empirical finding fits the general idea that well-being has been declining among girls in particular. But before accepting possible explanations based on broader narratives, in this study we aim to analyze the data from Leipzig more thoroughly for any hints as to *why* the gender gap might have grown. Thus, we are revisiting the data explicitly asking a reverse causal question (sensu Gelman & Imbens, 2013): *Why* does Y occur? This is quite distinct from the more usual research goal of answering forward causal questions: How does X affect Y? Such reverse causal questions may often lack the well-defined answers that can be generated for forward causal question, and in general it is less clear how to tackle them systematically. Nonetheless, asking them may be worthwhile to identify gaps in our current (implicit or explicit) model of the world, which in turn allows us to refine our models and ultimately improves our ability to explain the world.

Thus, beyond answering our specific research question, we also want to provide a template for how to tackle such reverse causal questions in a rigorous manner. We illustrate how to translate substantive explanations into suitable statistical analyses and how to transparently discuss limitations of the data which are inevitable in practice. This manuscript is accompanied by a website containing the full analysis code and model results with additional annotations: https://j-rohrer.github.io/Jugendstudienanalysen/.

Method

Design of the Leipzig Youth Surveys

The Office for Statistics and Elections of the City of Leipzig, Germany, has been conducting annual surveys of adult citizens on behalf of the mayor since 1991. In the years 1993, 2000 and 2006, this survey was supplemented with a survey on leisure targeting children and youths starting from the age of 12 which was collected in schools (Heinemann et al., 2011). From the 2010 survey onwards, this youth survey was supposed to be repeated every five years; however, after the 2015 survey, the COVID-19 pandemic necessitated a change of plans and so the 2020 survey was postponed to 2023 (Abel et al., 2023). These three most recent surveys—2010, 2015 and 2023—underlie our analyses.

The 2010 Youth Survey

Students between the ages of 12 and 17 were targeted within their respective schools and surveyed between October 18th and November 5th 2010 (Heinemann et al., 2011).[1] The initially targeted sample size was 3,000, which was distributed according to the actual distribution of students between the ages of 12 to 17 in the four types of schools included and the grade levels included:

- General secondary schools (*Mittelschule*, later renamed *Oberschule*), the lower secondary school track focused on practical education, grades 7 to 10
- Grammar schools (*Gymnasium*), the upper secondary school track focused on preparation for higher education, grades 7 to 12
- Vocational secondary schools (*Berufs-/Fachoberschule*), first and second year
- Special needs schools (*Förderschule*), grades 7 to 10

Schools were picked across Leipzig, prioritizing schools who had participated in earlier surveys to reduce organizational overhead and to ensure some degree of continuity. Within the selected schools, all students within eligible classes were assessed, even if they fell outside of the focal age range. This resulted in an initial sample of 3,459 students. Parents were informed upfront and had to consent to their children's participation; children could also deny to participate independently. Then, trained staff from the City of Leipzig went into classrooms during either school periods or free periods and handed out paper surveys. A total of 2,411 students (70% of the initial sample) filled out the survey, see Table 1.

[1] In 2010, the City of Leipzig also conducted a second parallel Youth Survey targeting people between the ages of 18 and 27 who had already left school and whom were contacted based on registry information. This survey was never repeated and the data were not included in our analyses.

Table 1

Overview of the Analyzed Leipzig Youth Surveys

	2010		2015		2023	
Included in	Data set	Analysis	Data set	Analysis	Data set	Analysis
Students	2,411	1,383	2,255	1,578	3,036	1,803
Classrooms	114	73	114	84	168	110
Schools	38	21	31	21	64	33
Schooltype						
General secondary	28%	46%	29%	41%	22%	35%
Grammar school	32%	54%	42%	59%	41%	65%
Vocational	36%	–	25%	–	32%	–
Special Needs	4%	–	3%	–	5%	–
Survey mode						
Pen and paper	100%	100%	100%	100%	34%	31%
Tablet	–	–	–	–	66%	69%
Gender						
Female	49%	51%	54%	55%	50%	50%
Male	50%	49%	46%	45%	46%	50%
Diverse/no response	–[a]	–[a]	–[a]	–[a]	3%[a]	–
No response	<1%	–	1%	–	1%	–
Age						
< 12	<1%	–	0%	–	0%	–
12	8%	14%	2%	2%	4%	6%
13	18%	29%	14%	18%	13%	20%
14	14%	21%	18%	24%	15%	22%
15	11%	16%	18%	25%	14%	20%
16	12%	10%	16%	18%	12%	17%
17	12%	6%	15%	11%	10%	10%
18	7%	3%	7%	2%	9%	6%
> 18	16%	–	10%	–	21%	–
No response	<1%	–	<1%	–	2%	–
Migration background						
No	89%[b]	90%[b]	90%[b]	91%	84%[b]	87%[b]
Yes	9%[b]	10%[b]	9%[b]	9%[b]	12%[b]	13%[b]
No response	2%	–	1%	–	4%	–

[a] In 2010 and 2015, only two gender response options were available. In 2023, a third response option labeled "divers or no response" was added.

[b] In 2010 and 2023, students provided detailed information on where they and their parents were born. Migration background was coded as yes if either the student or both parents were born outside of Germany. In 2015, students were instead asked to indicate whether the language mainly spoken at home was German or not. Migration background at home was coded yes if they indicated that they did not mainly speak German at home. See also Method section.

Throughout our analyses, we limit ourselves to students attending either general secondary school or grammar school. These school types are considered *allgemeinbildend*, that is, providing a general education, and they are the second step after primary education in the standard course of education. We thus focus on students within the normative educational course in Germany. After secondary school, students may move on to a vocational secondary school; however, these tend to be more heterogeneous – including young people who still live at home, young people who already moved out and may have already started a family, and older people in second chance education., These students were excluded as their lifestyle and daily routine can differ significantly from that of the rest of the sample . Likewise, students at special needs school are a more heterogeneous population; an additional concern here is that the inclusion criteria may have changed between repetitions of the youth surveys.[2] Thus, these students were also excluded.

The 2015 Youth Survey

Students between the ages of 12 and 17 were targeted within their respective schools; again, schools who had participated in previous youth surveys were prioritized. The initially targeted sample size was 3,000 students distributed over school types and classrooms according to the actual distribution in the population. One major change was that in grammar schools, only the grades 7 to 11 were included. This was because data were collected between May 7th and June 1st 2015, when the 12th grade students at grammar schools had already finished their final exit examinations (*Abitur*) and thus left school. The initial sample included 3,298 students, of which 2,277 (75%) filled out the paper survey according to the original report (Abel et al., 2015). The final data we received contained 2,255 students (Table 1).

The 2023 Youth Survey

Again, students between the ages of 12 and 17 were targeted within their respective schools. This time, to capture more variability, classrooms within schools rather than whole schools were selected and students at special needs schools were intentionally oversampled. The initially targeted sample size was 5,000 students which was expected to result in 3,000 usable responses. In fact, 3,050 filled out the survey according to the official report (Abel et al., 2023); the data we received contained 3,036 students (Table 1). In 2023, for the first time, two thirds of the students filled out the survey on tablets provided by the school, leading to a partial change in survey mode. The details of this will be discussed later when it becomes relevant to our analyses.

Measures of Interest

In all three youth surveys, students were asked eight pages of questions on various topics, such as their priorities in life, satisfaction with various areas of life, leisure time activities, athletic activities, drug consumption, and plans for the future. While many thematic blocks of questions re-occurred across surveys, many individual items were rephrased or completely exchanged, reducing the number of comparable variables across the three surveys. In the following, we only describe the measures analyzed for the purposes of the present study; any changes in phrasing across the years will be highlighted.

[2] In 2023, students at special needs school were intentionally oversampled, and the official report states that schools focusing on students with severe cognitive, social/communicative and emotional impairments (*Förderschwerpunkt geistige Entwicklung*) were excluded (Abel et al., 2023). No reference to such exclusion criteria can be found in the 2015 or 2010 reports (Abel et al., 2015; Heinemann et al., 2011)

Gender and Age

Gender and age: In 2010 and 2015, students were asked whether they were male or female. In 2023, a third response option labeled "diverse or no response" was added. In all three surveys, students were asked to write down their age.

Migration Background

In contemporary Germany, the term race is considered extremely fraught due to its association with Nazi ideology. Thus, surveys do not collect this variable but usually instead ask for "migration background", that is, migration history of a person or their parents. In 2010, students were asked to indicate whether they, their father, and their mother were born in Germany and, if not, to write down in which country they were born instead. In 2015, a simplified measure was chosen in which students indicated whether they mainly spoke German at home; if they did not, they were asked to write down their main language at home. In 2023, the survey switched back to the original measure of migration background, but this time students only indicated whether they, their father, and their mother were born in Germany or abroad—without any possibility to specify the birth countries. These changes in assessment make it harder to compare this variable across the surveys, although most of our analyses focus on the contrast between 2010 and 2023 when migration background was assessed in a comparable manner.

We generated a dichotomous variable representing migration background. In 2010 and 2023, this variable is coded as *yes* if either the students themselves or both of their parents were born abroad. In 2015, this variable is coded as *yes* if the main language spoken at home is not German.

