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Regular Article

Using I-MAIHDA to extend understanding of engagement in early years interventions: an example using the Born in Bradford's Better Start (BiBBS) birth cohort data

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ABSTRACT

Background: Intervention in the early years is essential for reducing health and social inequalities across the lifespan. The success of pregnancy and early years programmes depends on engagement from target parents and families, yet there is no consensus on which factors predict engagement. This could be due to differences between interventions at the local level, or due to unexplored interactions between factors in their relationships with engagement. This study highlights the value of the intersectional application of the multilevel analysis of individual heterogeneity and discriminatory accuracy (I-MAIHDA) approach for adding nuance to our understanding of inequalities in engagement in interventions.
Method: A context-driven, programme-specific analysis exploring factors relating to participation across the Better Start Bradford early years interventions acted as an applied example of the utility of I-MAIHDA. Two analyses were performed using data from the Born in Bradford's Better Start (BiBBS) birth cohort dataset to explore the effects of combinations of ethnicity, migrant status, spoken English ability and social support on participation in the interventions. Predicted prevalence of participation was obtained from the models.
Results: Combinations of English language ability, migrant status, social support, and ethnicity were found to be related to differential prevalence of participation in the interventions, with inequalities in participation between strata. Discriminatory accuracy of the models was low but not negligible (~5%), suggesting some of the variation in outcomes was due to the combined effect at the strata level.
Conclusions: The I-MAIHDA approach showed promise for extending knowledge of engagement in interventions through context-driven analyses which incorporates complex relationships between multiple covariates. This approach will be of interest to anyone working to increase participation in interventions, especially in under-represented or marginalised groups.

1. Introduction

1.1. Early intervention and Better Start Bradford

The first years of life have a profound impact on a child's future (Marmot, 2020; Marmot et al., 2010) with negative experiences such as poverty or early trauma being related to poorer health, wellbeing, and socioeconomic status (SES), and vice-versa. There are many and varied pathways through which this can occur, however early intervention is recognised as a key mechanism through which the effects of negative experiences may be ameliorated, and positive experiences increased (Pearce, Dundas, Whitehead, & Taylor-Robinson, 2019).

Better Start Bradford is one of five 'A Better Start' initiatives across England focusing on early intervention (The National Lottery Community Fund, 2023). Bradford is a metropolitan district in West Yorkshire in the North of England with high levels of ethnic diversity, and high levels of deprivation. The programme focuses on three areas of Bradford (Little Horton, Bowling and Barkerend, and Bradford Moor), all of which fall into the top 10% of the most deprived areas in England. These areas were chosen for the delivery of the programme due to these high levels of deprivation and poorer developmental outcomes for children compared to other areas in Bradford and to the rest of England (Dickerson et al., 2016). The programme aims to improve outcomes and change the future for children and families living in these areas, through

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(Better Start Bradford, 2024a):

- Improving the diet and nutrition of pregnant mothers and children in the first three years of life, to promote healthy development and protect against illness.
- Improving the social and emotional development of children through skills such as emotion management, developing positive relationships and dealing with difficult experiences.
- Improving speech, language, and communication in children, to support healthy emotional and relational development, academic and employment skills, and engagement with the wider world.
- Creating systems change to increase the focus on preventative and early intervention in the first 1001 days of life (pregnancy to age 2), using evidence-based approaches.

The programme incorporates a range of evidence-based interventions designed to achieve these goals. Examples include: free Doula support for pregnant women, courses providing healthy eating and lifestyle information for families, breastfeeding support, English language classes, speech and language support for children, and a range of parenting classes covering practical and emotional themes (Better Start Bradford, 2024b).

The Better Start Bradford Innovation Hub (BSBIH) was set up to independently evaluate the effectiveness of these interventions (Born in Bradford, 2024). To support this work, the 'Born in Bradford's Better Start' (BiBBS) interventional birth cohort was established, collecting data between 2016 and 2023 from pregnant women, their babies and partners in the areas eligible for Better Start intervention. A baseline questionnaire was completed by eligible women during their pregnancy, with questions designed to capture information on social and epidemiological determinants and health inequalities known to relate to child development (Dickerson et al., 2022). The resulting information is linked with routine health, education, and intervention data to allow evaluation of the effectiveness of the Better Start projects without the need for repeated data collection at the individual level (Dickerson et al., 2016).

A recent interim profile of the BiBBS cohort highlighted the level of diversity within the Better Start Bradford areas (Dickerson et al., 2022). Women were represented from a wide variety of ethnicities, with the largest group being Pakistani/British Pakistani (61%), and over half of those recruited were migrants to the UK (54%). Women in the cohort were also experiencing multiple disadvantages and vulnerabilities, for example difficulty understanding English (20%), lacking social support (12%), experiencing financial insecurity (23%), and reporting clinically significant levels of anxiety (10%) and/or depression (15%). There were also varying levels of participation across interventions, with 15% of mothers in the cohort not participating at all.

1.2. Engagement in early years interventions

For programmes such as 'A Better Start' to successfully reduce inequalities, parents and caregivers from all backgrounds must engage with programmes through enrolling in, attending, and completing the projects on offer. Differential engagement between populations is a concern due to the potential for intervention-generated inequality, where an intervention disproportionately benefits less marginalised groups and the gap in outcomes between the least and most advantaged is widened. It is important, therefore, to understand who is and isn't engaging in interventions.

