Modelling Intersectionality Within Quantitative Research

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Abstract

In the last decades, and especially since 2010, the intersectionality paradigm is being increasingly used as theoretical framework for examining and explaining social inequalities in various areas – both with qualitative and quantitative methods. So far, there is no standard for applying intersectionality in quantitative social research. Therefore, this paper aims to present how intersectionality can be applied in quantitative research and to elaborate on and evaluate several methodological approaches in this regard. More precisely, we describe the tenets of three different quantitative approaches: multivariate linear models, conventional multilevel analysis, and multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA). We compare the three approaches and outline their methodological benefits and limitations.

Keywords: intersectionality, quantitative, multilevel analysis, MAIHDA approach

Introduction, or the Rise of the Intersectionality Paradigm

Crenshaw, a US legal scholar, introduced the term *intersectionality* by pointing out that the cumulative disadvantages Black women face in several areas of life are “greater than the sum of racism and sexism” (1989: 140). In 1995, the first publication appeared on the *Web of Science*, and it took a decade for publications with the topic of intersectionality to be increasingly noted. From 2005 on, the number of intersectionality-related publications increased exponentially (see Figure 1).

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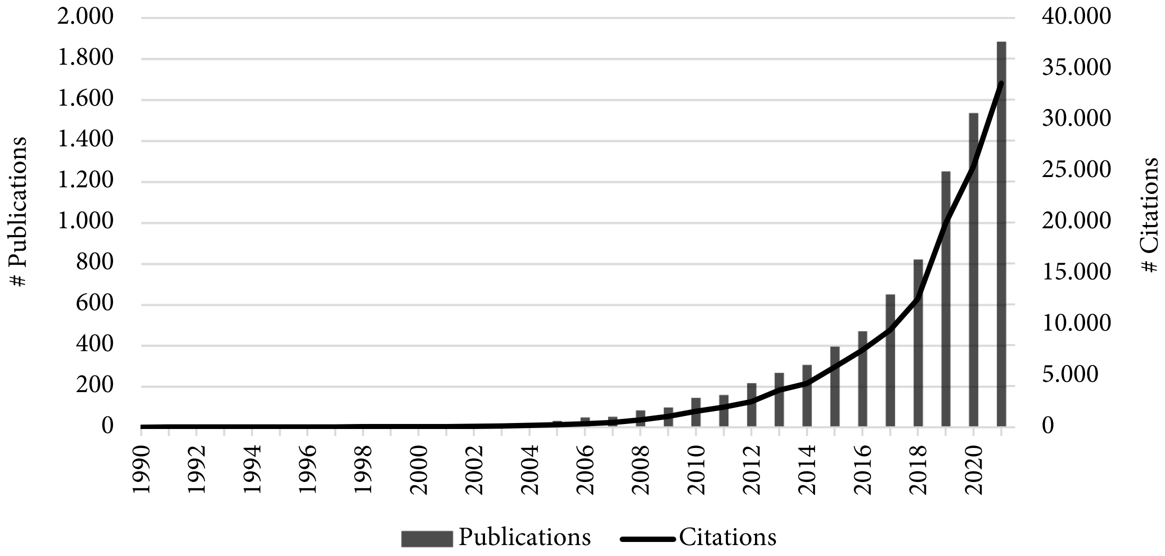
Figure 1: Result of Web of Science Search (total numbers)



Source: Own figure based on a search within the Web of Science (2022) for topic=intersectional; year≤2021.*

These publications stem from various disciplines including inequality, gender, feminist, and queer research from various theoretical perspectives, such as (de-)constructivist and socio-cultural (see Collins/Chepp 2013; McCall 2005), and increasingly from a critical rationalism, i.e., positivistic point of view (see Gross et al. 2016). While the openness of the paradigm may be one of the main reasons for its popularity (see Davis 2008a; Phoenix/Pattynama 2006) – especially in qualitative research, where it is assumed to be an ideal "analytical tool […] to capture and engage contextual dynamics of power" (Cho et al. 2013: 788) –, quantitative research with a focus on testing hypotheses derived from theories needs additional assumptions or theories to apply an intersectionality perspective.

However, since the rise of the intersectionality paradigm, social inequality research can hardly consider only one dimension of inequality without accounting for additional dimensions (*multidimensionality*), their confoundations (*intersectionality*), and the social context these dimensions occur in (*contextuality*).

The aim of this contribution is to present how the intersectionality approach can be applied in the framework of quantitative research with a special focus on multilevel approaches. We start with introducing the paradigm along its main pillars (multidimensionality, intersectionality, contextuality) and main forms of complexity (anti-, intra-, and intercategorical). To elaborate on the purposes, opportunities, and limitations of quantitative research designs to model intersectionality in the first place, we continue with contrasting the key characteristics of ideal-typical qualitative and quantitative research designs. Then, we present how to model intersectionality within the quantitative paradigm by applying and comparing multivariate linear models, the conventional multilevel approach, and the MAIHDA approach in the light of their respective benefits and limitations. This comparative overview aims to provide methodological insights that serve as practical guidelines for researchers who wish to quantitatively model intersectionality and need to make an informed decision on the best analytical strategy to do so.

We continue with an overview of previous applications of the paradigm in quantitative research and conclude with an outlook.

The Intersectionality Paradigm

For quantitative researchers, the key claims of the intersectionality paradigm may be broken down in the three pillars *multidimensionality*, *intersectionality*, and *contextuality*. Even though intersectionality theorists may perceive these pillars as oversimplification of a much more elaborated conceptual framework, we will present the key claims along these terms.

Multidimensionality refers to the claim that models with one dimension only are obsolete (Winker/Degele 2009: 10) and instead "multiple axis of differentiation […] intersect in historically specific contexts" (Brah/Phoenix 2004: 76). Which dimensions are relevant depends on the social context and is not provided by the paradigm itself, which impedes or even prevents the derivation of testable hypotheses from the paradigm alone. Whereas US-American research mainly focuses on the dimensions sex/gender, class, and race/ethnicity, there is an open discussion over additional dimensions within European intersectionality research (see Davis 2008b; Knapp 2008).

Analogously, the paradigm assumes the intersectional influence of these dimensions (*intersectionality*) without providing any assumptions about which dimensions interact with each other in which way. Whereas doing-difference approaches within qualitative methodology seem to handle this openness well (see e.g., Phoenix 2008, 2010), a quantitative methodology needs more differentiated assumptions (see, e.g., Gross et al. 2016; Hardmeier 2012).