This mapping is necessarily imperfect. Deutsche Welle (2019) reported based on microcensus data that in households with only one family member with immigrant background, German was the dominant language in 95% of the cases; these would be mapped consistently according to our mapping (no migration background, German main language at home). However, in households in which all members were immigrants, German was reportedly still the dominant language in 44% of homes; these would be mapped inconsistently according to our coding (migration background *yes* if sampled in 2010 or 2023; migration background *no* if sampled in 2015).[3]

[3] This mapping issue should lead to an underestimation of the number of students with migration background in 2015. We can confirm that this is the case by checking our numbers against official statistics issued by the City of Leipzig which reports the number of students with migration background by school type for 2010 and 2015 (Bein, 2023; Dütthorn & Gugutschkow, 2010). According to these numbers, and given the distribution of school types in our final analysis samples, we would expect that the number of students with migration background increased from 10.1% to 13.5% from 2010 to 2015. Accordingly, we would expect that the number of students with migration background in our data increased at least somewhat. Yet, in our data, it slightly

Satisfaction Items

In all three surveys, students were asked a block of questions about their satisfaction with various aspects of life. The question always opened with "How satisfied are you currently with…" and was always answered on a five-point response scale (1: very dissatisfied, 2: rather dissatisfied, 3: mixed, 4: rather satisfied, 5: completely satisfied). Some of the aspects of life asked for changed between the surveys, leaving the following eight items that are comparable over time:

- satisfaction with your life in general (*general life satisfaction*)
- satisfaction with your school grades (*school grades satisfaction*)
- satisfaction with your leisure time activities (*leisure satisfaction*)
- satisfaction with your relationships to friends (*friendship satisfaction*)
- satisfaction with your relationship to your father (*satisfaction with father*)
- satisfaction with your relationship to your mother (*satisfaction with mother*)
- satisfaction with the amount of money with which you have to get by (*financial satisfaction*)
- satisfaction with your housing situation (*housing satisfaction*)

The leisure time activities item switched from "how satisfied are you with your leisure time activities?" (2010) to "how satisfied are you with the opportunities for leisure time activities?" (2015, 2023). The school grades item switched the German word for school grades from *Zensuren* in 2010 and 2015 to the nowadays more common *Schulnoten* in 2023.

Statistical Models and Analysis Approach

Data analyses were conducted in the programming language R 4.4.2 (R Core Team, 2022) with the help of RStudio (Posit team, 2023). The packages *haven* (Wickham, Miller, et al., 2023) and *dplyr* (Wickham, François, et al., 2023) were used to assist in data wrangling; graphics were generated in *ggplot2* (Wickham, 2016) with help from *patchwork* (Pedersen, 2024) and *gridExtra* (Auguie, 2017). We fitted various statistical models using, apart from base *R*, the packages *MASS* (Venables & Ripley, 2002) and *brms* (Bürkner, 2017) and then relied on *marginaleffects* (Arel-Bundock et al., 2024) to query the models. The precise model specifications are explained and justified in the Results section since the mapping between substantive question and statistical model is central to the present study. All analysis code can be found on the companion website (https://j-rohrer.github.io/Jugendstudienanalysen/). Unfortunately, we are not able to share the data from the Leipzig youth surveys; these data are only available upon request from the data holder (City of Leipzig) due to legal requirements.

decreased from 10% in 2010 (migration background based on countries of birth) to 9% in 2015 (migration background based on language at home).

Results

Reproducing the Explanandum: Decreased Life Satisfaction in Girls in 2023

First, we reproduce the central observation that is to be explained – a widening gender gap in life satisfaction in 2023 – by fitting a simple linear model predicting life satisfaction from the categorical predictors *gender*, *survey year*, and their interactions. We then use *marginaleffects* to predict *life satisfaction* for different values of gender and survey year (see Figure 1) and to conduct various comparisons. To calculate the gender gap in life satisfaction, we rely on average counterfactual comparisons: For every student in the data, we predict their life satisfaction if they were a girl and their life satisfaction if they were a boy. We then take the difference between these two values and average across students, which results in a *ceteris paribus* contrast. Note that this results in the same conclusions as interpreting the regression coefficients.[4]

In all three years, girls reported lower satisfaction than boys. The gender gap grew from 0.22 scale points in 2010 (95% confidence interval: [0.13; 0.30]) to 0.28 scale points in 2015 (95% CI: [0.20; 0.36]) to 0.48 scale points in 2023 (95% CI: [0.41; 0.56]). Expressed in standard deviations of life satisfaction across all observations, the gap grew from 0.26 *SD* to 0.33 *SD* to 0.57 *SD*. The widening of the gap from 2010 to 2015 in itself was not statistically significantly different from zero (difference of 0.06 scale points, 95% CI: [0.06; 0.18]), but the widening in the gap from 2015 to 2023 was (0.20 scale points, 95% CI: [0.09, 0.31]). In total, from 2010 to 2023, the gender gap grew by 0.26 scale points (95% CI: [0.15, 0.38]), or by 0.31 *SD*.

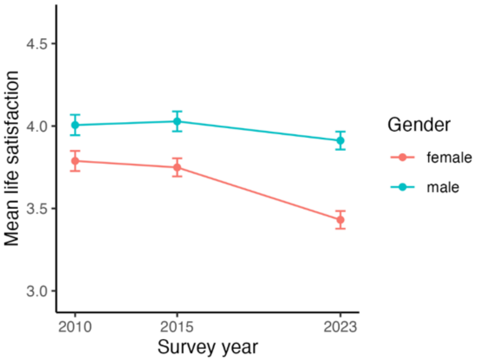


Fig. 1 Mean life satisfaction in boys and girls over time. Scale from 1 to 5, error bars are 95% confidence intervals.

[4] The differences in gender gaps in our analysis correspond to the coefficient of the interaction between *gender* and *survey year*, taking into account how the categorical predictor *survey year* is dummy-coded. Throughout our analyses, we rely on the comparisons generated with the help of *marginaleffects* because it allows us to directly generate confidence intervals for all quantities of interest, and facilitates interpretation of more complex analyses reported later in the manuscript.

Considering Alternative Satisfaction Measures

Widening gender gaps for any of the more specific satisfaction items could already point to potential explanations for the widening gender gap – maybe there are only certain aspects of life that girls became less satisfied with. Figure 2 presents results for all satisfaction items that were included across years.

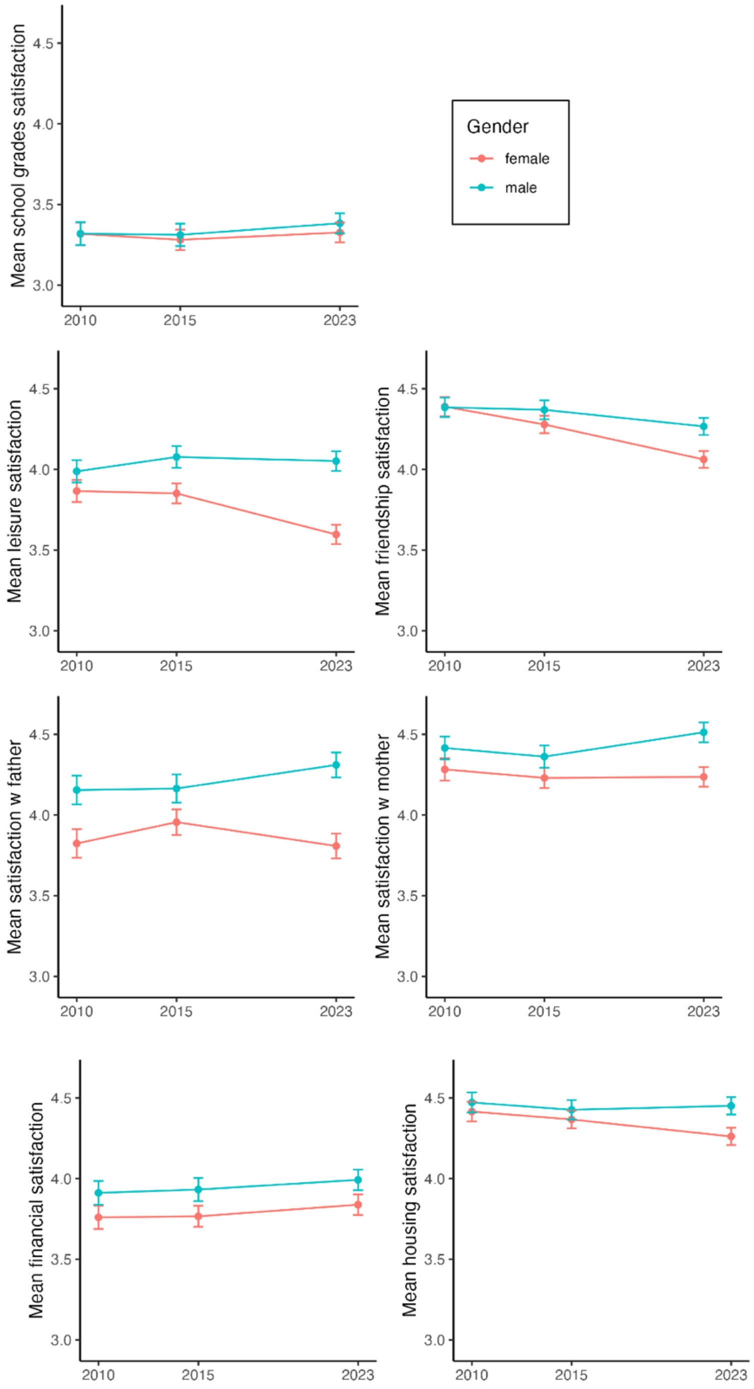


Fig. 2 Mean satisfaction with various aspects of life in boys and girls over time. Scale from 1 to 5, error bars are 95% confidence intervals

First of all, students' satisfaction with their grades is the odd one out as there is no gender difference in any of the years – and also no indication of a widening gap, with a negligible change in the gender difference from 2010 to 2023 of 0.06 scale points (95% CI: [-0.08; 0.19]). Note, however, that girls tend to have better school grades (Bayer et al., 2021; Uunk & Blossfeld, 2025; Voyer & Voyer, 2014), so the non-existent gender difference in satisfaction may still imply a “satisfaction advantage” for boys.