The literature identifies myriad factors which may act as barriers or enablers to engagement. Differences based on parental sociodemographic factors such as age, SES, ethnic origin, education, and employment have all been found (Houle, Besnard, & Bérubé, 2022), many of which are related to markers of inequality or marginalisation. Axford, Lehtonen, Kaoukji, Tobin, and Berry (2012), for example, mention the difficulties found in some studies in recruiting parents from minoritised ethnic groups, or in retaining parents with lower levels of education or lower SES. External factors such as access to transport, timing of classes or lack of childcare may also affect ability to engage in programmes and could also feasibly be related to SES (e.g., not having own transport due to financial constraints). No consensus has been reached, however, regarding which of these factors are key and many do not predict engagement consistently, especially parental sociodemographic characteristics (Axford et al., 2012; Berry et al., 2023; Houle et al., 2022; Kleinman et al., 2023). A recent systematic review, for example, found strong evidence that parental SES did not influence recruitment into early childhood prevention programmes and contradictory evidence regarding the influence of features such as employment and ethnicity (Houle et al., 2022). What drives inequalities therefore may not drive engagement, and further research is needed to clarify these relationships.

Although there is not yet any peer-reviewed literature regarding engagement with the Better Start Bradford interventions, grey literature is available in the form of reports (Ahern et al., 2018; Dharni et al., 2018; Dickerson et al., 2018a, b; Dunn et al., 2019; Nielsen et al., 2019; Warwick Consortium, 2019). Key factors highlighted in these reports as driving engagement are ethnicity, migrant status, English language ability, health (physical and mental), family commitments and availability of childcare. For example, in a 2019 participation and engagement report some ethnic groups were identified as being long-established in the community (e.g., those of Pakistani ethnicity) whereas some were smaller and had more recently arrived in the area (e.g., those of White Central and Eastern European ethnicity). English language ability was identified as a barrier to engagement broadly, but especially for those in more newly established communities for whom translation or transliteration may not be as readily available. This suggests a combined effect of migrant status, ethnicity and spoken English ability which may be driving differences in engagement between groups. Lack of social support and isolation were also identified as barriers to participation, with perceived differences in availability of support between different communities. For example, a volunteer specifically described the isolation she had noticed in migrant women from Eastern European countries. As in the broader literature, social positions associated with more marginalised groups such as migrant communities were identified as barriers to participation in the Better Start Bradford interventions.

1.3. I-MAIHDA for exploring differential engagement in interventions

These findings concur with recent recommendations in the literature (e.g., Houle et al., 2022) that exploring interacting combinations of factors relating to differential participation in early years interventions may help understand this complex area. The Better Start Bradford reports also highlight the importance of local context, especially where groups may not be representative of the wider population. The need for tailored interventions which account for local and individual contexts is understood to be essential to effective engagement (Houle et al., 2022; Kleinman et al., 2023) and it is possible that what drives engagement in one context may not be as relevant in another. The focus to date on exploring individual predictors of engagement and the assumption that these will have the same meaning in multiple contexts could explain the contradictory findings discussed.

In this paper, we highlight a statistical approach which may provide a deeper understanding of relationships between factors associated with engagement in interventions. MAIHDA is based on an approach to multilevel modelling that explores variations in outcomes within and between contexts (such as neighbourhoods). The method allows the heterogeneity in individual outcomes at the context level to be understood separately from heterogeneity at the individual level. The ability of the context to accurately differentiate between those with and without the outcome is known as its discriminatory accuracy (DA) (Merlo, 2003; Merlo, Wagner, Ghith, & Leckie, 2016). In this paper, we use a particular application of MAIHDA developed for application within the intersectionality framework (Evans, Williams, Onnela, & Subramanian, 2018; Merlo, 2018), hereafter referred to as I-MAIHDA (Evans, Leckie, Subramanian, Bell, & Merlo, 2024). In I-MAIHDA the context is defined by multi-dimensional strata created from all unique combinations of selected social identities or positions (for example sex, ethnicity, or SES). The DA of the strata shows how effective that combination of positions/identities is in discriminating between those with and without the study outcome. This in turn can inform how interventions to change outcomes should be planned and delivered, especially within the widely accepted context of proportionate universalism (Marmot, 2020; Marmot et al., 2010) which suggests that interventions should aim to be universal, but delivered with a scale and intensity proportionate to the level of disadvantage or need. In this way, interventions can effectively address the social gradient of health. Where outcomes within each stratum are very similar (i.e., the strata have high DA), it many be more appropriate to target or tailor interventions to groups represented by specific strata, and where individual variation within strata is high (i.e., low DA) a more universal approach may be more effective to improve outcomes across all individuals. In this way, I-MAIHDA provides valuable information as to the necessary degree to which interventions should be universal or targeted (Merlo, Wagner, & Leckie, 2019).

A further benefit of the I-MAIHDA approach is the ability of the multilevel model to manage smaller sample sizes than would be required to explore relationships between all combinations of variables using other methods (for example models including multiple interactions) (Bell, Holman, & Jones, 2019; Evans et al., 2018). Shrinkage in the multilevel model also guards against false-positive (Type 1) errors that may occur due to large effects relating to very small sample sizes in some strata, as estimates for strata with smaller sample sizes are adjusted ('shrunk') towards to the global multilevel mean (Bell et al., 2019; Evans et al., 2018, 2024).

I-MAIHDA also allows an understanding of how much of the difference in outcomes is due to the interactive effect of the strata dimensions, and how much is due to the contextual (additive) effects of the variables used to define the strata. Predicted prevalence of the outcome for each dimension of the strata can be extracted and plotted, to map differences in average outcomes and patterns of inequalities across the study population. Mapping inequalities in this way allows all levels of relative privilege and disadvantage to be understood and moves away from a more traditional 'reference group' approach which most often places the most privileged groups as the reference against which all other groups are measured (Evans et al., 2018). Results from I-MAIHDA models can therefore provide valuable information for enacting tailored and relevant changes to improve outcomes.