Which dimensions and intersections lead to advantages or disadvantages depends on the social context (*contextuality*). Social context may be understood as (a) topic (e.g., women are on average disadvantaged regarding the income-level; however, they may benefit from being female when it comes to custody rights), as (b) regional or historical context with a direct effect on the outcome (e.g., the beneficial position of people living in developed countries regarding access to education and healthcare), or as (c) regional or historical context influencing the effect of inequality dimensions (e.g., being gay in contemporary San Francisco may be approved, whereas it goes along with a life-threatening situation in contemporary Iran and used to in San Francisco a few decades ago).

McCall (2005) has identified three different forms of intersectionality research in terms of how they treat analytical categories to methodologically examine social life: *anti*-, *intra*-, and *inter*categorical complexity. Research assigned to the anticategorical branch usually tries to deconstruct analytical categories, whereas research within the intercategorical approach uses categories strategically to show differences. Within this continuum, the intracategorical approach lies somewhere in between, showing the wider range of phenomena assembled within one category.

Researchers within the *anticategorical* branch consider social life including subjects and structures as being too complex and fluid to be arranged in categories. In McCall's (2005: 1773) words:

> *Social life is considered too irreducibly complex – overflowing with multiple and fluid determinations of both subjects and structures – to make fixed categories anything*

> *but simplifying social fictions that produce inequalities in the process of producing differences.*

Categories are assumed to be linguistic artifacts rather than empirical reality but still scientifically accessible, for example by historical examinations of the emergence and development of categories, deconstructive literature analyses, or ethnographic methods. Anticategorical research, while devided, is largely inspired by poststructuralist and postmodern philosophers such as Derrida or Foucault.

Research within the *intracategorical* branch is rooted in the critique of a feminist tradition to be focussed on white intellectual women only, ignoring the multiple disadvantages women of color face in other social strata such as the working poor. Intracategorical research emphasizes “neglected points of intersection” (McCall 2005: 1774) and illustrates the wide range of diversity *within* any social category that is usually not questioned or criticized itself. Although intracategorical research in contrast to anticategorical research does not reject all categorization, it still challenges “homogenizing generalizations” (McCall 2005: 1783) about the members of any social and inherently diverse category.

Intercategorical research “requires that scholars provisionally adopt existing analytical categories to document relationships of inequality among social groups and changing configurations of inequality along multiple and conflicting dimensions” (McCall 2005: 1773). Among the three branches, it is the only one whose analyses inherently focus on inequality “among multiple social groups within and across analytical categories” (McCall 2005: 1786). It examines all possible combinations of the dimensions of the analytical categories under study rather than one specific intersection or a subset of intersections. It adopts a holistic perspective, follows a comparative logic, but also necessarily requires categorization, which entails the risk of oversimplification and becomes more and more complicated to implement with each additional analytical category taken into account. Intersectionality studies within social stratification research – most of it quantitative empirical in its nature – serve as example of the intercategorical branch.

While most of the studies that evaluate intersectionality in the light of quantitative research come to the quick conclusion that quantitative research is located within the intercategorical, oversimplifying branch (only), we would like to elaborate on this view and add two ideas in the sense of what quantitative researchers could learn from both the anti- and the intracategorical view:

First, anticategorical research points out the limitations and blind spots within quantitative research. While discrete variables or rather categories (e.g., gender: female/male) are easy to analyze within a quantitative framework and most people have no difficulties in categorizing themselves or others as female or male, the anticategorical scepticism may serve as a warning light. For example, the gradual extension of the LGB movement, originally referring only to sexual orientation, towards LGBTQIA*, also including different gender identities and those who reject these categories altogether, such as non-binary/genderqueer people, illustrates the – temporally and historically – limited validity of discrete categories.

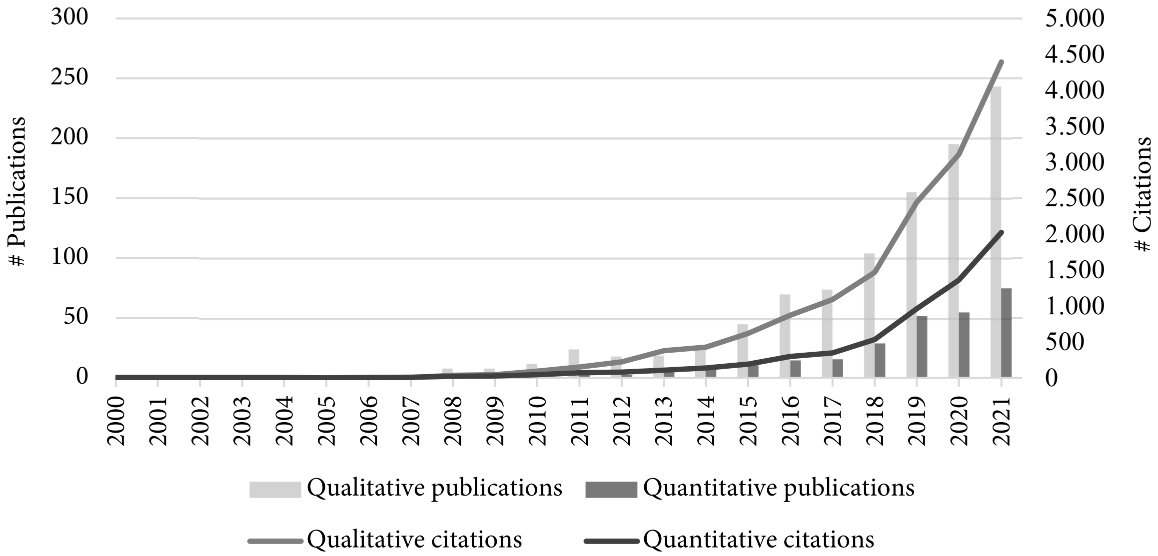
Second, quantitative researchers could use intracategorical ideas to overthink their operationalization. For example, since the emergence and later legal implementation of the third gender category has challenged the idea of a dichotomous gender variable (and a second gender dummy variable with too few cases can hardly be handled adequately), quantitative researchers have put forward the idea of a continuous gender variable (see Hyde et al. 2019; Reilly 2019); however, usually a one-dimensional one. Thus, the operationalization of analytical categories in quantitative research should proceed with caution to capture the empirical reality as precisely and distinctive as possible.

Quantitative Versus Qualitative Applications of the Paradigm

While the intersectionality paradigm is very popular within the qualitative approach, its acceptance within the quantitative approach is ambivalent. A *Web of Science* search for the topic of intersectionality has resulted in a total of 5,786 publications with an H-Index[3] of 119 (Web of Science 2022). The distribution of these publications are also shown in the introduction of this contribution (see Figure 1).

Searching for topic=intersectionality & topic=*qualitative* yields 737 publications; searching for topic=intersectionality & topic=quantitative results in 221 publications, even though peer-reviewed journal articles prefer the publication style of quantitative researchers over that of qualitative researchers, which is why qualitative publications are usually underrepresented in this area. However, we find a steep rise over the years in both approaches (see Figure 2).