Gender gaps widened or opened in the first place in both leisure satisfaction and friendship satisfaction. Considering leisure satisfaction, the gender gap grew from 2010 to 2023 by 0.33 scale points (95% CI: [0.20; 0.46]) or 0.36 *SD*. Note that for this item, the phrasing changed from 2010 to 2015 (see Method section); however, the gap also widens from 2015 to 2023 when the same phrasing was used. For friendship satisfaction, the gender gap grew by 0.21 scale points (95% CI: [0.10; 0.32]), or by 0.26 *SD*. Likewise, from 2010 to 2023, gender gaps slightly widened considering satisfaction with one’s parents: by 0.14 scale points concerning mothers (95% CI: [0.01; 0.28]; 0.15 *SD*) and by 0.17 scale points concerning fathers (95% CI: [0.00; 0.34]; 0.14 *SD*). And the gender gap in housing satisfaction widened to a comparable degree (0.13 scale points, 95% CI: [0.02; 0.25], 0.16 *SD*). At the same time, there was no widening gap in satisfaction with one’s financial situation (difference in the gap of 0.00 scale points, 95% CI: [-0.14; 0.14]).

In sum, the pattern of widening gender gaps in satisfaction – always with girls growing relatively less satisfied – is clearly visible for both friendships and leisure time. It also shows up for the relationship with one’s parents and housing satisfaction, albeit somewhat weaker. In contrast, the gender difference in financial satisfaction was stable, as was the (essentially non-existent) gender difference in satisfaction with school grades. With these results in mind, we will turn back to the gender gap in general life satisfaction and try to generate explanations for it. In the end, we will return to the other satisfaction items to see whether our preferred explanations can satisfyingly explain patterns across different areas of life.

Could this Pattern Be a Scaling Artifact?

So far, we have analyzed life satisfaction as if it was a continuous variable – which it is not. Data were collected on a five-point response scale, resulting in an asymmetric distribution (Figure 3). In particular, while many students report a fairly high score of 4, surprisingly few choose the highest response option, 5. This corresponds to observations for life satisfaction scales that go all the way up to 10 – despite high average values, few respondents usually report a 10, and cognitive interviews suggest that for many respondents 8 out of 10 constitutes the “top of the scale”, with higher values being hard to conceive for them (Fabian et al., 2024).

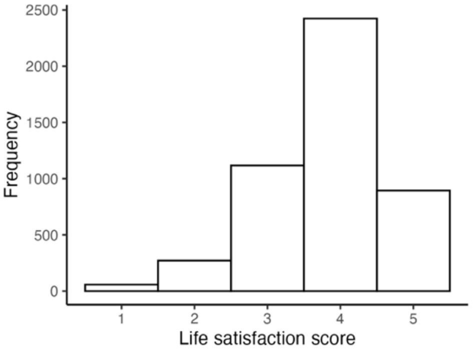
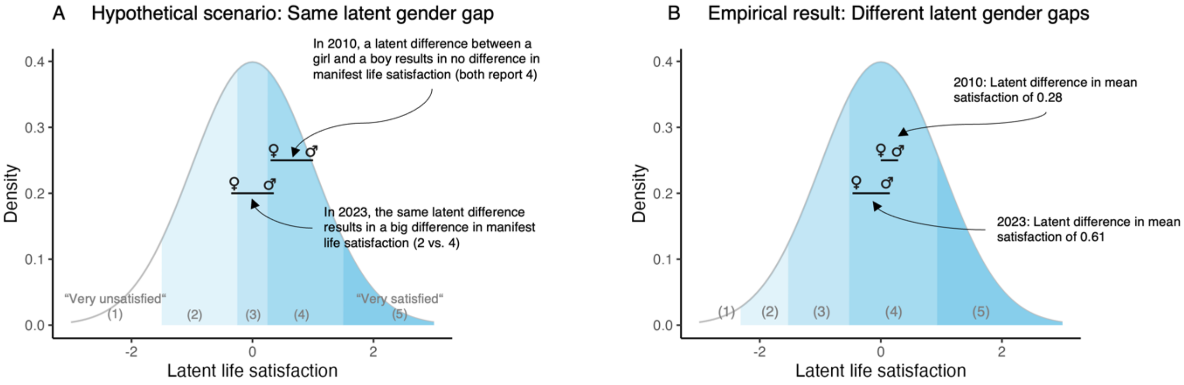


Fig. 3 Distribution of life satisfaction scores across all youth surveys

In general, categorical response scales can cause trouble if the psychological differences between response options are not the same – for example, if the difference between a 2 (rather dissatisfied) and a 3 (mixed) is smaller than the difference between a 4 (rather satisfied) and a 5 (completely satisfied). In those scenarios, simply modeling the mean of a continuous (normal) distribution—as we did above—may not accurately capture central tendencies. Most importantly for the present purposes, uneven differences between response options could also dissolve the observation of a widening life satisfaction gap. This pattern is an interaction effect, and interactions are scale-dependent: they can appear, disappear, or even reverse depending on how the data are scaled (Rohrer & Arslan, 2021).

Consider the hypothetical scenario depicted in Figure 4, Panel A. This shows the density curve of latent life satisfaction as a continuous variable which is normally distributed. When respondents have to report their (continuous) life satisfaction on the five-point response scale presented to them, their response is determined by certain cut-off values (so-called thresholds) that translate the unobserved continuous variable into an observed categorical variable. Two horizontal lines mark the gap in latent life satisfaction between a girl and a boy in 2010 and 2023. In both years, this line has the same length, so the difference in latent life satisfaction remains the same. However, in 2023, the whole line is shifted to the left. This affects how the latent life satisfaction scores and their differences are translated into observed categorical values. In 2010, the boy and the girl fall into the same category and report a 4; thus, there would be no observed difference in life satisfaction on the five-point scale. In 2023, the boy and the girl fall into different categories – while the boy ends up reporting a 4, the girl ends up reporting a 2. We thus end up with a much larger observed difference in life satisfaction, despite the underlying latent life satisfaction difference remaining the same. Following the same logic, the widening gender gap we observed earlier could actually be a scaling artifact insofar that on the latent level, gender differences in life satisfaction may have remained unchanged.


A Hypothetical scenario: Same latent gender gap

In 2010, a latent difference between a girl and a boy results in no difference in manifest life satisfaction (both report 4)

In 2023, the same latent difference results in a big difference in manifest life satisfaction (2 vs. 4)

B Empirical result: Different latent gender gaps

2010: Latent difference in mean satisfaction of 0.28

2023: Latent difference in mean satisfaction of 0.61

Fig. 4 In principle, the widening gender gap could be a scaling artifact (Panel A), but the data do not support this conclusion (Panel B).

To test whether this is the case, we again regressed life satisfaction on gender, survey year, and their interaction, this time using an ordered probit model. These models correspond to the mapping process depicted in Figure 4, Panel A: Latent life satisfaction is assumed to follow a normal distribution that is translated into an ordinal categorical variable according to thresholds which are estimated empirically. The results, including the estimated thresholds, are depicted in Figure 4, Panel B. In line with the observed distribution of responses (Figure 3), the thresholds separating a life satisfaction score of 4 from lower or higher scores are quite far apart – a large chunk of the area under the density curve falls into this category. Importantly, on the estimated latent continuous life satisfaction variable, we still observe a widening gender gap; relative to 2010, the gender gap widens from 0.28 to 0.61, or by 0.33 *SD* of the latent variable (95% CI: [0.18; 0.48]). This closely matches the results from our linear regression model above, where we observed a widening of 0.31 *SD* of life satisfaction across all observations. Thus, we can discard the idea that the widening gender gap is a simple scaling artifact.[5]

Ordinal modeling has thus resulted in conclusions that are very similar to those resulting from linear regression models. For the sake of simplicity, we will thus switch back to linear regression models for now. However, once we have determined a preferred explanation for the life satisfaction pattern, we will check again whether that pattern also holds in an ordinal model that more accurately captures the nature of the outcome variable.

Can Demographic Variables Explain Widening Gender Gaps?

Another explanation for the widening gender gap could be changes in demographic variables. For example, maybe the gender gap in life satisfaction varies by age (e.g., larger gender gap among older students) and maybe the age composition of the sample was different in 2023 (e.g., more older students). Such a change in the composition of the sample may either be due to changes in the composition of the underlying population (e.g., students in Leipzig have indeed become older) or due to changes in the sampling procedure (e.g., older students have become more likely to be included in the study). In either case, it could contribute to an explanation of the widening gender gap. In our analysis, we consider three demographic variables: students' age, the type of school they attend, and their migration background.

Age can be included in models in different ways. For example, we may include it as a continuous linear predictor which forces any age trend we estimate to be linear. Alternatively, we may include it as a categorical

[5] Notice that this analysis still assumes that girls and boys use the scale in the same manner. As demonstrated in analyses on the companion website, we can relax this assumption and allow the thresholds to vary by gender in Bayesian ordered probit models. Doing so results in a great amount of uncertainty about the gender-specific thresholds and the coefficient of gender since we run into a problem of underidentification – in essence, any observed pattern in the data would be compatible with any coefficient of gender because we could simply pick the corresponding gender-specific thresholds to make the model fit; the Bayesian priors ensure that nonetheless point estimates are returned. But this uncertainty does not affect the *interaction* between gender and survey year, and so despite not knowing how gender affected life satisfaction in 2010, we can still conclude that whatever gender gap there was had grown by 0.32 *SD* of the latent variable (95% Credible interval: [0.17; 0.47]) in 2023.

predictor (without any binning, i.e., considering every year of age its own category) which does not impose any functional form, but may render some estimates quite imprecise as individual age groups may be quite small, in particular when considering interactions). Here, we pick something in between those two extremes and include age b-splines with 3 degrees of freedom (i.e. the default setting). This allows our estimates to pick up the underlying functional form in a quite flexible manner but still smooths trajectories a bit, so that the individual estimates do not become overly imprecise. Note that the precise modeling of age does not impact conclusions regarding the widening of the gender gap.