Currently, I-MAIHDA is increasingly applied within an intersectionality framework. Intersectionality is a critical theory with its roots in Black feminism (Crenshaw, 2013). The term was coined in 1989 b y Kimberlé Crenshaw, to describe how social positions or identities such as race and sex combine (i.e., intersect) to create unique experiences of disadvantage and marginalisation for those who hold them, and how this is reflective of wider structures of power and privilege such as racism or sexism. The theory originated outside of health research but has migrated across in recent years and is now applied broadly in qualitative and quantitative research. Studies using I-MAIHDA often apply the intersectionality framework across the whole study, and usually with a focus on individual social identities (e.g., sex or race) (Bauer et al., 2021). We have not taken an explicitly intersectional approach in this study, but a multi-categorical one which focuses on using the I-MAIHDA approach to map how key factors relating to social contexts predict differential engagement in the Better Start Bradford interventions.

2. Methods

2.1. Data

This was a secondary analysis of data from an interim sample of BiBBS participants, who were enrolled between 2016 and 2019 (Dickerson et al., 2022). All women living in one of the Better Start Bradford areas at this time, who were registered to give birth at Bradford Teaching Hospitals NHS Foundation Trust and were not planning to move away from Bradford before the birth of their baby were eligible to participate. Women could be recruited for subsequent pregnancies within the study period (i.e., BiBBS data are at the pregnancy level). For more information on the BiBBS recruitment and data collection process, see Dickerson et al. (2016) and for up-to-date intervention information see Better Start Bradford (2024b). This analysis was at the individual level and so only the entry for the first eligible pregnancy was retained. Fig. 1 shows a path diagram of those included and excluded from the analyses.

2.2. Dependent variable

Data from 14 of the Better Start Bradford projects were available at

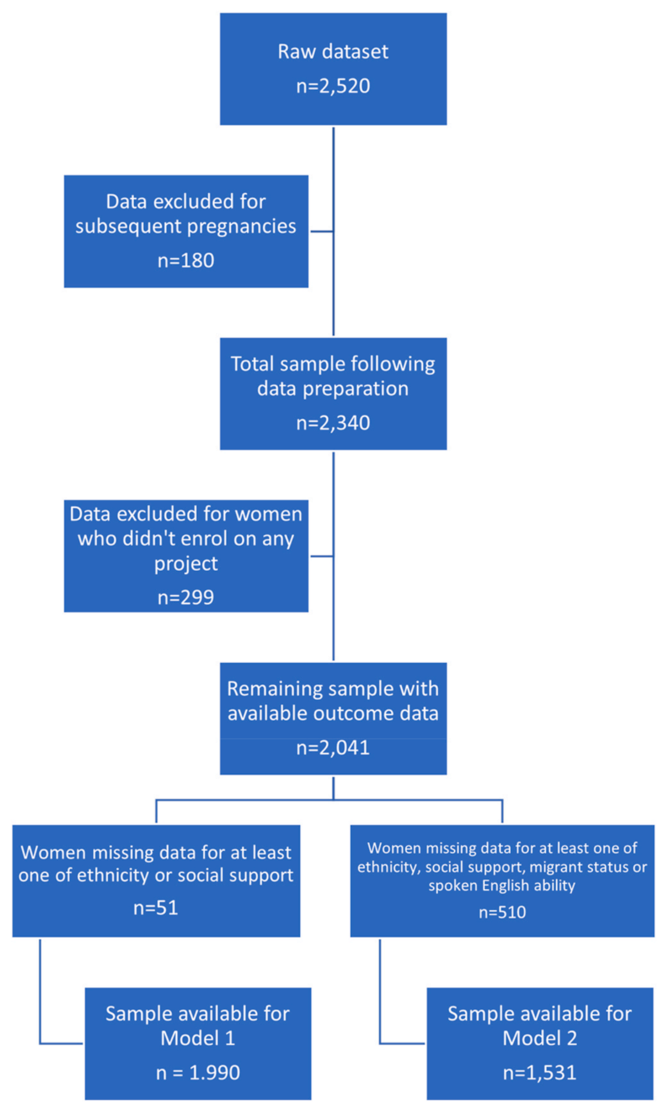

Fig. 1. A path diagram showing numbers of women included and excluded from the analyses.

the time of analysis (see Table 1 for details). Given the low numbers of women enrolled on or participating in many of the projects, we combined data to generate a single outcome variable to measure engagement. We chose to use participation as a proxy for engagement, and focused on projects which required some level of active participation, as several were delivered as part of usual care or received automatically and so did not require a woman to necessarily 'engage' with the intervention to receive it. Based on the 10 projects which required some active participation, we created a dichotomous variable:

User = participated in one or more of the 'active' projects.

Non-user = 'passive' project(s) only OR enrolled on 'active' project (s) but did not participate.

2.3. Social strata dimensions

As the sample size available was relatively small for the analysis type, we focused on four key factors hypothesised as being important to engagement in the Better Start Bradford interventions and as potentially interacting in their relationship with participation (discussed in Section 1).

2.3.1. Spoken English ability

Responses were dichotomised based on whether a woman indicated she spoke English as a first language, very well or well, or had only some or no spoken English ability.

2.3.2. Migrant status

This variable indicated whether a woman was a migrant to the UK and was based on percentage of life spent in the UK. All women who had spent less than 100% of their lives in the UK were included in the migrant group.

2.3.3. Ethnicity

Four ethnicity categories were created: 'South Asian/British South Asian' (including Pakistani, Indian and Bangladeshi), 'White British and Irish (B&I)', White Central and Eastern European (CEE) and White Other (including Polish, Slovakian, Romanian, Czech and White Other), and all 'Other' ethnicities (including mixed/multiple ethnicities, African, Caribbean, Chinese and Other).

2.3.4. Social support

Women indicated in the BiBBS questionnaire how many people they had to count on in times of need. Three groups were created based on these responses, indicating level of social support: High (8–10 people), Medium (3–7 people) and Low (0–2 people).