Figure 2: *Result of* Web of Science Search *(total numbers by methodological approach)*



Source: Own figure based on a search within the Web of Science (2022) for topic=intersectional & topic=qualitative & year≤2021 versus topic=intersectional* & topic=quantitative & year≤2021.*

Table 1 contrasts some key characteristics of the ideal-typical qualitative and quantitative approaches to elaborate on the purposes, opportunities, and limitations of quantitative research designs to model intersectionality. As the table is intended to give an illustrative overview, it

[3] Meaning that there are at least 119 publications with at least 119 citations.

necessarily presents the characteristics in a simplified way. The ideal-typical qualitative approach deals with a limited number of cases and tries to develop theories and a conceptual understanding of the research object by drawing conclusions from the case to the pattern (theory) in an inductive manner using hermeneutical tools and text interpretation (see Aspers/Corte 2019; Schwandt 2007; Yin 2010). Qualitative data includes, for example, texts generated from interviews, video or photo material, images, observations, and so on. By contrast, the ideal-typical quantitative approach deals with variables, which are used to test theoretically derived hypotheses based on inferential statistics. Quantitative data is usually organized in data sets with data generated, for example, by surveys, experiments, or even digital tracking apps to observe behavior. The higher the number of cases included, the higher the statistical power. Note, however, that although the quantitative approach usually derives causal relationships between theoretical constructs from theory, the methodological implementation often does not allow for causal interpretations. This holds, in particular, in social inequality research, where the inequality dimensions such as gender, migration background, and socioeconomic status cannot be varied experimentally and where laboratory experiments with fictitious persons are highly contestable with regard to their external validity.

Table 1: *Comparison of the ideal-typical qualitative and quantitative approaches*

	Qualitative Approach	**Quantitative Approach**
Methods of reasoning	Inductive	Deductive
Research goal	Generate new findings, development of theories or conceptual understanding	Testing hypotheses, examining the impact of variables on outcomes, statistical significance
Methods to generate data	Interviews, observations, group discussions, etc.	Surveys, experiments, observations, etc.
Data format	Text (words), images, etc.	Datasets (numbers)
Data analysis techniques	Text interpretation, hermeneutic, e.g., grounded theory, phenomenological approaches, narrative analysis, discourse analysis	Techniques mainly based on inferential statistics, multivariate and multi-level modelling
# cases	≤ 20, more cases possible but time-consuming to analyze	> 30; the more, the better (statistical power depends on sample and effect size)
Strengths regarding intersectionality perspective	Ability to manage anti-, intra- and intercategorical approaches, strong focus on cases with possibility to account for specificities	Strong persuasive power for policy makers, ability to test statistically whether dis/-advantage can be explained by (multiple) group memberships in an additive form,

		causal interpretation depending on analytical strategy
Shortcomings regarding intersectionality perspective	Combinations of numerous dimensions cannot be generalised due to limited case numbers and non-representative samples, no causal interpretation possible	Need to oversimplify complex categories such as gender or ethnic background for operationalisation, anti- and intracategorical approach cannot be examined adequately

Source: Adaption of Gross et al. (2016: 65).

Within the ideal-typical qualitative approach, all forms of categorical complexity can be easily examined, and specificities can be accounted for in detail. However, the detailed findings do not allow causal interpretation or even a wider generalization of the findings. As a result, the persuasive power of these findings is limited, and they can easily be doubted. By contrast, this is the biggest strength of the quantitative approach: The results from ideal-typical quantitative intersectionality research can illustrate advantages and disadvantages by group membership, e.g., the net of meritocratic criteria, and can therefore be easily used for policy purposes. However, the quantitative approach is inadequate when it comes to modeling categorical complexity. Within the quantitative approach, anticategorical complexity cannot be modeled. Usually, quantitative research examines intercategorical complexity, e.g., by analyzing wage gaps by gender, or health status by migration background. However, the quantitative approach may be also used to show intracategorical complexity, e.g., by illustrating the broad distribution of wages among all women or to show the wide range of family orientation among all men. Recent ideas within the quantitative paradigm also discuss measuring gender on a continuous scale. Since both methodological approaches have their own strengths and weak spots, one strategy could be to combine the strengths of both approaches in following a mixed-methods design.

Modelling Intersectionality Within the Quantitative Approach

An increasing number of studies within intersectionality research apply quantitative methods (see, e.g., Covarrubias 2011; Rouhani 2014; Strand 2014), most of them focusing on the differences and inequalities *between* groups (see Scott 2010; Spierings 2012), i.e., mainly modeling intercategorical complexity. In this chapter, we describe the methodological foundations of the three afore-mentioned approaches to quantitatively model intersectionality, namely simple multivariate (linear) models, conventional multilevel models, and the MAIHDA approach. In the literature, there are many introductions to the two former approaches, therefore, we confine ourselves to their methodological essentials with regard to intersectionality. Yet the latter, the MAIHDA approach, is still novel and therefore introduced in a little more detail.

Multivariate linear models

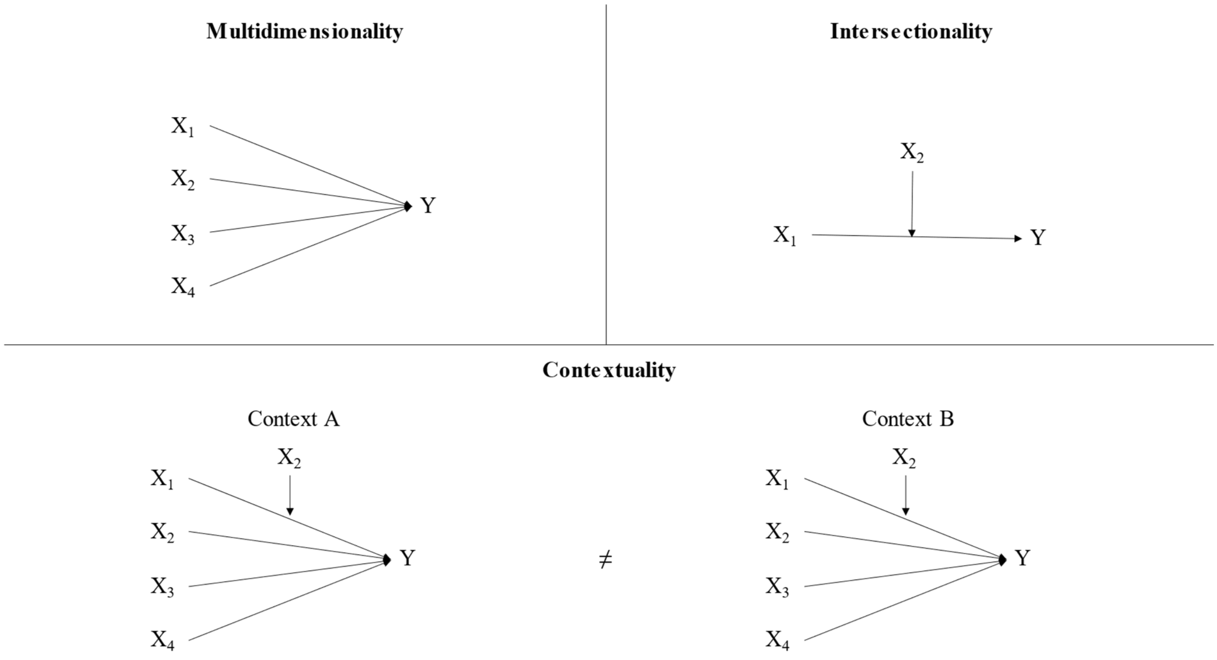
While the intersectionality paradigm presents the idea that privileges and disadvantages in different life areas are fostered by more than one inequality dimension (*multidimensionality*) as a new insight, the idea of multivariate analysis within quantitative methods is not new at all. Within a simple multiple linear regression, the outcome Y is estimated by adding independent variables (that measure the inequality dimension), such as gender (X_1), migration background (X_2), and socioeconomic status (X_3):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \tag{1}$$