More importantly, as the widening that we want to “explain away” is an interaction (gender*year), we have to include the interactions between all demographic variables and gender and year – interactions require interaction controls (Simonsohn, 2019; Yzerbyt et al., 2004). Beyond this, we will also include the three-way interaction between each demographic variable and gender and year (e.g., we include migration background*gender*year). Adding this flexibility allows us to rule out that the observed pattern can be attributed to changes in how demographic variables relate to the outcome in either boys or girls over time. Since we rely on *marginaleffects* for model interpretation, we do not need to worry about the fact that these complexities render the coefficients hard to interpret as we do not directly consider them. Likewise, it is inconsequential that some of the coefficients will be estimated with a lot of uncertainty as only the uncertainty of the predictions matters here. Our final model is a linear regression in which we regress life satisfaction onto gender, survey year, and, to account for demographic differences, age splines, schooltype (categorical variable with two levels) and migration background (categorical variable with two levels). All variables in the model are interacted with gender and survey year, and also interacted with the gender*survey year interaction. Additionally, moving forward, when querying our models, we will ensure that the standard errors are clustered at the level of the classroom to account for nesting in the data.

Do Demographics Explain Away the Widening Gender Gap?

To find out whether changes in demographic variables explain the widening gender gap, we now query the model in a particular manner. We calculate model-implied gender gaps for the individual survey years *in a world in which the distribution of the demographic variables was exactly the same in every survey year*. If, in such a world, our model does not imply any widening of the gender gap, we have successfully explained it away.

We can, of course, imagine many different worlds in which the distribution of the demographic variables did not change over the years – and since we allowed all predictors to interact, the gender gap and how it changes over time may look somewhat different across worlds. One sensible choice could be a world in which the distribution of demographic variables is always the distribution of our baseline survey year, 2010. For such a world, our model implies a gender gap of 0.22 scale points in 2010, 0.31 scale points in 2015, and 0.50 scale points in 2023. From 2010 to 2023, the gap thus widens by 0.27 scale points (95% CI: [0.15; 0.39]) or by 0.32 *SD*, which is virtually the same pattern that we observed when ignoring demographic variables. Thus, changes in the demographic variables do not explain the widening gender gap. We arrive at the same conclusion if we evaluate the model in a world in which the distribution of demographic variables equals the distribution in 2015 or 2023; in fact, in these worlds, we would conclude that the widening is even slightly more pronounced (0.41 *SD*, 0.36 *SD*).

Do Demographics Modify the Widening of the Gap?

Our model also allows us to investigate whether the widening of the gender gap is *modified* by demographic variables. For example, maybe the gender gap widens in particular among older students, or in particular among grammar school students. To evaluate such modification, we calculate gender gaps for the survey years and for specific values of the demographic variables, and then contrast the results for different groups.

Considering age, the results imply that the gender gaps widen most strongly among students aged 14-16 (Figure 5). However, notice that now we are evaluating a three-way interaction (gender*survey year*age), which results in a lot of statistical uncertainty around the estimates. Even if we selectively tested the largest contrast here – comparing the widening of the gender gap between 12-year-olds and 15-year-olds – the difference is estimated with a large amount of uncertainty (difference in the widenings of the gender gap = 0.42, 95% CI: [-0.82; -0.02]). Likewise, considering the two different school types (general secondary school vs. grammar school), we find that the widening is somewhat more pronounced in general secondary schools (widening of 0.32 scale points) than in grammar schools (widening of 0.23 scale points), but the difference between these interactions is uncertain (difference of 0.09 scale points, 95% CI:[-0.33; 0.15]).

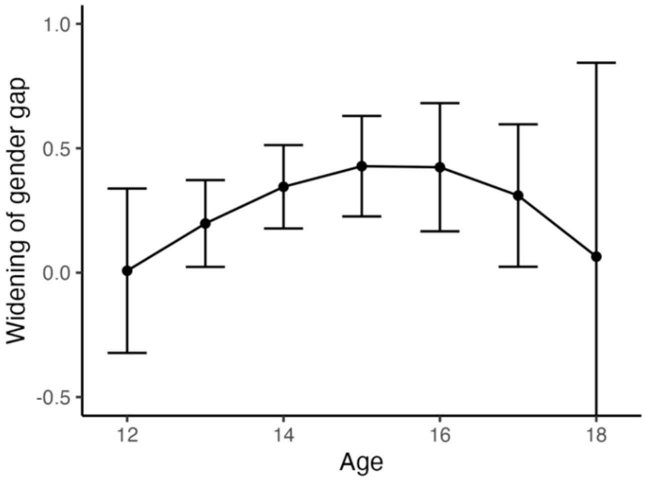


Fig. 5 Model-implied widening of the gender gap from 2010 to 2023 for students of different ages in scale points. Scale from 1 to 5, error bars are 95% confidence intervals.

The most pronounced difference in the widening of the gaps arises for migration background. Among students without a migration background, the gender gap widens by 0.22 scale points (95% CI:[0.10; 0.35]); among students with a migration background, the gender gap widens by 0.72 scale points (95% CI:[0.29; 1.14]) – amounting to a difference between the widenings of the gap of 0.49 scale points (95% CI:[0.05; 0.94]). This difference is descriptively large, which is why moving forward, we always considered the widening of the gap separately for students with and without migration background. Figure 6 summarizes the preliminary results, contrasting the model-implied means over time by migration background while holding the remaining demographic variables (age and schooltype) constant at their 2010 distribution.

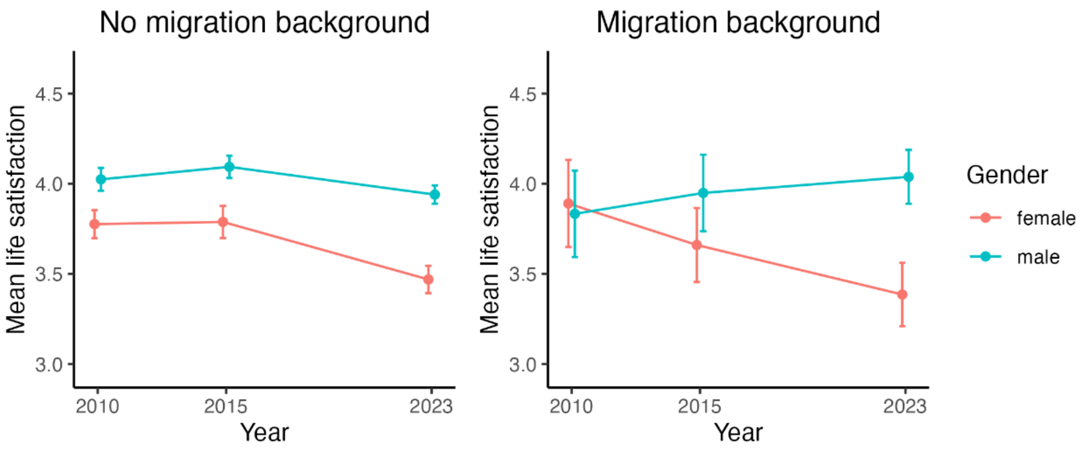


Fig. 6 Model-implied life satisfaction in boys and girls over time, separately for students with and without a migration background. Scale from 1 to 5, error bars are 95% confidence intervals, demographic variables held constant at their 2010 distributions. Note that in 2015, migration background was inferred from whether or not German was the main language students spoke at home

Could this Pattern Result from Changes in Survey Mode?

In 2023, an important change happened that we have ignored so far: For the first time, tablets were introduced as an assessment mode. This change in survey mode may have affected how students reported their life satisfaction. Importantly, not all students used tablets in 2023 with 31% of participants still filling out the survey on paper. First, in some schools, leadership decided against tablets, so that whole schools filled out the survey on paper. Second, sometimes not enough tablets were available because multiple classrooms were surveyed at the same time, or because tablets were needed for other classroom activities elsewhere, so that whole classrooms filled out the survey on paper. Third, sometimes there were not enough tablets for all students in the classroom, in which case some students in a classroom filled out the survey on paper; or a battery failed, in which case individual students switched to paper.

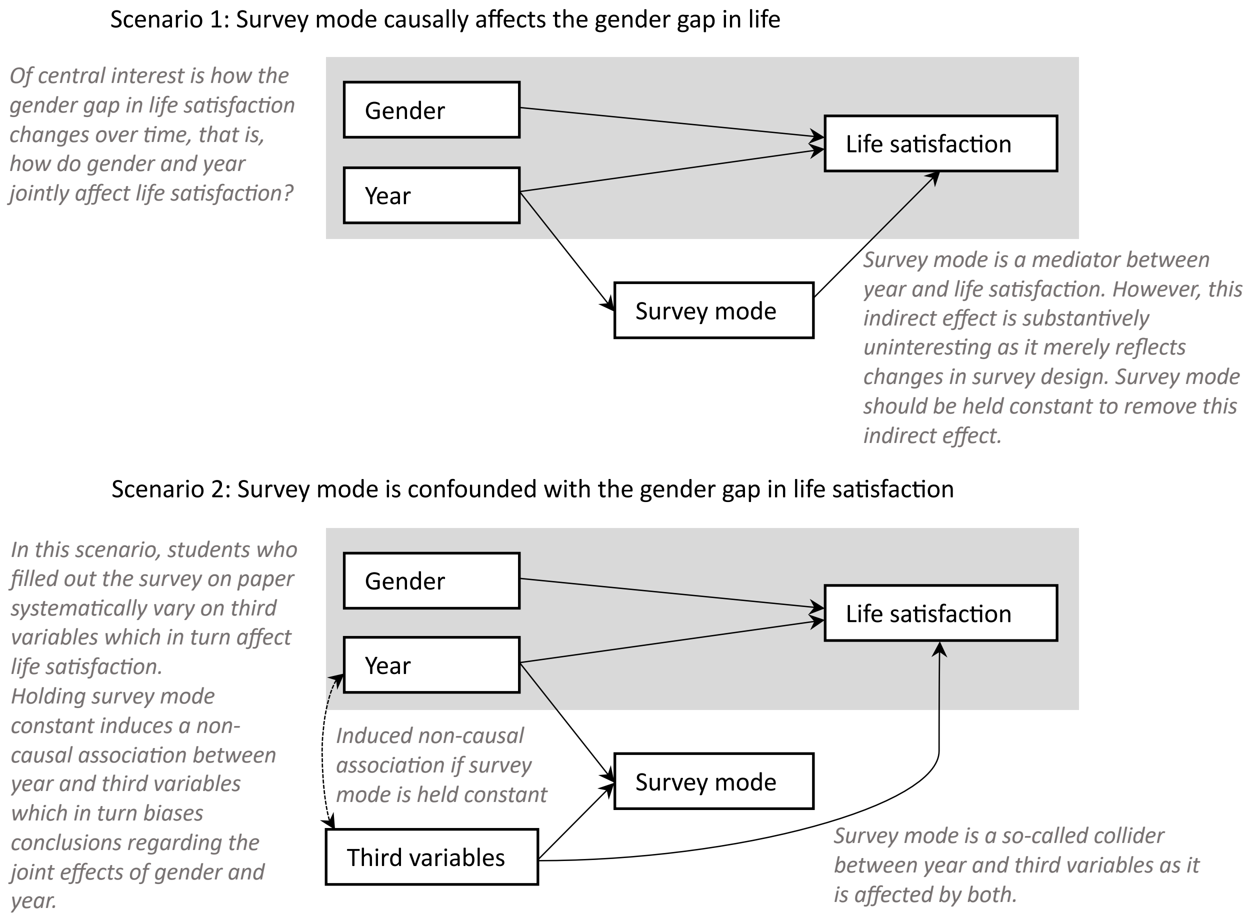
The variability in survey mode outlined above allows us to examine its association with life satisfaction and whether this relationship differs by gender. For this purpose, in the 2023 data, we regressed life satisfaction onto survey mode, gender, and their interaction. This model predicted that girls reported higher satisfaction on paper (*M* = 3.55) than on tablet (*M* = 3.38), with a difference of 0.17 scale points (95% CI: [0.06; 0.29]). In contrast, boys reported the same average satisfaction on paper (*M* = 3.91) as on tablet (*M* = 3.91). The offset in the survey mode differences between the genders (i.e., the interaction between gender and survey mode) was 0.17 scale points [0.02, 0.32].