2.3.5. Social strata

We constructed two sets of social strata using these variables. The first combined all unique combinations of social support and ethnicity, to give 12 dimensions. The second combined all unique combinations of social support, ethnicity, migrant status and spoken English ability to give 48 dimensions.

2.4. Demographics of the sample

The distribution of the study sample across the strata dimensions is shown in Table 2, in total and by level of the user group outcome. The majority of women in the study dataset were of (British) South Asian ethnicity, over half were migrants to the UK, and English language ability was mixed. Around one quarter of women had low social support (0–2 people to count on). Distributions of women among these groups was similar to those found in the interim profile, which was in turn representative of the population of eligible pregnant women in the Better Start Bradford areas (Dickerson et al., 2022).

Differences in participation between ethnicities reflected the observations made in the grey literature, with women of White CEE/other backgrounds being least likely to participate and (British) South Asian women most likely. Having lower social support was associated with higher proportions of women participating in interventions, however, which was contradictory to the observations from the report. These factors had been highlighted as potentially interacting in their relationships to engagement, both together and with other factors such as migrant status and spoken English ability. The I-MAIHDA models allowed us to explore these relationships simultaneously, and in more detail.

2.5. Analysis

Analyses used complete cases only, therefore only participants who could be assigned to the strata (i.e., did not have missing data for one or more of the variables used to construct the strata) were included. For Model 1, all dimensions of the strata had associated participants, and sample sizes were over the recommended n = 10 (Evans et al., 2018). 51 women had missing data for at least one of ethnicity or social support,

Table 1
projects included in the study dataset, with enrolment and participation information for the study sample.

Project name	Enrolled (n)	Participated (n)	Participated (% of enrolled)
Baby Steps[a]	117	85	72.65
Better Start Imagine	1492	1492	100.0
Breastfeeding support[a]	519	251	48.36
Cooking for a Better Start[a]	44	43	97.73
Family Action[a]	149	140	93.96
Forest Schools	77	64	83.12
HAPPY[a]	61	47	77.05
HENRY 1:1 (one-to-one)[a]	13	13	100.0
HENRY group[a]	35	34	97.14
Incredible Years Toddler[a]	88	75	85.23
Personalised Midwifery – Clover	174	174	100.0
Personalised Midwifery – Opal	704	704	100.0
Talking Together – intervention[a]	402	365	90.80
Talking Together – screening[a]	942	841	89.28

[a] Denotes 'active participation' projects.

Table 2
Demographics of the study sample in total and by levels of the outcome variable.

	Non-user (n (row %))	User (n (row %))	Totals (row n (column %))
	Total = 837	Total = 1204	Total = 2041
Ethnicity			
(British) South Asian	546 (37.37)	915 (62.63)	1461 (71.97)
White B&I	100 (48.31)	107 (51.69)	207 (10.20)
White CEE & other	97 (61.78)	60 (38.22)	157 (7.73)
Other ethnicities	88 (42.93)	117 (57.07)	205 (10.10)
Total	831 (40.94)	1199 (59.06)	2030
Migrant status			
Non-migrant	393 (42.58)	530 (57.42)	923 (46.34)
Migrant	423 (39.57)	646 (60.43)	1069 (53.66)
Total	816 (40.96)	1176 (59.04)	1992
English language ability			
First language/speaks English well	540 (40.88)	781 (59.12)	1321 (82.93)
Some-no spoken English	120 (44.12)	152 (55.88)	272 (17.07)
Total	660 (41.43)	933 (58.57)	1593
Social support (people to count on)			
High (8–10 people)	278 (45.13)	338 (54.87)	616 (30.85)
Medium (3–7 people)	346 (40.09)	517 (59.91)	863 (43.21)
Low (0–2 people)	187 (36.10)	331 (63.90)	518 (25.94)
Total	811 (40.61)	1186 (59.39)	1997

meaning the sample size available for analysis was 1990 (/2041; 97.5%). For Model 2, 32 of the 48 strata dimensions had associated data, with 10 of these having fewer than 10 participants. There were 510 women with missing data for at least one of ethnicity, social support migrant status or spoken English ability, meaning the sample size available for analysis was 1531 (/2041; 75.01%).

2.6. I-MAIHDA

We fit two sets of I-MAIHDA multilevel logistic regression models for the relationship with the user groups outcome, with individuals (level 1) clustered in the strata (level 2). Model 1 used the strata created by combining Ethnicity and social support, and Model 2 used the strata created by combing ethnicity, migrant status, spoken English ability and social support. Two versions were fit for each model:

Model A was the 'null' model, including only the intercept and the relevant social strata at the second level. For this model, the variance partition coefficient (VPC) was calculated, to quantify how much of the individual variance in participation could be accounted for by the combination of variables at the strata level. The VPC is a measure of discriminatory accuracy (DA) (Merlo et al., 2016; Merlo et al., 2019); in this case it quantified the ability of the strata to discriminate between users and non-users. The VPC was calculated as follows (Fisk et al., 2018), where σ_u^2 is the between-stratum variance:

$$VPC = \left(\frac{\sigma_u^2}{\sigma_u^2 + 3.29}\right) \times 100$$

Model B was the 'main effects' model, which included each of the variables used to construct the strata for the model simultaneously as main-effects. VPC was again calculated, along with proportional change in variance (PCV) which quantified the percentage of the between-stratum variance from the null model that had been explained by the addition of the main-effects. The PCV was calculated using the between-stratum variance (σ_u^2) from the null (A) and main-effects (B) models (Evans & Erickson, 2019):

$$PCV = \left(\frac{\sigma^2_{u,modelA} - \sigma^2_{u,modelB}}{\sigma^2_{u,modelA}}\right)$$

For all analyses, estimates and confidence intervals were exponentiated to give odds ratios, and values of the stratum-level residuals were ranked and plotted. Predicted prevalence of participation (measured in %) along with 95% confidence intervals (CI) was extracted from the main effects (B) models and average prevalence of participation per social strata dimension plotted to give a visual mapping of inequalities between strata.