> … with the constant β_0 illustrating the intercept with the y-axis (outcome Y) when all terms $\beta_i X_i$ equal 0,
>
> … with the coefficients β_1, β_2, β_3 describing the impact of each inequality dimension X_i on the outcome Y net of all other dimensions within the model (*ceteris paribus* condition), and
>
> … with the error term ε being a vector that includes all deviations between estimated and empirical values accounting for the non-deterministic character of the linear connection between X_i and Y.

Intersectionality researchers have often criticized that the discrimination people face due to their multiple group memberships such as being male, working class, and a person of Color cannot be explained by simply adding up single penalties for each dimension (e.g., Bowleg 2008; Hancock 2007), since, e.g., Black working-class men face more disadvantages than white men or Black upper-class men. However, please note that you do not necessarily need any additional interaction term to model cumulative disadvantages (see also Gross et al. 2016). Only in the case that discrimination of a special subgroup is more than the sum of each dimension, you need to introduce interaction terms to model the intersectionality pillar adequately (see Figure 3).

Figure 3: *Modeling the three intersectionality pillars within a simple linear regression*



Source: own figure.

Since the intersectionality paradigm itself is too open and broad to indicate which single interactions should be tested, the researcher is left with the decision to model all possible interactions terms. The number of possible interactions terms I_{max} increases exponentially with the number of dimensions (independent variables) k:

$$I_{max} = 2^k - k - 1 \tag{2}$$

The pitfall in doing so is obvious and twofold: First, you need a fairly large case number to sufficiently analyze the exploding number of interaction terms (besides main effects). Second, you get numerous false significant coefficients (on average 5 false positive coefficients per 100 coefficients tested assuming a significance level of 5%).

Even the third pillar of the paradigm – *contextuality* – can be modeled within simple linear models to a certain extent. Note that contextuality, in general, can be understood in different ways:

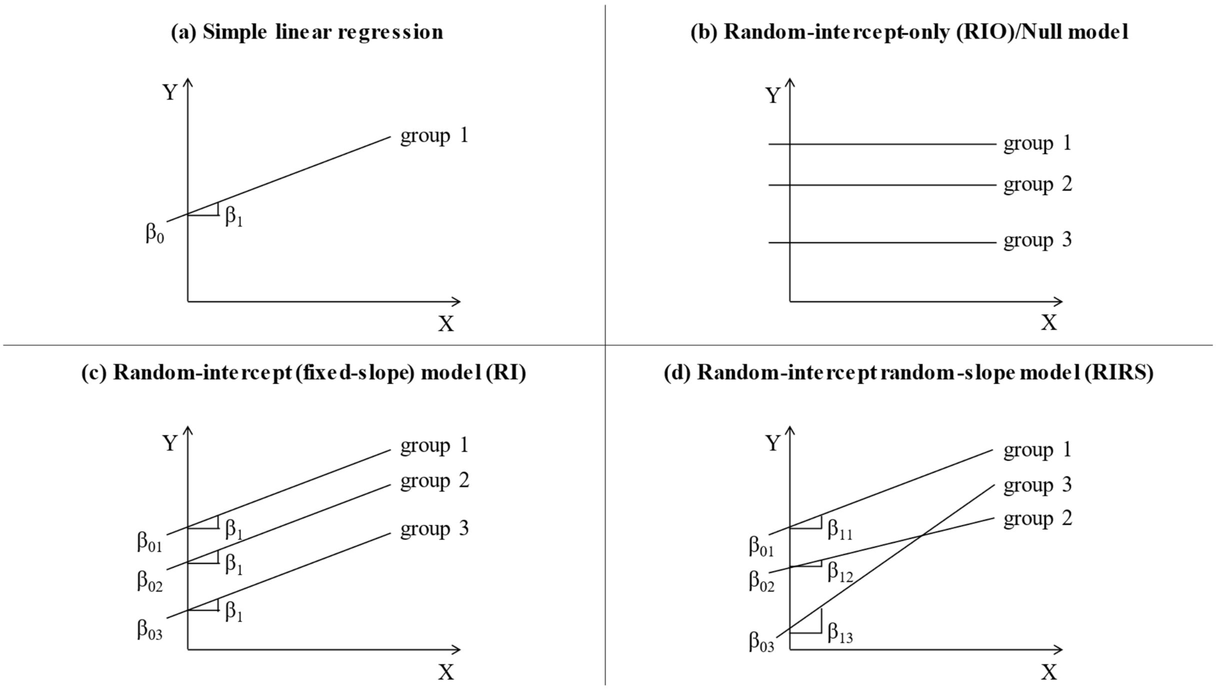
a It depends on the context, understood as topic/field such as education, work, physical training, etc., which inequality dimension goes along with which discrimination.
b A context variable itself has a direct effect on the outcome.
c It depends on the value of a context variable, for example, if the country is France or Germany, which inequality dimension goes along with which discrimination.

With a simple multiple linear regression, you could test interpretation (a) by using the same set of independent variables, run regressions with different dependent variables, and test for significant differences in the coefficients, e.g., by using a Chow-Test (Chow 1960). Interpretation (b) can be tested better within a multilevel analysis framework (see next chapter). To test the (c) interpretation of contextuality, one could estimate regressions for each social context, e.g., one regression with the German subsample and one with the French subsample using the same independent variables, and then again use the Chow-Test to test if the coefficients vary significantly between countries. Alternatively, one could use interaction terms for inequality dimensions and context variables; however, this would be the second-best option.