Two Explanations for the Survey Mode Differences

So, girls appear unhappier on tablet than on paper, boys don't. *If* these differences reflect causal effects of the assessment mode, they could partially explain the widening gender gaps – reporting on tablet leads to lower responses in girls but not in boys and thus to a widening of the gender gap, and tablets were only introduced in 2023. In that case, it would be appropriate to call the induced pattern an artifact, as it was caused by arbitrary changes in survey design rather than by substantive changes over time. To check whether there is a widening of the gender gap beyond such mode artifacts, one would need to limit the analysis over years to students who used the same survey mode – here, this would necessarily be paper, since tablets were only used in the last survey wave.

But it is not a given that the observed survey mode differences are actually causal effects of the assessment, considering that survey mode was not randomized. In particular, schools or classrooms that used paper rather than tablets may have been systematically different with respects to third variables (e.g., socio-economic status of the neighborhood), and these third variables in turn result in different gender gaps, without survey mode actually having any causal effect on top. In this case, we could simply ignore survey mode as it does not induce any artifacts. In fact, in this scenario, limiting the analysis over years to students who used the same survey mode – paper – could *induce* bias. The intuition behind this is that we would compare the *full* 2010 and 2015 samples to a subsample of the 2023 data which systematically differs in the third variables (e.g., socio-economic status of the neighborhood) that led to paper being used despite the availability of tablets. Figure 7 presents causal graphs visualizing the two different scenarios (see Elwert & Winship, 2014 for more on collider bias; Rohrer, 2018 for a general introduction to such graphs).[6]

[6] In practice, survey mode may also *both* affect life satisfaction and be confounded with life satisfaction. In such a scenario, including only one response mode in the analysis may simultaneously remove one type of bias and induce another one. From that angle, the following analysis can be taken as an attempt to figure out which type of bias would be worse and thus which analysis is to be preferred.



Scenario 1: Survey mode causally affects the gender gap in life

Of central interest is how the gender gap in life satisfaction changes over time, that is, how do gender and year jointly affect life satisfaction?

Survey mode is a mediator between year and life satisfaction. However, this indirect effect is substantively uninteresting as it merely reflects changes in survey design. Survey mode should be held constant to remove this indirect effect.

Scenario 2: Survey mode is confounded with the gender gap in life satisfaction

In this scenario, students who filled out the survey on paper systematically vary on third variables which in turn affect life satisfaction.
Holding survey mode constant induces a non-causal association between year and third variables which in turn biases conclusions regarding the joint effects of gender and year.

Induced non-causal association if survey mode is held constant

Survey mode is a so-called collider between year and third variables as it is affected by both.

Fig. 7 Two different explanations for the observation that in 2023, the gender gap in life satisfaction varied between the two survey modes (paper and tablet)

The central question to determine how to analyze our data – in particular, whether we *should* limit the analysis to responses on paper – is whether or not students who filled out the 2023 survey on paper are systematically different, and whether or not we still observe an association between survey mode and the gender gap in life satisfaction after accounting for *all* such differences. In case we still observed an associations, we would conclude that survey mode causally affects responses (Figure 7, Scenario 1), and it would be appropriate to limit analyses to a single survey mode.

Accounting for Observed Differences in Demographic Variables

In our 2023 data, we indeed find that students who filled out the survey on paper (rather than on tablet, which would have been the default) systematically differed. In particular, only 11% of students at general secondary schools used paper, as opposed to 41% of students at grammar schools (χ2 test: *p* < .001). Furthermore, students who filled out the survey on paper were slightly younger (*M* = 14.55 years) than students who filled out the survey on tables (*M* = 14.83 years, Welch Two-Sample t-test for the difference: *p* < .001). We observed no significant association between survey mode and whether or not student had a migration background (*p* = .32).

To check whether these differences in demographics can explain why girls (but not boys) were more satisfied on paper than on tablets, we re-ran the previous regression comparing the two survey modes, this time additionally including the predictors age (included again with the help of splines), schooltype, and migration background, as well as their interactions with survey mode and gender. Using this model, we calculated the counterfactual contrasts by survey mode (predicted life satisfaction if everybody filled out the survey on paper vs. predicted life satisfaction if everybody filled out the survey on tablet) separately by gender. Again, our model implied that girls were happier on paper than on tablet (difference of 0.16 scale points, 95% CI: [0.03, 0.29]) but boys were not (difference of -0.01 scale points, 95% CI: [-0.11, 0.10]), with a difference between the differences of 0.17 scale points (95% CI: [0.01; 0.32]). These unchanged conclusions support a scenario in which survey mode indeed causally affects life satisfaction (Figure 7, Scenario 1)—unless there are additional possibly unobserved confounders affecting both survey mode and life satisfaction (Figure 7, Scenario 2).

Accounting for School-Level Confounding with School-Fixed Effects

Given that survey mode was not randomized, it is of course still possible that there are unobserved confounders – classrooms that opted out of tablet usage may have been different in subtle ways which in turn explain why girls in them were more satisfied. We cannot rule out this possibility in general due to the study design. However, it turns out that in 12 schools, both survey modes were used. This, in turn, allows us to conduct additional analyses that can rule out unobserved confounders on the level of the school.

More specifically, we modified our previous linear regression model (analyzing associations with survey mode in the 2023 data) with the focal predictors gender and survey mode (as well as their interactions with schooltype, age, and migration background) and included (1) dummy variables representing the 12 different schools to estimate school-specific intercepts and (2) the interaction between these dummies and gender to allow for unique gender gaps in each of the schools. This fixed-effects model uses only within-school information to evaluate differences in life satisfaction by survey mode and gender. If this model still implies a gender-specific effect of survey mode, we can rule out that this is due to unobserved confounding on the school level.

In this model, we again find that girls are happier on paper than on tablet, this time by 0.23 scale points (95% CI:[0.07; 0.39]). Again, this does not seem to be the case for boys, who report descriptively slightly lower well-being on paper (-0.05 scale points, 95% CI:[-0.17; 0.06]). The difference between these differences amounts to 0.29 scale points (95% CI:[0.06; 0.51]).

It follows that unobserved school-level variables—such as neighborhood SES or other neighborhood characteristics—cannot explain away the particular association between survey mode and life satisfaction that we observe in girls. There could still be classroom-level confounders—for example, maybe teachers who particularly dislike digital devices also happen to behave in certain ways that positively affect girls' well-being. As we do not consider such an explanation particularly plausible, here, we are going to instead assume that survey mode is exogeneous with respects to the explanandum, and that the association between survey mode and life satisfaction actually reflects a causal effect: filling out the survey on the tablet makes girls (but not boys) report lower values than on paper. In this scenario, survey mode should be held constant when comparing the years to prevent it from introducing differences between the years that are not substantively relevant (Figure 7, Scenario 1). Holding constant, in turn, requires us to limit the analyses to students who used paper, since nobody filled out the survey on paper in 2010 and 2015.

Re-assessing the Explanandum Only for Responses on Paper

We now return to the model which we used to evaluate the widening of the gender gap while holding constant the distribution of age, schooltype, and migration background across the years (allowing each of these variables to interact with the survey year and gender). This time, we fit it on data from 3519 students who filled out the survey on paper (all students from the 2010 and 2015 surveys, as well as the 558 students from the 2023 survey who used paper). We can again evaluate the implications of this model for various covariate-distributions which will slightly shift all numbers. Therefore, we are going to evaluate everything at the 2010 distribution which serves as the baseline.

In this model specification, the gender gap widens from 0.22 scale points in 2010 to 0.31 scale points in 2015 to 0.41 scale points in 2023. This constitutes a widening by 0.19 scale points (95% CI: [-0.02, 0.40]), or 0.22 *SD* of life satisfaction across all observations. Note that this widening is not as stark as the widening implied by the same model fitted on the whole sample (including both survey modes), which was 0.31 scale points. Thus, assuming that survey mode does indeed causally affect life satisfaction reports of girls, changes in survey mode can explain away about 30% of the widening that we observe in models that ignore survey mode.