All data manipulation and analysis was performed in R (R Core Team, 2023). The I-MAIHDA was performed using MLWiN (Charlton, Rasbash, Browne, Healy, & Cameron, 2024), called to the R environment using the R2MLWiN package (Zhang et al., 2016, 2024). Markov chain Monte Carlo (MCMC) estimation was used (Browne, 2023; Evans et al., 2018, Supplemental Technical Note 2) with 50,000 iterations, 500 burn in phase and 50 as a thinning factor (Balloo, Hosein, Byrom, & Essau, 2022; Fisk et al., 2018; Jaehn et al., 2020). All other settings were R2MLWiN defaults, including non-informative priors (Zhang et al., 2016).

3. Results

Results of the I-MAIHDA models are shown in Table 3, and Figs. 2–4. For Model 1, the VPC showed that 5.59% of the total variance was at the between-strata level. This suggests a modest DA (Evans & Erickson, 2019; Fisk et al., 2018) i.e., that the strata had some ability to discriminate users from non-users. When ethnicity and social support were added as main effects the VPC was 0.42% and PCV was 92.87%, indicating that most of the heterogeneity between the strata was due to the additive effect of the strata variables. This is also demonstrated in Fig. 1 which shows plots of the strata-level residuals for the null (1A) and main-effects (1B) models. As shown, all residuals fell to almost zero in the adjusted models, with large confidence intervals that crossed the null boundary (i.e., none were statistically significant from zero). In this model, therefore, predicted outcomes were mostly explained by the additive main-effects in the model rather than any additional interactive (combined) effect. Fig. 2 shows predicted prevalence (%) of participation for each stratum. Overall, women of White CEE/other ethnicity were the least likely to participate, with inequalities within and between ethnic groups depending on level of social support. For example, women of South Asian ethnicity with high social support had similar prevalence of participation to women of White B&I ethnicity with low levels of social support. For all groups, however, having high levels of support was associated with reduced prevalence of participation. Looking at additive effects, women of all ethnicities had lower odds of being in the user group than (British) South Asian women with the lowest odds for White CEE/other women (OR = 0.35, CI: 0.24–0.52). Having lower social support was associated with higher odds of being a user, with those with low social support (0–2 people) having 1.54 times the odds of those with high support (CI: 1.12–2.15).

The pattern of results for Model 2 was similar. In the null model (2A)

Table 3
I-MAIHDA results for all models.

Fixed-effect	Model 1A: null		Model 1B: main-effects		Model 2A: null		Model 2B: main-effects	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Intercept	1.16	0.86–1.53	1.38	1.08–1.75	1.25	0.98–1.54	1.28	0.97–1.71
Ethnicity (ref: S. Asian)								
White B&I			0.66	0.46–0.94			0.70	0.46–1.04
White CEE/other			0.35	0.24–0.52			0.27	0.16–0.44
Other			0.74	0.53–1.04			0.66	0.42–0.98
Social support (ref: high)								
Med			1.27	0.94–1.70			1.27	0.94–1.75
Low			1.54	1.12–2.15			1.49	1.06–2.16
Migrant status (ref: non-migrant)								
Migrant							1.35	0.94–1.84
Spoken English (ref: first lang/well)								
Some-none							0.69	0.49–1.02
Model values								
Variance (95% CI)	0.19	0.04–0.54	0.01	<0.001–0.08	0.18	0.04–0.43	0.02	0.001–0.12
VPC (%)	5.59		0.42		5.16		0.61	
PCV (%)			92.87				88.66	
N of observations	1990		1990		1531		1531	