Conventional multilevel analysis

While the simple linear model is able to model multidimensionality, intersectionality, and at least to some extent also contextuality (see Figure 3), the conventional multilevel framework is ideal to model various interpretations of contextuality. A complete introduction in conventional multilevel analysis would exceed the scope of this paper, but we provide an intuitive understanding of how conventional multilevel approaches allow to model the three pillars of the intersectionality paradigm. Figure 4 compares the main types of conventional multilevel models with the simple linear model. The simple linear model (*a* in Figure 4) treats the whole sample as unique entity and assumes all cases to be independent from each other.

Figure 4: *Conventional multilevel models in comparison with simple linear regression*



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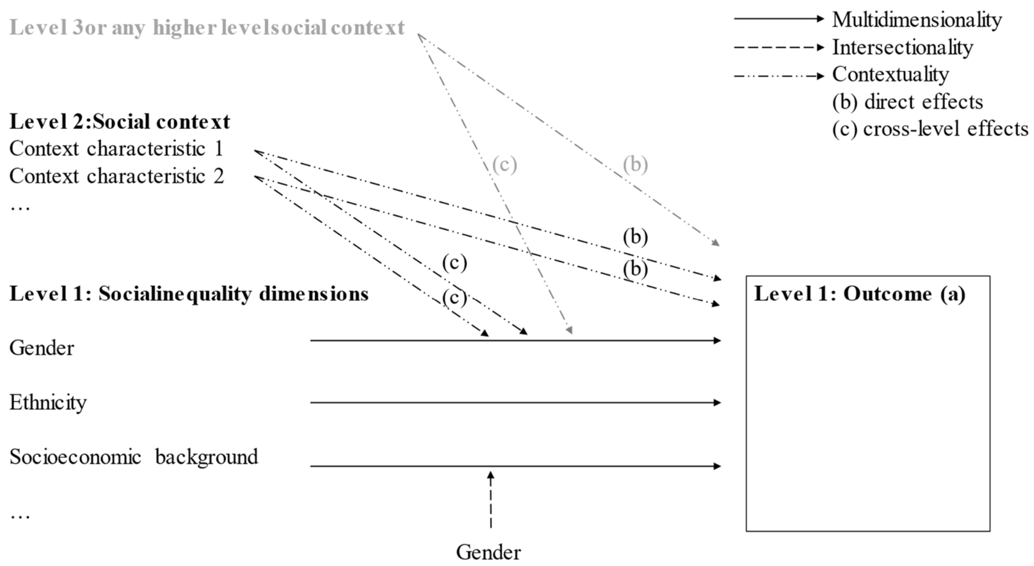
The random-intercept-only (RIO) model (*b* in Figure 4, also known as empty model or null model) examines if the outcome varies by level 2, i.e., the context variable, without any covariates considered (it follows the logic of a simple analysis of variance, ANOVA). The RIO model is a good starting point for showing whether it is necessary to use multilevel models in the first place and if so, how much of the total variance in the outcome can be explained by the group variable by computing the intra-class-correlation (ICC). The RIO model is sufficient to test whether the grouping variable (e.g., the grouping in schools) plays a role for the outcome (e.g., the students' competencies). In other words, one could examine if the social context (e.g., grouping in schools) is relevant for the outcome variable.

The random-intercept (RI) model (*c* in Figure 4) also estimates one intercept β_{0j} for each group and additionally allows for covariates in the model. In doing so, it can not only examine whether the grouping on a higher level plays a role but also which covariates on a higher level explain the differences of the outcome by group membership. However, it assumes that all covariates have the same influence on the outcome, no matter which group is considered (fixed-slopes).

This last assumption is relaxed by the random-intercept and random-slope (RIRS) model (*d* in Figure 4) allowing each group to have not only an own intercept β_{0j} but also an own slope, e.g., β_{1j}. The RIRS model allows for contextuality (how the inequality dimension affects the outcome); however, it cannot explain it. To explain which group characteristics affect differences in the effect of a lower-level variable, e.g., a social inequality dimension, you need to additionally include cross-level interaction terms displayed in Figure 5 (dashed and dotted lines with b).

Figure 5 gives a final overview and illustrates how to model all pillars including all interpretations of contextuality within a single multilevel model.

Figure 5: *Modelling the three intersectionality pillars within a conventional multilevel analysis*



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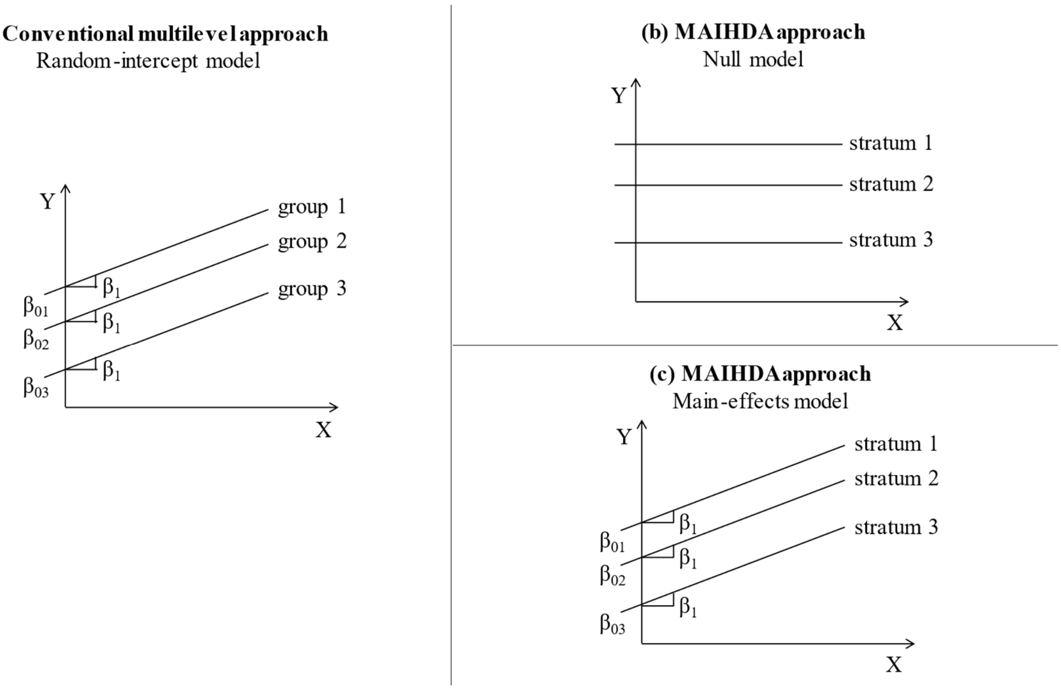
Multilevel analysis of individual heterogeneity and discriminatory accuracy – the MAIHDA approach

Another approach for modeling intersectionality within quantitative research is the multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA). The MAIHDA approach is an innovative and still quite novel multilevel approach. Referring to their own and others' earlier works (Evans 2015; Green et al. 2017; Jones et al. 2016), Evans, Williams, Onnela, and Subramanian (2018) introduced the MAIHDA approach for analyzing intercategorical intersectional inequalities using an example from the field of health research. More precisely, they examined inequalities in regard to body mass index at the intersection of five social dimensions (gender, race/ethnicity, income, education, and age) among a sample representative of the US-American population.