Before, we had already seen that widening of the gender gap varies by migration background, with a much more significant widening for students with a migration background/who do not speak German at home. As can be seen in Figure 8, this is still the case when we limit the sample to students who filled out the survey on paper. In fact, in this model, the widening of the gender gap for students without migration background has shrunk to a mere 0.11 scale points (95% CI: [-0.11; 0.33]) or 0.13 *SD* of life satisfaction across all observations; the two lines in the left panel of Figure 8 are close to parallel. Restricting the survey mode to paper has halved the gap that results from the same model fitted to the whole sample. In contrast, the widening of the gender gap among students with migration background is still very strong at 0.88 scale points (95% CI: [0.27; 1.48]); in fact, it is descriptively slightly larger than if we did not restrict survey mode. This corresponds to a widening of the gender gap by 1.03 *SD* of life satisfaction across all observations. Contrasting the widening of the gap, it is stronger in students with a migration background by 0.77 scale points (95% CI: [0.14; 1.41]).

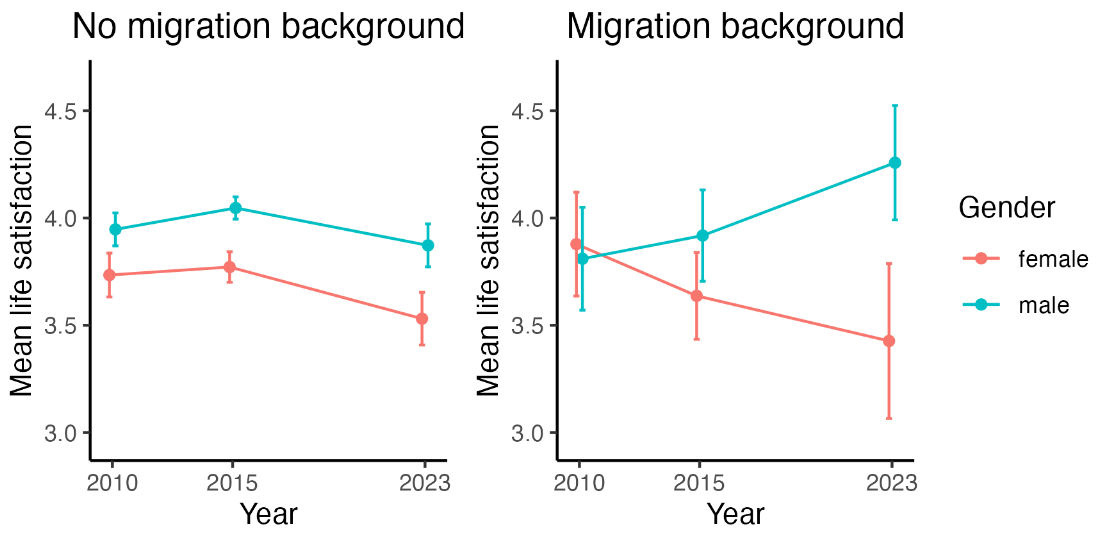


Fig. 8 Model-implied life satisfaction in boys and girls over time, separately for students with and without a migration background, only including responses on paper. Scale from 1 to 5, error bars are 95% confidence intervals, demographic variables held constant at their 2010 distributions. Note that in 2015, migration background was inferred from whether or not German was the main language students spoke at home.

Confirming Findings with an Ordinal Model

Do these conclusions also hold up in an ordinal model? For this purpose, we take our last model specification and once again fit an ordered probit model.[7] Evaluating the predictions of the model on the underlying (standardized) latent variable, we find that the gender gap grows from 0.29 in 2010 to 0.42 in 2015 to 0.54 in 2023. This corresponds to a widening of the gender gap of 0.25 SD of the latent variable (95% credible interval: [0.04; 0.55]). Again, the widening among students who do not have a migration background is fairly weak (0.15; 95% CI: [-0.15; 0.46]), in particular when compared against the widening among students with migration background (1.16, 95% CI: [0.49; 1.79]). Comparing these differences, the widening is 1 SD stronger in students with a migration background (95% CI: [0.29; 1.69]). Thus, the ordinal model produces qualitatively the same pattern of results, although the widening of the gap appears more pronounced.

[7] This time, we fit the ordered probit model in its Bayesian version in the *brms* package, using the default (noninformative to weakly regularizing) priors. This change is purely for pragmatic reasons—*brms* natively supports predictions on the scale of the link function which are of interest here.

Can We Explain Patterns on Alternative Satisfaction Measures in the Same Manner?

So far, we have only tried to understand the widening gender gap in overall life satisfaction. But before, we had already observed a similar pattern in other satisfaction variables. What happens to these gaps if we hold constant the distributions of age, schooltype, and migration background; limit analyses to respondents who filled out on paper; and break the gender gaps down by migration background? The results are depicted in Figure 9.

To focus on the broad patterns – in our initial analyses of the additional satisfaction measures (Figure 2), we had observed no overall widening of the gender gap for satisfaction with grades. This is still the case for our updated analyses; however, note that for student with a migration background, we actually observe that a gender gap in favor of girls now closes. In our initial analyses, we had observed widening gender gaps for both satisfaction with leisure time activities and satisfaction with the relationship to one's friends. These are still noticeable, and they are supported by aligned trends among both students with and without migration background. We had also originally observed widening gender gaps in satisfaction with one's parents, but our updated analysis reveals that this is exclusively driven by trends among students with migration background. Lastly, we had observed a widening gender gap in life satisfaction for housing satisfaction but not financial satisfaction. Our updated analysis suggests that for both of these variables, there may be widening gender gaps exclusively among students with a migration background. Detailed results can be found on the companion website.

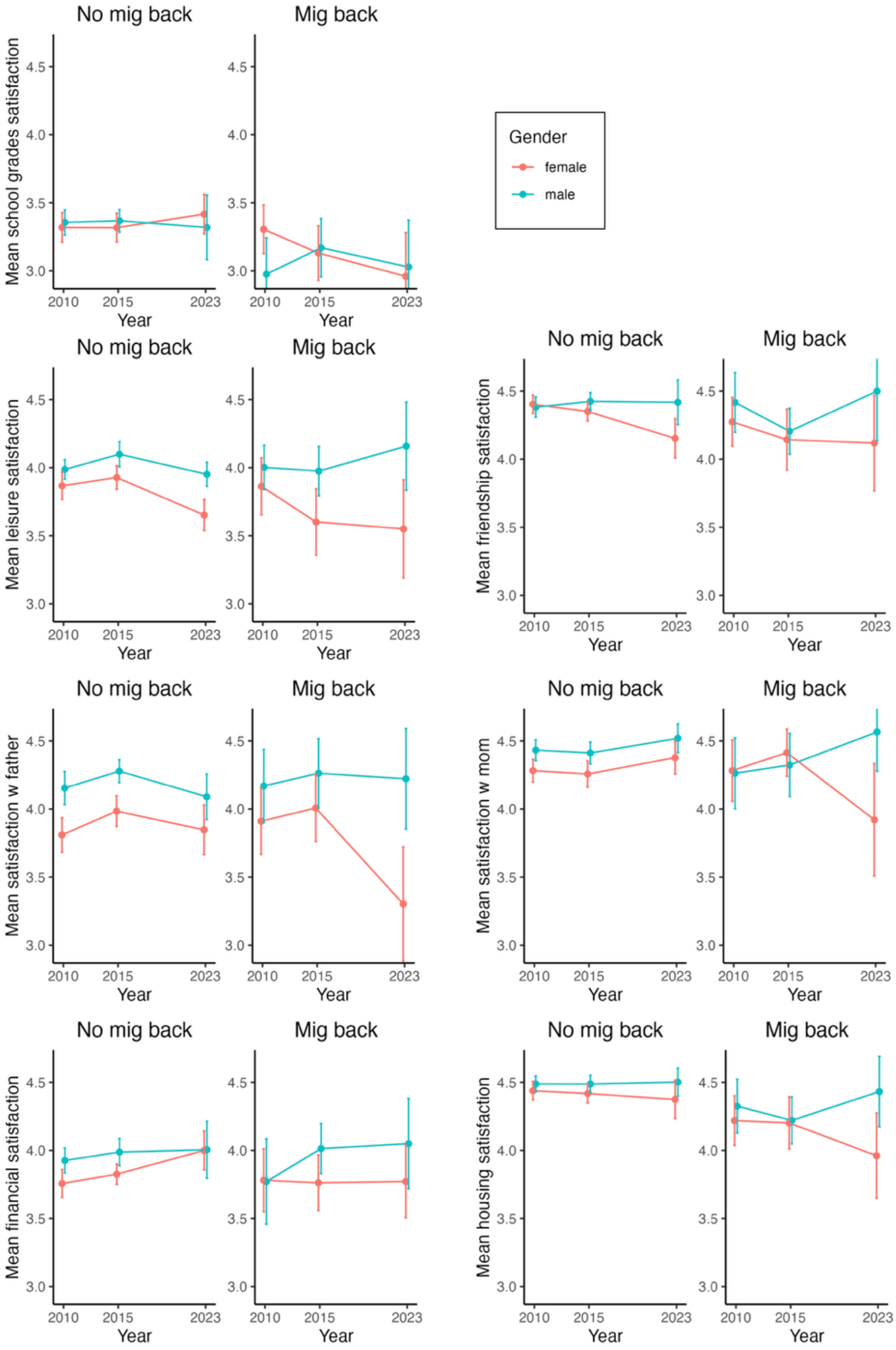


Fig. 9 Model-implied satisfaction with various aspects of life in boys and girls over time, separately for students with and without a migration background (mig back), only including responses on paper. Scale from 1 to 5, error bars are 95% confidence intervals, demographic variables held constant at their 2010 distributions. Note that in 2015, migration background was inferred from whether or not German was the main language students spoke at home.