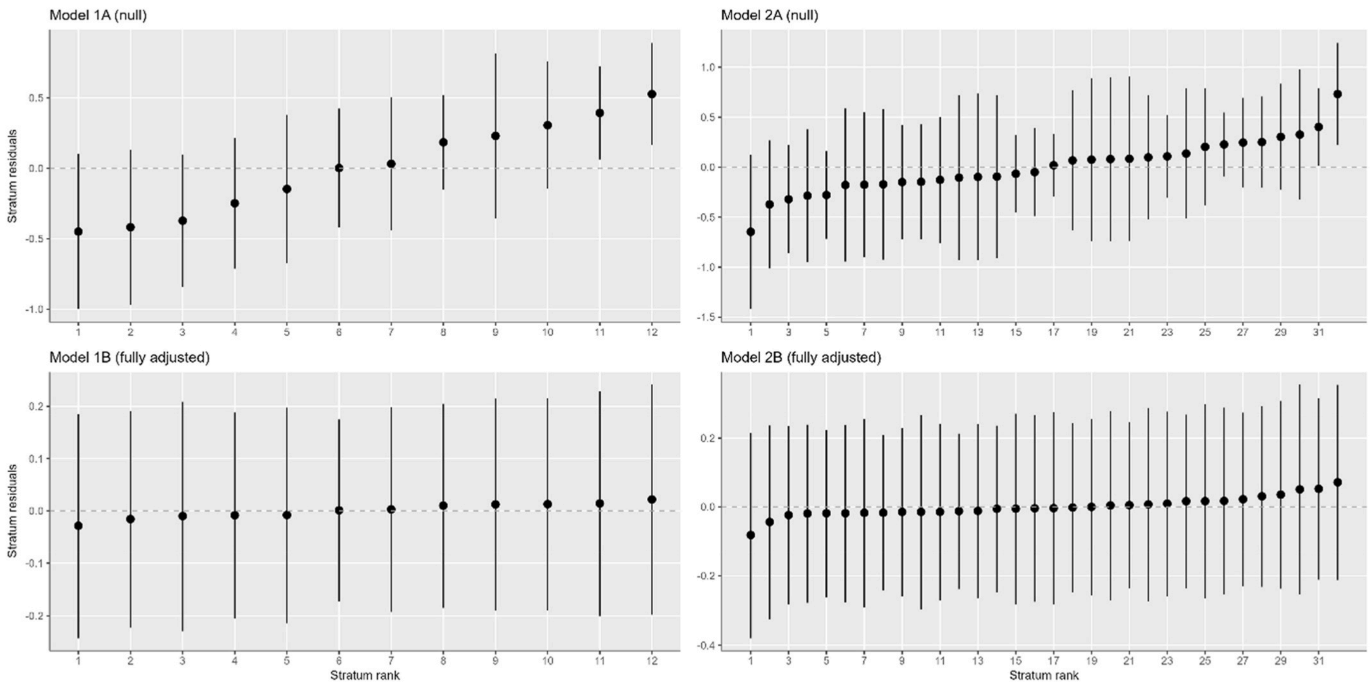

Fig. 2. Ranked stratum-level residuals before and after adjusting for main-effects, for both analyses.

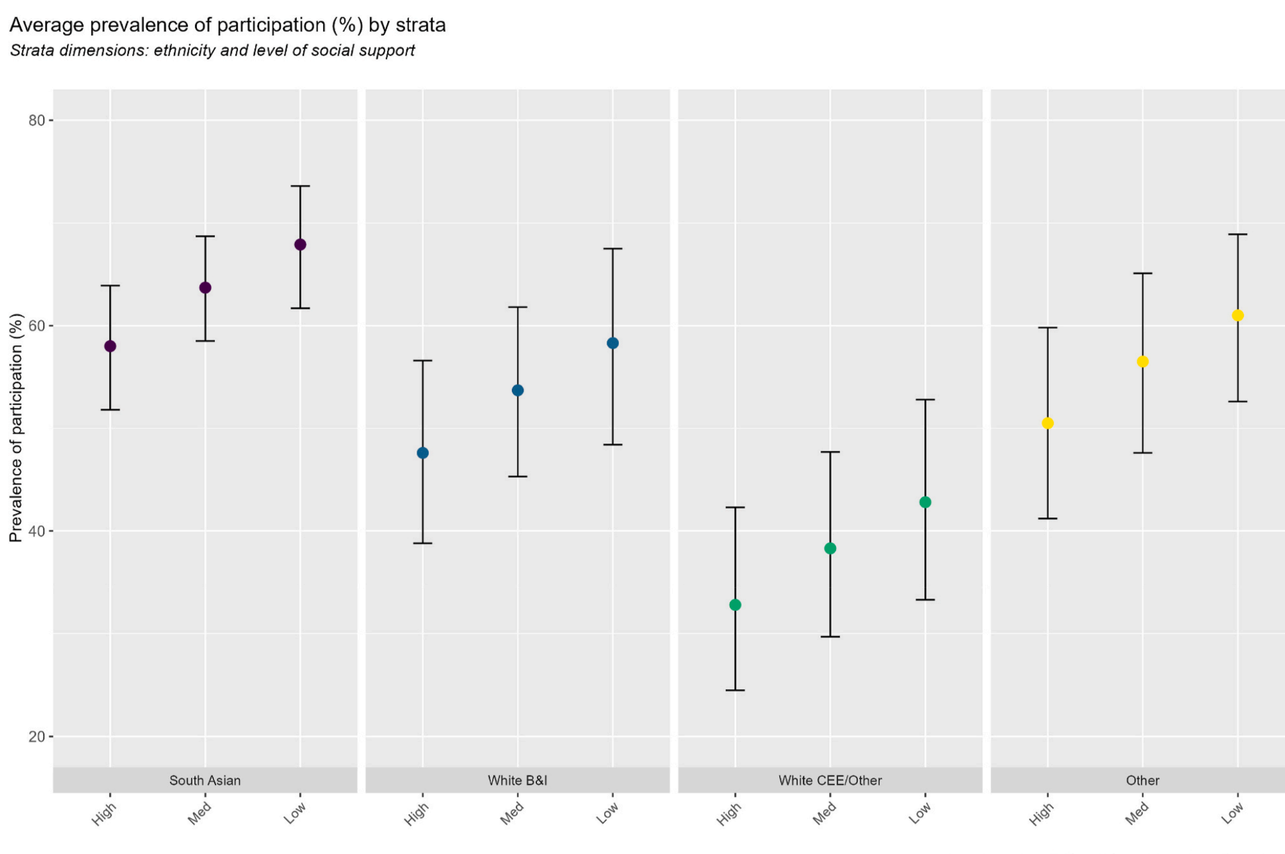

Fig. 3. Average predicted prevalence (%) of participation by strata for Model 1B.

5.16% of the total variance was explained by the strata, again demonstrating a modest DA. When the four variables were included as main effects, the PCV was 88.66% and VPC reduced to 0.61% which again suggested that the difference between strata was due mainly to the additive effects of the variables. Patterns of the strata-level residuals shown in Fig. 2 were as per Model 1, with none being significantly different from zero following inclusion of the main-effects (Model 2B). In this model, several strata had n < 10 which were excluded from the