Typically, multilevel analyses are used to account for the clustering of data, such as individuals clustered in countries or judgments clustered in people (e.g., for factorial survey data), since the statistical assumption of independence of the cases and thus the uncorrelatedness of the residuals is violated and needs to be accounted for. In addition to these examples of clustering in data, Evans et al. (2018) suggest a more abstract source of clustering among individuals: their intersectional social identities. The authors assume that individuals (level 1) can be clustered within social dimensions (level 2), which is methodologically realized by including the social dimensions as level-2 indicators in two-level hierarchical random intercept models. The approach allows to examine all possible combinations of the respective social dimensions under study – i.e., their intersections – which are referred to as *strata*. The approach allows to examine an extremely high number of intersectional strata at the same time. It models the heterogeneity within and between these intersectional strata by partitioning the total variance into two levels: the *between*-strata level and the *within*-strata level. The *discriminatory accuracy* in the name of the approach refers to the aim "to understand how well the chosen social positions or identities are actually able to predict and account for variation in the outcome" (Mahendran 2020: 27).

The MAIHDA approach requires the estimation of two multilevel models: a *null model* and a *main effects model* (or rather intersectional interaction effects model). The null model is a random-intercept model with individuals at level 1 and the intersectional strata at level 2 that "decomposes the total variance in the outcome […] into variance that can be attributed to (a) mean-level differences between intersectional strata […] and (b) interindividual differences within intersectional strata" (Keller et al. 2022: 13). The main effects model is the null model to which the level-2 social dimensions are added as fixed (or rather main) effects to control for the dimensions' additive effects. In other words, the main effects model adjusts for the additive main effects of the social dimensions that define the intersectional strata. The estimates of the main effects model can be used to predict outcome values for each intersectional stratum, which allows to identify both strata that are particularly disadvantaged and strata that are particularly advantaged in terms of their intersectional social characteristics. Figure 6 compares the conventional random-intercept multilevel model with the two models necessary for the MAIHDA approach. Whereas the former (*a* in Figure 6) estimates one intercept β_{0j} for each level-2 group, the MAIHDA approach examines whether the outcome varies by the intersectional strata with the null model (*b* in Figure 6) including no covariates and with the main-effects model (*c* in Figure 6) including the social dimensions as covariates and estimating one intercept β_{0j} for each stratum.

Figure 6: *MAIHDA models in comparison with conventional random-intercept multilevel model*



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The existence and extent of intersectional inequalities in the outcome variable can be assessed from the two models' ICCs. The ICC is a measure of discriminatory accuracy and gives the proportion of total variance in the outcome variable that is due to the strata level, i.e., the between-strata variance. The null model's ICC "represents the upper bound of the explanatory power of the intersectional strata and includes both the additive and potential interaction effects of the variables that define the strata" (Keller et al. 2022: 16). A high ICC indicates that individual differences in the outcome variable can be attributed to between-strata variance. An ICC of 0 would indicate that the intersectional strata are not associated with individual differences in the outcome variable at all. By contrast, the main effects model's ICC represents the between-strata variance that results exclusively from intersectional interaction effects regarding the social dimensions under study.

Both models' ICCs also serve to calculate the proportional change in the between-strata variance (PCV). The PCV is the difference in both models' ICCs and can be converted into a percentage. It indicates how much of the between-strata variance in the null model can be explained by intersectional interaction effects:

> *Low PCV values imply that the main effects cannot fully explain the variation in the outcome and that the remaining between-strata variance is due to the existence of intersectional interaction effects between the social categories defining the intersectional strata. In contrast, high PCV values indicate that the main effects explain a large proportion of the mean-level differences between intersectional strata in the outcome. (Keller et al. 2022: 17).*

Thus, a non-zero difference in the ICCs implies an interactional effect above and beyond the additive effects of the social dimensions under study that reflects the multiplicative nature of intersectional inequalities.

Taken together, the approach allows to determine the impact of intersectionality and to explore specific intersections. Though it can be used for continuous as well as binary outcomes, it is particularly appropriate for the analysis of inequalities in binary outcomes if the sample size is small relative to the number of intersections studied (see Mahendran et al. 2022).

The conventional fixed effects approaches presented above capture intersectionality and its non-additivity by including interaction terms between the social dimensions under study. If these are statistically significant, an intersectional effect between the dimensions involved is assumed. By contrast, the MAIHDA approach does not require any interaction terms because the interaction effect is reflected by the stratum-level residual for each stratum.

Nevertheless, the MAIHDA approach has – compared to conventional approaches with interaction terms – so far been only occasionally employed for studying intersectional inequalities (see Bauer et al. 2021) and is subject to methodological discussions (see Bell et al. 2019; Evans et al. 2020; Lizotte et al. 2020; Mahendran 2020; Merlo 2018). Methodological criticism of MAIHDA relates to the interpretation of its fixed effect estimates and between-strata variance. According to a simulation study by Lizotte, Mahendran, Churchill, and Bauer (2020), MAIHDA's stratum-level residuals cannot be directly interpreted as intersectional effects and their fixed effect estimates are neither additive effects (see Evans et al. 2018) nor population average effects (see Evans 2019a) but rather average effects "standardized to a fictional population where all intersections are of equal size" (Lizotte et al. 2020: 398), which usually does not correspond to reality and is therefore not meaningful. Another simulation study by Mahendran (2020) has shown that this holds only for regressions on continuous and count outcomes, whereas the meaning of the fixed effects for binary outcomes is unknown. Both Lizotte et al. (2020) and Mahendran (2020) suggest refraining from interpreting the fixed effects and the between-strata variance and to use MAIHDA only for predicting outcomes by intersectional strata, which would, however, render the method's advantage largely obsolete as the outcomes can similarly be predicted from regression models with interaction terms.