Discussion

Why has the gender gap in life satisfaction among adolescents in Leipzig increased? Our analyses suggest that the pattern cannot easily be explained away as a scaling artifact, nor can it be explained by changes in underlying demographic variables (age, school type, migration background). However, we do observe a much more pronounced widening of the gender gap among students with a migration background. In the last wave of data, we also observe a wider gender gap when looking at responses on tablets (as opposed to paper). We suggest that this reflects effects of survey mode which should not be interpreted as part of any underlying substantively meaningful trend over time. Once we take into account survey mode effects, the life satisfaction gender gap among students without a migration background may actually not open at all. However, even when taking into account all of this, we still find widening gender gaps in satisfaction with leisure time activities and in satisfaction with relationships to friends, among both students with and without migration background.

Migration Background: Pronounced Changes in the Underlying Population

Why would the gender gap widen in such a pronounced manner among students with a migration background? One explanation to consider is that something happened in Leipzig that made the city a worse place for girls but not for boys with a migration background. However, the explanation that we consider both more parsimonious and more plausible here is that the widening gender gap mainly reflects changes in the composition of the underlying population.

At schools providing a general education (such as the schools considered in this study), in Leipzig in 2010, a fairly large share of students with a migration background had Vietnamese parents (Dütthorn & Gugutschkow, 2010). This is due to specific historic circumstances: In the German Democratic Republic (now East Germany, including Leipzig), Vietnamese “contract workers” came over in the context of treaties between socialist countries to tackle shortages of skilled labor. Until 1988, female workers who became pregnant faced deportation unless they aborted their pregnancies (*„Vertragsarbeiter“ in der DDR*, n.d.). Despite legal uncertainties following the fall of the Berlin wall in 1989 which negated the previous bilateral treaties (*„Vertragsarbeiter“ in der DDR*, n.d.), many Vietnamese contract workers went on to have children after deportation was no longer a guaranteed consequence. The oldest cohort of these children would have been around 20 years old in 2010 and thus past school age during the first data collection. However, those born slightly later are represented in our 2010 data. In our data, when a student reported that a parent was not born in Germany, Vietnam was the most frequently named country of birth.

The relative composition of the population with migration background in Leipzig then started to shift with strongly increasing numbers of refugees from Syria, Iraq, and Afghanistan in 2015, and refugees from Ukraine starting in 2022 (Bein, 2023; Dütthorn & Gugutschkow, 2010, 2016). Comparing the number of migrants in Leipzig based on their origin, the number of migrants with a Vietnamese background did increase somewhat (2009: 2 758, 2011-2015: 2 742, 2022: 3 882), but this is nothing in comparison to the more than 20-fold increase in the number of migrants with a Syrian background (2009: 447, 2011-2015: 516, 2022: 12 104). The number of migrants with a Ukrainian background also strongly increased (2009: 3 038, 2011-2015: 3 046, 2022: 12 970), although it is unclear how many adolescents would have already attended regular German secondary schools in 2023. Of course, ideally, we would want know the precise migration background of the students in our 2023 data. These data unfortunately were not collected, but based on the shifts in the underlying population, it is plausible that the relative share of students with a Vietnamese background declined, whereas the number of students with a background from most noticeably Syria increased.

Thus, the population of Leipzig students with a migration background in 2010 likely looks quite different from the population of Leipzig students with a migration background in 2023, with very different representation of various countries of (parental or own) origin. We consider it plausible that this is the main factor driving the widening gender gap among students with a migration background. Groups with larger gender gaps may simply be more strongly represented in the sample. We considered testing this hypothesis with the data available to us but discarded the idea due to small sample sizes (only between 140 to 240 students with migration background, spread out over many different countries of origin) and a lack of information on their country of origin in the 2023 sample, as well as a measure of migration background in 2015 (language spoken at home) that are hard to compare. We did not explicitly test any hypotheses for *why* the gender gap may vary between different groups. However, the very strong widening of the gender gap in satisfaction with the relationship to one's parents from 2015 to 2023 may suggest that the relationship between adolescents and their parents may be part of the story—maybe adolescent girls with parents from more gender-conservative countries such as Syria experience more friction with their families than their male counterparts.

The literature provides various lines of research pointing toward such potential frictions. For example, Nilles et al. (2023) compared gender role attitudes among German adolescents without a migration background, and adolescents with migration backgrounds from Syria, Afghanistan and Iraq. The authors found that the adolescents with migration background held more traditional attitudes, which may cause more friction, especially for girls, when seeking greater autonomy as a young adult. Further friction may occur from a higher expectation to take on caretaker responsibilities (i.e. instrumental and emotional *parentification*) – if only because the children acculturate faster and outperform their parents socio-culturally (Titzmann, 2012). In combination with traditional views of women as caretakers or homemakers this may burden boys and girls differently. Earlier findings comparing father–daughter and father-son dyads in Turkish-German families suggest that second-generation daughters showed a significant shift towards more egalitarian values, while sons remained as conservative as their fathers (Idema & Phalet, 2007) – which may produce very different experiences with regard to the bond they have with their parents, and the organization of family live on a day-to-day basis. While none of these findings could explain our data in particular and no two cultural backgrounds or even families are alike, they may serve to indicate some tendencies that need to be considered when discussing the life satisfaction particularly of young women in families with migration background.

Suvrey Mode: Why Would Girls Report Lower Satisfaction on Tablets?

It is less easy to explain why girls would report lower life satisfaction on tablets than on paper. While conducting our analyses, we did consider explanations such as differences in presentation on the tablets, or the possibility that on the tablets, answering all questions may have been mandatory (which may have led to differences in selectivity between tablets and paper). However, we did not find any satisfactory explanation; presentation of the survey was very similar and students could skip questions on either medium. We are thus left with our best guess that survey mode does indeed causally affect the gender gap in reported life satisfaction, without knowing anything specific about the underlying mechanisms. One may speculate that there are gender differences in familiarity with tablets, or maybe—in line with the idea that social media hurts girls in particular—girls have less pleasant associations with the mode than boys, who may be more likely to use tablets for gaming rather than browsing. We also do not know whether the tablet gender gap or the smaller paper gender gap more accurately reflects differences in underlying life satisfaction. To our knowledge, no such gendered mode effects has been reported before, we thus cannot confidently rule out that this pattern is just a chance fluctuation.

Other Outcome Measures: Widening Gender Gaps in Leisure Satisfaction and Friendship Satisfaction

Both the migration background and the survey mode pieces of the puzzle may suggest that any widening gender gap is just an artifact arising from changes in population composition and from changes in survey design. However, these factors cannot explain away widening gender gaps in students' satisfaction with their relationships to friends, and students' satisfaction with their leisure time activities. These observations are compatible with accounts in which social media impairs well-being specifically in girls more so than in boys (Twenge & Martin, 2020), although in our data this pattern would be limited to two domains that are plausibly directly affected by social interactions online in students' leisure time. Of course, alternative or additional explanations exist. The opening of the gender gap may also reflect the differential impact of the COVID-19 pandemic on the social lives and leisure time activities of girls in comparison to boys.

General Discussion

Our investigation started as the search for an explanation of a highly local observation: a widening gender gap in life satisfaction from 2010 to 2023 among adolescents in Leipzig. What, if any, generalizable insights arise from this? After all, we wouldn't necessarily expect widening gender gaps in life satisfaction in other places, and we certainly wouldn't assume that the specifics of the context of our data—such as strong compositional changes in the population of people with a migration background, and partial changes in survey mode—would occur elsewhere.

However, we believe that there are generalizable insights with respects to how such data and how such a reverse causal question over time should be approached. First, the composition of the population of interest played a major part in our explanation. As far as we can tell, such changes are rarely considered in psychological well-being research. At best, researchers may "control for" third variables such as migration background. However, notice how in our case, this would not have been sufficient to understand what is happening. We needed to additionally take into account how the associations vary between groups (i.e., we need to explicitly model an interaction with migration background), and then we additionally needed to consider the broader historical context to make sense of the observed patterns.

The change in survey mode from 2015 to 2023 is an unfortunate variation from the perspective of us as researchers who are interested in change over time. This issue can of course be prevented in the design phase of a study by ensuring no changes in survey mode; however, researchers may often rely on pre-existing longitudinal or repeated cross-sectional survey studies when investigating well-being over time and thus have little control over these matters. In fact, obstacles in implementation and the resulting variations in the sample are part of the day-to-day reality of large-scale survey studies, and may even be considered typical, especially in the context of educational research.

Our analyses are our best attempt at dealing with such variations in a transparent manner; we hope that they can provide one example with how to deal with unintended and unplanned stratifications, and how to work through their overall influence on a research question. For example, our final analyses rest on the assumption that survey mode causally affects the gender gap in life satisfaction; if, as we spelled out, the association is instead mainly to be attributed to selection effects, then the results underlying Figure 6—with a larger life satisfaction gap among students without migration background in 2023—would provide a more accurate picture. Of course, other “measurement artifacts” may also matter; for example, when investigating the incidence of mental health issues over time, changes in screening procedures and diagnoses (Guthrie et al., 2013; Wallace-Wells, 2024) may bias results beyond changes in the actual underlying phenomena.

Our analyses also highlight the value of considering multiple well-being measures in parallel, which results in a more nuanced picture potentially supporting some explanations while ruling out others. Of course, multiple outcomes need to be disclosed transparently—including multiple dependent variables but only reporting those that return the “right” results increases the risk of false-positive findings (Simmons et al., 2011). A good template here may be personality psychology, a field in which it is very common to report results for all Big Five personality traits (extraversion, emotional stability, agreeableness, conscientiousness, openness to experience), which reduces the risk of null results ending up in the file drawer (Atherton et al., 2021).