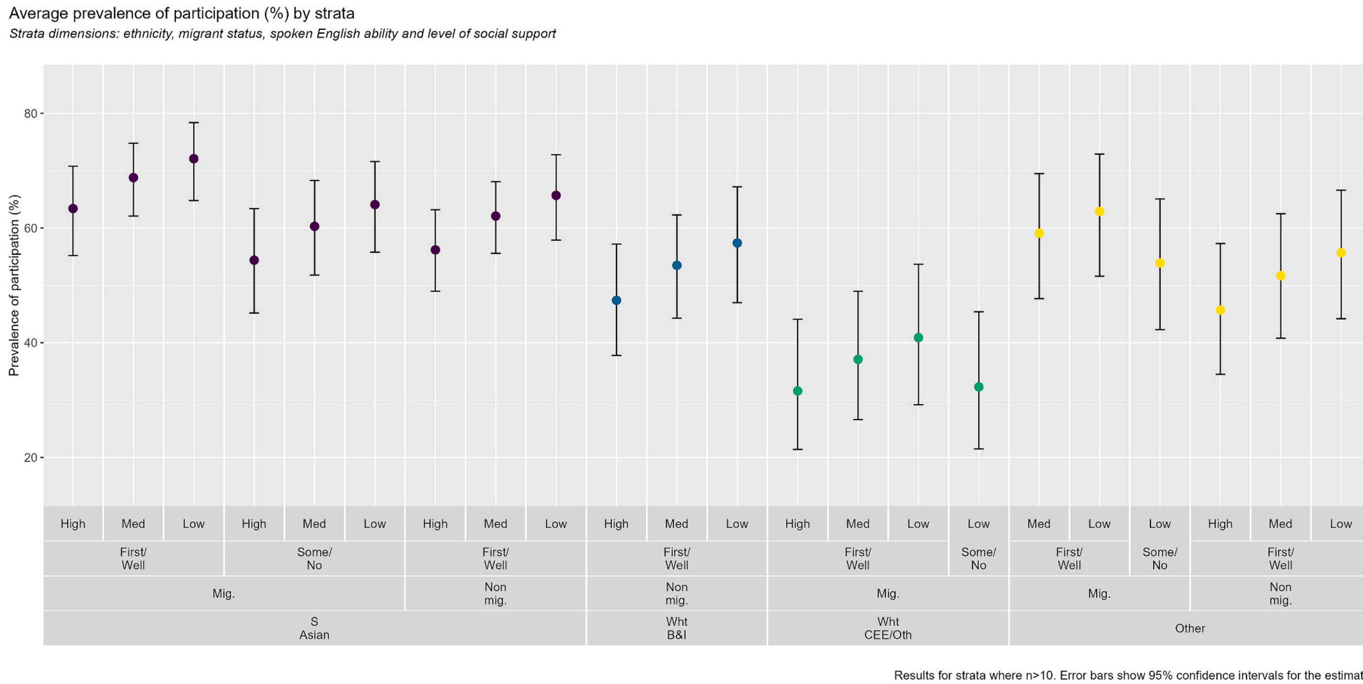

Fig. 4. Average predicted prevalence (%) of participation by strata for Model 2B (for strata where n>10).

chart of predicted prevalence shown in Fig. 3. For women in strata with more than 10 participants, those of White CEE/other ethnicity again had the lowest prevalence of participation overall, and inequalities between strata were evident depending on differing combinations of the other strata variables. South Asian women who were migrants, with some-no spoken English and high social support, for example, had lower prevalence of participation than women in a similar position who spoke English well or as a first language. Additive relationships for ethnicity and social support were similar to Model 1, while being a migrant was associated with higher odds of being a user (OR = 1.35, CI: 0.94–1.84), and having some-no spoken English associated with lower odds (OR = 0.69, CI:0.49–1.02), though CIs for these relationships included the null value.

4. Discussion

4.1. Summary

Using I-MAIHDA analyses, we mapped how combinations of ethnicity, social support, spoken English ability and migrant status related to participation in the Better Start Bradford interventions. Our results were broadly reflective of the findings from the grey literature, with participation differing across dimensions of the strata. Results indicated that (British) South Asian women who were migrants tended to be more likely to participate in interventions, but this was not the case for White CEE/other migrant women. Women who were migrants and had limited or no spoken English tended to be less likely to participate than those who spoke English well or as a first language. More positively, we found that those with low social support were more likely to participate.

These results suggest that spoken English ability and ethnicity are differentially related to participation for migrant women in the dataset, and there may be features of being a migrant to Bradford from a CEE country that affect participation in a way that is not as relevant for women from (British) South Asian backgrounds. We consider structural factors that may drive these differences. Programmes such as Better Start aim to support all groups in their populations, however it is likely that the largest and most established groups will be the easiest to provide support for. In the case of Better Start Bradford this is women of Pakistani ethnicity (61% of the population), and support for smaller, less well-established groups such as White CEE women may not be as easy to provide. When supporting women with limited spoken English to participate in such an ethnically diverse area, for example, it may not be feasible to provide support for every language spoken or understood, and so the focus may fall on the larger and more accessible groups where the highest number of women can benefit. The composition of the community could then combine with the structure of the organisation to perpetuate this barrier. A key strength of the Better Start Bradford programme is the high level of community involvement; volunteers for interventions often come from within the community, and are often also recruited following participation in an intervention (Warwick Consortium, 2019, p. 11). Women who are less visible in the community may be less easy to target for community involvement, and those who are less likely to participate will also be less likely to become volunteers. This then compounds the difficulty in finding individuals to provide translation and transliteration for less commonly spoken languages. This highlights how even a positive feature of a programme such as community involvement may act in unforeseen and unintended ways and demonstrates the importance of having a nuanced understanding of the community context in which interventions are delivered.

The DA of the strata in both cases suggested that the associated combinations of variables had modest ability to predict participation in the Better Start Bradford interventions. While these results were mostly due to the contextual (additive) effects of the dimensions used to define the strata, rather than a combined interactive effect, the differences are still relevant and of interest for those seeking to understand inequalities in participation relating to social and socioeconomic contexts. However, the high levels of heterogeneity within strata suggested that our models did not fully explain participation in the interventions. These results are in line with previous research discussed which has identified myriad factors relating to intervention engagement.