In a response to this methodological criticism, Evans, Leckie, and Merlo (2020) have clarified the meaning of MAIHDA's fixed effects as precision-weighted grand means and unfolded how the scenarios simulated by Lizotte et al. (2020) are unrealistic and exaggerated as well as why the reweighting of the estimations with respect to strata size is meaningful, intentional and an immanent benefit of MAIHDA. They claim that MAIHDA's fixed effects and between- strata variance can very well be interpreted meaningfully, as suggested by Evans et al. (2018), and that MAIHDA is, in general, well-suited for modeling the intersectionality paradigm's pillars.

To conclude, the meaningfulness and appropriateness of MAIHDA are not yet conclusively assessed. Therefore, further contributions to the ongoing methodological discussion are required and best practice standards need to be developed.

Benefits and limitations

The afore-mentioned approaches to quantitatively study intersectional inequalities each have their benefits and limitations regarding methodological and theoretical issues; these are outlined in the following. Note that the following elaborations are by no means exhaustive.

A first important methodological aspect relates to model parsimony of both approaches and to the possible numbers of social dimensions to be considered. In contrast to multivariate linear models and conventional multilevel analysis, the MAIHDA approach allows to parsimoniously explore large numbers of social dimensions and their interactions "because rather than the number of interaction terms required increasing geometrically with every added social position, for MAIHDA the number of fixed effects increases linearly, with only one extra fixed-effect term required for each additional social position" (Mahendran 2020: 23); while the number of intersectional strata, which are calculated only in the background and not directly depicted in the regression output but only indirectly in the between-strata variance, increases geometrically in MAIHDA. Thus, MAIHDA combines model parsimony and analytical breadth. For example, Evans et al. (2018) were able to simultaneously study 384 intersections, or rather intersectional strata, resulting from all possible combinations of the five social dimensions under study and their respective categories, whereas other approaches would have been restricted to a few intersections because the number of possible interaction terms increases exponentially with the number of covariates representing the social dimensions investigated (see formula 2). As a result, such models can only include a very limited number of social dimensions to remain feasible and straightforward in interpretation. Furthermore, the more interaction terms are tested, the larger the number of observations needed to ensure sufficient statistical power. Therefore, the MAIHDA approach offers methodological advantages for modeling both multidimensionality and intersectionality.

However, concerning the scale level of the social dimensions investigated, the MAIHDA approach is limited regarding multidimensionality. While approaches relying on interaction terms have the advantage that these terms can include both categorical and continuous variables – for example, age in years or income in €/month – the MAIHDA approach requires the social dimensions to be binary or categorical and continuous strata indicators to be categorized into discrete strata (Evans et al. 2018: 71).

Another methodological aspect concerns the handling of small numbers of observations at the intersections or rather intersectional strata under study (Evans et al. 2018: 68). The MAIHDA approach produces realistic estimates also for strata with few observations as it adjusts the strata estimates depending on their sample size. More precisely,

> *[t]he intersection residuals are shrunk towards the population mean with a weighting according to sample size, where a smaller intersection will be weighted more towards the mean. This is seen as preventing the residuals estimated for smaller intersections from being erroneously identified as larger than expected, due to extreme outliers. (Mahendran 2020: 23).*

By contrast, multivariate linear models and conventional multilevel analysis produce biased estimates for intersections with low numbers of observations. Nevertheless, a sufficient proportion of strata with reasonable numbers of observations is still necessary for the MAIHDA approach.

The MAIHDA approach is also said to solve the multiple-testing problem, which constrains the validity of the results of the other approaches and results in erroneously finding effects as statistically significant because of chance. As "intersectional effects [in MAIHDA] are automatically shrunk toward their mean" (Bell et al. 2019: 88), they are less likely to be statistically significant by chance. However, according to Bell, Holman, and Jones (2019), MAIHDA outperforms other approaches only slightly and reduces the multiple-testing problem only under certain assumptions. They call for further development of the method in this regard. In addition, there are possibilities to adjust for multiple testing in conventional approaches, e.g., through Bonferroni correction.

All of these considerations would be void, however, if the previously presented harsh methodological criticism of MAIHDA by Lizotte et al. (2020) and Mahendran (2020) were to be validated in future research. This would imply that main effect estimates and between-strata variance could not be meaningfully interpreted and that MAIHDA could only be used for predicting outcomes and their differences by the intersectional strata, which would raise the question of what the method's benefit is and thus contest its general justification because outcomes for intersectional groups can also be predicted from regression models with interaction terms.

From a theoretical perspective, all afore-mentioned approaches also have benefits and limitations regarding modeling key assumptions of the intersectionality paradigm. In general, the paradigm assumes complex interplays between the categories of different social dimensions that can lead to multiple privileges, multiple disadvantages, or mixes of privilege and disadvantage. The MAIHDA approach allows to simultaneously study all intersections or rather combinations of all categories of the social dimensions under study, and thus, mixes of privilege and disadvantage. Therefore, the MAIHDA approach is well-suited for impartially exploring the existence of intersectional inequalities. By contrast, approaches working with interaction terms can only evaluate one interaction term at a time for each combination of the social dimensions under study. Thus, these approaches require some preliminary idea or, optimally, some theoretically derived expectation about intersectional inequalities in the outcome under study so that the effects can be estimated accordingly. Contradicting Evans et al.'s (2018: 65) claim that only the MAIHDA approach allows to assess the outcome of all intersectional groups, including those with multiple privileges, multiple disadvantages, or mixes of privilege and disadvantage, both approaches with interaction terms do in fact provide post-hoc analyses to predict and contrast the outcome for all intersectional groups (see, e.g., Gross et al. 2016).

The social context in which inequalities are studied is a key aspect of intersectionality because specific intersectional inequalities may occur in one social context but not in another. For the MAIHDA approach, there is so far no standard procedure for accounting for the social context or varying contexts, only first attempts at implementation (see Evans 2019b; Kern et al. 2020). However, it is inherent to conventional multilevel approaches to model varying social contexts by using context variables as level-2 (or higher) indicators in analyses, which is also the reasoning behind multilevel modeling of intersectional inequalities in the first place.

Previous Applications in Quantitative Research

As noted earlier, the intersectionality paradigm is increasingly being applied in quantitative studies – with different methods for measuring intersectional inequalities and with regard to different outcomes. In the following, we outline some of the key features of quantitative studies of intersectionality in the last three decades in three categories: (a) general study characteristics, (b) engagement with intersectionality theory, and (c) methodological implementation of the theory. The elaborations refer to a comprehensive systematic review on the emergence and the application of intersectionality in quantitative research by Bauer, Churchill, Mahendran, Walwyn, Lizotte, and Villa-Rueda (2021). Following the *preferred reporting items for systematic reviews and meta-analyses* (PRISMA) guidelines, they have systematically reviewed more than 700 peer-reviewed articles that used quantitative methods and explicitly applied intersectionality as theoretical framework.