Lastly, we hope we have convinced readers that addressing reverse causal questions can be an insightful endeavor. Certainly, the introduction sections of psychological research articles often invoke such questions (why Y?); however, this often seamlessly transitions into a narrow forward causal question (how does X affect Y?) just before the Method section starts, which results in the standard format of many empirical journal articles. In contrast, entertaining multiple explanations that may hold true at the same time results in a more complex article structure. This is compounded by the fact that causal inference usually involves many uncertainties; However, we believe that these complexities and uncertainties, communicated transparently, are worth sharing if we want to tackle reverse causal questions more seriously and improve our understanding of the world.

References

Abel, F., Bittner, J., Ehlert, T., Greunke, P., Hemming, K., Kachel, G., Köbler, T., König, R., Lagrange, M., Netwall, N., Schultz, A., & Waschipky, M. (2023). *Jugend in Leipzig 2023 [Youth in Leipzig 2023]*. Stadt Leipzig. https://static.leipzig.de/fileadmin/mediendatenbank/leipzig-de/Stadt/02.1_Dez1_Allgemeine_Verwaltung/12_Statistik_und_Wahlen/Stadtforschung/Jugend-in-Leipzig-2023.pdf

Abel, F., Heinemann, J., Lehmann, K., Schultz, A., Lamperti, K., & Bischof, M. (2015). *Jugend in Leipzig 2015 [Youth in Leipzig 2015]*. Stadt Leipzig. https://static.leipzig.de/fileadmin/mediendatenbank/leipzig-de/Stadt/02.1_Dez1_Allgemeine_Verwaltung/12_Statistik_und_Wahlen/Stadtforschung/Jugend_in_Leipzig_2015.pdf

Arel-Bundock, V., Greifer, N., & Heiss, A. (2024). How to Interpret Statistical Models Using marginaleffects for R and Python. In *Journal of Statistical Software* (Vol. 111, Issue 9, pp. 1–32). https://doi.org/10.18637/jss.v111.i09

Atherton, O. E., Chung, J. M., Harris, K., Rohrer, J. M., Condon, D. M., Cheung, F., Vazire, S., Lucas, R. E., Donnellan, M. B., Mroczek, D. K., Soto, C. J., Antonoplis, S., Damian, R. I., Funder, D. C., Srivastava, S., Fraley, R. C., Jach, H., Roberts, B. W., Smillie, L. D., … Corker, K. S. (2021). Why has personality psychology played an outsized role in the credibility revolution? *Personality Science*, *2*. https://doi.org/10.5964/ps.6001

Auguie, B. (2017). *gridExtra: Miscellaneous Functions for "Grid" Graphics*. https://CRAN.R-project.org/package=gridExtra

Bayer, M., Zinn, S., & Rüdiger, C. (2021). Grading in secondary schools in Germany – the impact of social origin and gender. *International Journal of Educational Research Open*, *2*(100101), 100101.

Bein, C. (2023). *Migrantinnen und Migranten in Leipzig 2022 [Migrants in Leipzig 2022]*. Stadt Leipzig, Amt für Statistik und Wahlen. https://static.leipzig.de/fileadmin/mediendatenbank/leipzig-de/Stadt/02.1_Dez1_Allgemeine_Verwaltung/12_Statistik_und_Wahlen/Analysen_zur_Stadtgesellschaft/001-Migrantinnen-und-Migranten-2022.pdf

Bürkner, P.-C. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. In *Journal of Statistical Software* (Vol. 80, Issue 1, pp. 1–28). https://doi.org/10.18637/jss.v080.i01

Deutsche Welle. (2019, September 10). *Most migrant families speak German at home*. Deutsche Welle. https://www.dw.com/en/german-is-the-most-spoken-language-in-immigrant-households/a-50374819

Dütthorn, P., & Gugutschkow, S. (2010). *Migranten in der Stadt Leipzig 2010 [Migrants in the City of Leipzig 2010]*. Stadt Leipzig, Amt für Statistik und Wahlen in Kooperation mit dem Referat für Migration und Integration. https://static.leipzig.de/fileadmin/mediendatenbank/leipzig-de/Stadt/02.1_Dez1_Allgemeine_Verwaltung/12_Statistik_und_Wahlen/Stadtforschung/Migranten2010.pdf

Dütthorn, P., & Gugutschkow, S. (2016). *Migrantinnen und Migranten in Leipzig 2015 [Migrants in Leipzig 2015]*. Stadt Leipzig, Amt für Statistik und Wahlen in Kooperation und Referat für Migration und Integration. https://static.leipzig.de/fileadmin/mediendatenbank/leipzig-de/Stadt/02.1_Dez1_Allgemeine_Verwaltung/12_Statistik_und_Wahlen/Stadtforschung/Migranten2015.pdf

Elwert, F., & Winship, C. (2014). Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable. *Annual Review of Sociology*, *40*, 31–53.

Fabian, M., Kaiser, C., Panasiuk, S., Funk, S., Pountney, L., & Brett, C. (2024). *Evidence Against the Simple Validity of Life Satisfaction Scales from Long Cognitive Interviews*. https://iariw.org/wp-content/uploads/2024/08/FINAL-Fabian-et-al.-Cognitive-Interviewing-IARIW.pdf

Gelman, A., & Imbens, G. (2013). *Why ask Why? Forward Causal Inference and Reverse Causal Questions* (No. w19614). National Bureau of Economic Research. https://doi.org/10.3386/w19614

Guthrie, W., Swineford, L. B., Nottke, C., & Wetherby, A. M. (2013). Early diagnosis of autism spectrum disorder: stability and change in clinical diagnosis and symptom presentation: Stability of early diagnosis and symptoms in ASD. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *54*(5), 582–590.

Haidt, J. (2024). *The anxious generation: How the great rewiring of childhood is causing an epidemic of mental illness*. https://strategylab.ca/wp-content/uploads/2024/07/The-Anxious-Generation-Supplemental-Resources.pdf

Heinemann, J., Lehmann, K., Rosk, G., & Schultz, A. (2011). *Jugend in Leipzig – Ergebnisse einer Befragung 2010 [Youth in Leipzig – Results from a 2010 Survey]*. Stadt Leipzig. https://static.leipzig.de/fileadmin/mediendatenbank/leipzig-de/Stadt/02.1_Dez1_Allgemeine_Verwaltung/12_Statistik_und_Wahlen/Stadtforschung/Jugendstudie2011.pdf

Jugendstudie 2023: Lebenszufriedenheit der Schüler sinkt deutlich [Youth Survey 2023: Life satisfaction of students declines markedly]. (2023, December 7). https://www.leipzig.de/newsarchiv/news/jugendstudie-2023-lebenszufriedenheit-der-schueler-sinkt-deutlich

Nakazawa, D. J. (2022). *Girls on the Brink: Helping our daughters thrive in an era of increased anxiety, depression, and social media*. https://books.google.de/books?hl=en&lr=&id=xKZUEAAAQBAJ&oi=fnd&pg=PT10&dq=Girls+on+the+Brink+Donna+Jackson+Nakazawa&ots=_2ARmf8TlT&sig=vTgqrNeMKkPTEKJ8sUiVi2711zs

Nilles, H., El-Awad, U., Kerkhoff, D., Braig, J., Schmees, P., Kilinc, Y., Rueth, J.-E., Eschenbeck, H., & Lohaus, A. (2023). Gender role attitudes and well-being of German and refugee adolescents-same or different? *BMC Psychiatry*, *23*(1), 663.

Pedersen, T. L. (2024). *patchwork: The Composer of Plots*. https://CRAN.R-project.org/package=patchwork

Posit team. (2023). *RStudio: Integrated Development Environment for R*. Posit Software, PBC. http://www.posit.co/

R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rohrer, J. M. (2018). Thinking Clearly About Correlations and Causation: Graphical Causal Models for Observational Data. *Advances in Methods and Practices in Psychological Science*, *1*(1), 27–42.

Rohrer, J. M., & Arslan, R. C. (2021). Precise Answers to Vague Questions: Issues With Interactions. *Advances in Methods and Practices in Psychological Science*, *4*(2), 25152459211007370.

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, *22*(11), 1359–1366.

Simonsohn, U. (2019). [80] Interaction Effects Need Interaction Controls. http://datacolada.org/80

Titzmann, P. F. (2012). Growing up too soon? Parentification among immigrant and native adolescents in Germany. *Journal of Youth and Adolescence*, *41*(7), 880–893.

Twenge, J. M., & Martin, G. N. (2020). Gender differences in associations between digital media use and psychological well-being: Evidence from three large datasets. *Journal of Adolescence*, *79*(1), 91–102.

Uunk, W., & Blossfeld, P. (2025). Gender-specific development of mathematics and language performance in lower secondary education in Germany. *Zeitschrift Für Bildungsforschung*, *15*(1), 95–119.

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S* (Fourth). Springer. https://www.stats.ox.ac.uk/pub/MASS4/

„Vertragsarbeiter" in der DDR. (n.d.). DOMiD | Dokumentationszentrum und Museum über die Migration in Deutschland. Retrieved May 13, 2025, from https://domid.org/news/vertragsarbeit-in-der-ddr/

Voyer, D., & Voyer, S. D. (2014). Gender differences in scholastic achievement: a meta-analysis. *Psychological Bulletin*, *140*(4), 1174–1204.

Wallace-Wells, D. (2024, May 1). Opinion. *The New York Times*. https://www.nytimes.com/2024/05/01/opinion/smartphones-social-media-mental-health-teens.html

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis. Springer.

Wickham, H., François, R., Henry, L., Müller, K., & Vaughan, D. (2023). *dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr

Wickham, H., Miller, E., & Smith, D. (2023). *haven: Import and Export "SPSS", "Stata" and "SAS" Files*. https://CRAN.R-project.org/package=haven

Yzerbyt, V. Y., Muller, D., & Judd, C. M. (2004). Adjusting researchers' approach to adjustment: On the use of covariates when testing interactions. *Journal of Experimental Social Psychology*, *40*(3), 424–431.