The BiBBS dataset is not necessarily representative of the wider UK population and so these findings are most relevant in the local context. However, we have demonstrated how the I-MAIHDA approach can be applied to local-level, context-driven analyses to explore factors relating to engagement in interventions. In mapping how particular combinations of individual-level features relate to differential participation, we have provided an applied example of this application of I-MAIHDA. Though caution should be taken where within-strata heterogeneity is high (i.e., where there is low DA) to explore differences within as well as between stratum (Evans, Leckie, & Merlo, 2020), this mapping of averages across the dimensions of social and socioeconomic contexts defining the strata is valuable information that may be practically applied as part of the process of understanding and ultimately increasing engagement.

4.2. Future research, policy, and practice

This study provides several avenues for future research. Applying I-MAIHDA to explore engagement in early years and parenting interventions in a range of contexts and settings is recommended to further understand its value in this research area. Qualitative research with groups identified by the strata could follow this type of analysis, to allow a deeper understanding of reasons for (non-)participation within and between strata groups. This would be especially important in cases such as the present study, where we found high levels of heterogeneity within the strata.

As discussed, I-MAIHDA provides an understanding of the DA of the strata, which provides vital information when planning strategies to increase participation. The Better Start Bradford programme aims for an approach in line with proportionate universalism (as discussed in Section 1.3) and results from the I-MAIHDA can be used to inform this. Where a model has high DA, it may be appropriate to use the strata dimensions to inform targeting or tailoring of interventions to reduce barriers to engagement (for example through a programme specifically aimed at increasing participation in White CEE/other migrant women with some-no spoken English). In the case of this study, however, where heterogeneity was high within strata (i.e., the strata had modest DA), a less targeted approach may be more appropriate. This could take the form of a broader programme tailored to increase participation in interventions across all women in the Better Start Bradford areas, but with adaptations to account for the fact that women with lower levels of spoken English ability (for example) or who are multiply disadvantaged in this context may need additional support to participate. This broader focus also avoids stigmatisation of individuals based on combinations of their social identities or positions that may not in fact have salience in explaining outcomes. In both cases, intervention may be tailored to account for differences in social and cultural context, but the I-MAIHDA allows a deeper understanding of the level of targeting and/or tailoring that is necessary and appropriate (Merlo et al., 2019).

4.3. Strengths and limitations

In this study we have highlighted a novel approach for the exploration of engagement in early years and parenting interventions. I-MAIHDA adds nuance to our understanding of inequalities in participation between demographic groups, which is of practical value to organisations involved in planning and delivering interventions. The study was also able to provide more detailed information regarding participation in the Better Start Bradford projects specifically, and which groups of women were more and less likely to participate following enrolment. This type of information is valuable to those aiming to provide the more tailored and context-based approach to intervention recommended by many authors.

I-MAIHDA has been more commonly applied to large sample sizes in previous research; this study demonstrated its utility to explore multi-dimensional interactions at a relatively low sample size. Whereas an analysis including interactions between all combinations of included variables would not have been effective with the available data, I-MAIHDA provided a nuanced and effective option for exploring inequalities in engagement with interventions in smaller samples. The ability of the multilevel model to account for strata with low numbers through shrinkage was especially crucial to analysis of a dataset of this size and we consider it a key benefit of I-MAIHDA in this context.

The study also had some limitations. Though the dataset could be explored using the I-MAIHDA and findings were of interest, many of the strata had small numbers of associated participants. This may have decreased the size of the between-strata variance and therefore led to a potential underestimate of the strata effect (Evans et al., 2018). Similarly, the lower sample size restricted the number of variables which could be selected to generate the strata dimensions, and it is possible that other important factors were excluded such as health or SES. There was also a loss of information when combining ethnic groups. Given the small sample sizes for some groups, this was necessary for anonymity and effective analysis, however it is possible that differences exist within these broader groupings which were not identified here. We were also unable to assess the effects of the different features of the interventions (such as place or mode of delivery) as this information which was lost in combining data from across interventions to create the outcome variable for analysis.

Although the analysis was able to add nuance to the understanding of factors relating to participation in the interventions, our findings give no information regarding cause and effect. Further exploration with women in the Better Start Bradford population (for example through qualitative research, as previously suggested) would therefore be useful in extending our understanding of engagement. Finally, this dataset was provided in 2019 and so is a pre-COVID sample. Intervention delivery changed during the pandemic, with many interventions moving online and a post-COVID sample would be required to assess whether this has affected engagement. We have demonstrated how the I-MAIHDA method could be applied in this case, with results compared between pre- and post-COVID datasets.

4.4. Conclusion

We have demonstrated how the I-MAIHDA approach can be applied in a context-driven, programme-specific analysis to explore engagement with early years interventions, and how the resulting findings may be of interest to organisations to inform the planning and delivery of interventions in their local areas. The approach allowed simultaneous exploration of the relationships between multiple variables, and how the social and socioeconomic context defined by these combinations of features related to differential engagement. Charts of predicted prevalence were produced that were simple and easily interpreted, and clearly highlighted inequalities in participation between the sub-groups represented by the strata, while the ability to assess discriminatory accuracy gave an understanding of how this information may best be used to improve participation within and across groups. This information is valuable to anyone working to increase participation in interventions, especially in under-represented or marginalised groups.

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Ethics

BiBBS has ethical approval to collect and link data and to share this anonymously with research collaborators via the Bradford Leeds NHS Research Ethics Committee (reference: 15/YH/0455) (NHS Health Research Authority, 2023). As this was a secondary data analysis of the

BiBBS data, no further ethical approval was required.

CRediT authorship contribution statement

Jennie Lister: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Catherine Hewitt:** Writing – review & editing, Supervision. **Josie Dickerson:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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