(a) With regard to the papers' *general study characteristics*, Bauer et al. (2021) find – similar to Figure 2 – that quantitative intersectional papers were mostly published from 2010 onwards, mainly in journals on psychology (24.0 %), sociology (23.1 %), medical and life sciences (21.2 %), and other social sciences (16.7 %), as well as journals with a special focus on gender and sexuality (14.9 %). 40.8 % of the papers have studied a health-related outcome. Furthermore, 73.8% of first authors are from an US-American institution (73.8 %).

(b) Interestingly, Bauer et al. (2021) attribute an insufficient *engagement with theory* to a substantial part of the papers investigated due to "a limited understanding and application of intersectionality" (2021: 3). More precisely, 26.9 % of the papers did not provide any definition of intersectionality and 32.0 % did not cite any of the authors foundational to intersectionality. While 1.5 % and 44.3 % of the papers considered only one or two social dimensions, respectively, in their analyses, 28.9 % considered three dimensions and 25.3 % four or more dimensions. Thus, nearly half of the papers investigated only a limited number of social dimensions and their intersections. The social dimensions considered most often were sex/gender (76.7 %), race/ethnicity (71.4 %), socio-economic status/income/education (33.2 %), sexual orientation (20.7 %), age/generation (16.3 %), and immigration status (13.1 %).

(c) When it comes to the *methodological implementation of the theory*, Bauer et al. (2021) find that most of the papers were exclusively quantitative (91.9 %) and only a few papers used mixed methods (8.1 %). In addition, the papers primarily used cross-sectional data (81.6 %). What is particularly interesting for the present article is the question of which specific methods were used for statistical analyses in general and which of the ones presented above in particular. Most common were regressions that use intersections of social dimensions as categorical predictor or stratification variables (29.7 %), followed by regressions with interaction terms (28.8 %), both of which belong to the above-mentioned multivariate linear models. Some papers only estimate regressions with the social dimensions as main effects and do not account for their intersections at all (17.3 %), while others are limited to descriptive analyses (13.5 %). More sophisticated methods are quite seldom; the above-presented multilevel approach is already rare (8.1 %), but the MAIHDA approach is even rarer (1.5 %), which reveals potentials for future quantitative research on intersectional inequalities. Taken together, Bauer et al.

(2021) call for further development of quantitative applications of intersectionality and a deeper understanding of the theory.

Other – less systematic and/or comprehensive – literature reviews on quantitative research of intersectionality point to similar findings: e.g., that quantitative intersectional research frequently examines health- or education-related inequalities, often does not adequately fulfill the theory's key assumptions, has a special focus on the intersection between sex/gender and race/ethnicity, and is mainly conducted in the US or North America (see Codiroli Mcmaster/Cook 2019; Guan et al. 2021; Harari/Lee 2021; Mena/Bolte 2019).

While multivariate linear models are used in all subject areas, conventional multilevel approaches seem to be prevalent in educational research, which may be due to the frequent occurrence of hierarchical clustered data in this field, with students clustered in classes, schools, and/or countries. Examples of outcomes in intersectional studies in educational research are school performance and competencies of students (see Gottburgsen/Gross 2012; Gross/Gottburgsen 2013; Jang 2018; Jang/Alexander, 2022; van Dusen/Nissen 2020) By contrast, the MAIHDA approach is prevalent in health research, which presumably stems from the fact that it was developed and first applied in the field of epidemiology (see Evans 2015; Evans et al. 2018; Green et al. 2017). In previous research, the MAIHDA approach has been used to examine intersectional inequalities in various health outcomes, such as smoking behaviour (see Axelsson Fisk et al. 2021), the risk of cancer attributable to air toxics (see Alvarez/Evans, 2021), body mass index (see Evans et al. 2018; Hernández-Yumar et al. 2018), medication intake and prescription (see Ljungman et al, 2022; Persmark et al. 2019, 2020; Zettermark et al. 2021), eating disorders (see Beccia et al. 2021), and depression (see Evans/Erickson 2019).

A recent study by Keller, Lüdtke, Preckel, and Brunner (2022) has also applied the MAIHDA approach to educational inequalities. They study social inequalities in students' reading competencies based on German PISA data, but instead of clustering the students by schools, they cluster them by their multiple social identities, namely by their gender, migrant background, parental education, parental occupational status, and all of their intersections. Using this example, the authors demonstrate how the MAIHDA approach can be expanded and successfully applied to subject areas other than health; however, while ignoring the students' clustering within schools (resulting in the violation of the independence assumption of cases).

Outlook

In this paper, we have shown that the intersectionality paradigm is increasingly being applied in quantitative studies and what methods are used for this purpose. We have discussed that the intersectionality paradigm is too open to allow a theoretically driven development of hypotheses. To derive hypotheses within an intersectionality framework, researchers need to add additional assumptions, which are not provided by the paradigm itself. As a result, we encourage theorists to further develop the intercategorical branch of the paradigm to allow theoretically driven hypotheses that are testable in a deductive manner.

By now, it seems that there is a large gap between intersectionality theorists and quantitative researchers going along with a poor understanding of each other's work. While most of the work quantitative researchers publish has no deep understanding of the paradigm, intersectionality theorists often criticize quantitative work without any understanding and acknowledgment of what has been common practice in quantitative research for decades (e.g., multidimensionality within multiple regression models, or modeling cumulative disadvantages with main effects only, or modeling context or composition effects) and use technical terms inaccurately (e.g., non-additive or multiplicative). We would therefore like to encourage closing this gap by starting or continuing a serious dialogue of informed researchers from both groups.

Previous quantitative intersectional research is mostly cross-sectional, although cumulative disadvantages develop over the life course. Therefore, we additionally encourage future research to integrate a life course perspective in both the development of the theoretical approach and the application of longitudinal methods for an adequate integration of theory and methods applied.

Given that the intersectionality paradigm arose from US Black feminism and gender studies, it comes as no surprise that most quantitative intersectional research (a) is conducted and originates in the US and (b) focuses primarily on the intersection between sex/gender and race/ethnicity. For this reason, future quantitative research should address intersectional inequalities beyond the scope of the US and the intersection between sex/gender and race/ethnicity. Quantitative research within the intersectionality framework currently focuses primarily on health- and education-related inequalities, leaving the potential to also examine other outcomes and inequalities untapped.

So far, there is no methodological standard for investigating intersectional research questions by quantitative means and data. Each of the presented approaches has its benefits and limitations, but especially the more sophisticated approaches, such as conventional multilevel analyses and MAIHDA, have great potential, although the MAIHDA approach requires further development. With this paper, we aim to further contribute to making the approach more popular, especially with European researchers and research areas beyond health research.

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