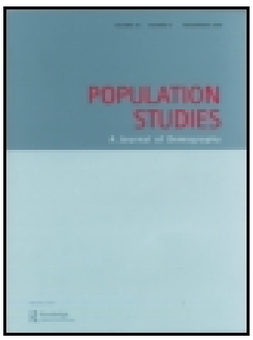

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Women's fertility and allostatic load in the post-reproductive years: An analysis of the Indonesian Family Life Survey

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We know little about the effects of the reproductive health burden in contexts where unsafe abortions, miscarriages, stillbirths, and low-quality maternal care are common. The aim of this study is to investigate the use of allostatic load to understand the impact of reproductive histories on later-life health. We applied path models to the Indonesian Family Life Survey with a sample of 2,001 women aged 40+. Although number of children was not associated with allostatic load, pregnancies not ending in live birth and parenthood before age 18 were both negatively associated with health. We also identified clear cohort and educational effects and a possible rural advantage. Our contribution is twofold: we highlight the importance of reproductive histories beyond live births on women's later-life health in a context of increasing population ageing, and we demonstrate the applicability of using allostatic load to measure health outside the Global North.

Keywords: allostatic load; women's health; fertility; pregnancy; life course; Indonesia

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Introduction

Little research exists on the impact of large numbers of pregnancies (whether resulting in live births or not) on women's bodies in low- and middle-income countries (LMICs). More generally, even in high-income countries (HICs), studies on the mechanisms behind the relationships between reproductive histories and health, longevity, and ageing (defined here as the gradual deterioration of bodily functions, such as mobility, hearing, and cognition, generally starting in adulthood) have so far been inconclusive.

This general lack of evidence for LMICs is also compounded by the absence of analysis on later-life health, with an overall absence of data and analysis around measures of health linked to biometrics and biomarkers, such as weight, blood pressure, and blood sugar levels. To date there have been no studies examining allostatic load (AL)—a composite measure of the body's wear and tear—as an outcome of reproductive experiences throughout the life course in LMICs. This study aims to explore the use of AL to understand the impact of reproductive experiences on health in a context outside the Global North.

Many women currently in mid- or older adulthood in LMICs have faced high fertility, intrapartum complications, and unsafe induced abortions, all of which could have left them at risk of poor later-life health. This is particularly the case for poor women, for whom individual ageing is likely to be precocious and health needs are less likely to be met (United Nations 2013). Restricted access to health services, caring responsibilities, timing of menopause (whether late or early), and poverty can all lead to deteriorating health (Hammoudeh et al. 2017; Sujarwoto and Tampubolon 2020). A failure to acknowledge and address the health needs of women from midlife onwards is potentially detrimental, particularly in the long term, given the global context of emerging non-communicable diseases and the increasing burden that growing numbers of older adults are placing on weak or non-existent long-term-care systems.

Early entry to parenthood, nulliparity, and high fertility (more than four/five children) are often

associated with higher mortality and morbidity risks later in life (Hurt et al. 2006; Grundy and Read 2015; Read and Grundy 2016). However, the findings are often not generalizable. As pointed out by several studies (e.g. Gagnon et al. 2009; Grundy and Read 2015), the effects of fertility histories on health are challenging to disentangle for three key reasons: (1) the dual causality of the relationship (fertility might affect health, but health is also linked to e.g. fecundity and likelihood of finding a partner); (2) the diversity of the modelling tools; and (3) the different definitions of high fertility used in studies. Moreover, their complex association is likely intersectional (Geronimus et al. 2006; Grundy and Read 2015). Often, due to inadequate sample sizes and/or the stage of the country's fertility transition, there may not be enough cases for studying the impact of high fertility. Furthermore, most studies consider live births only, ignoring miscarriages and induced abortions.

Few studies have explored the link between reproductive histories, ageing, and later-life health in high-fertility settings, mainly because of lack of data. The few existing LMIC studies have suggested a potentially different role of fertility in explaining later-life health than in HICs. In Brazil, early childbearing was seen to accelerate ageing, but no association was found between parity and later health (Câmara et al. 2015). In another example, among historical populations in Utah and Quebec, there was little evidence of high and early fertility having an impact on post-reproductive survival (Gagnon et al. 2009). Neither of these studies examined the importance of pregnancies not ending in live birth.

Another shortcoming in low-resource settings is the availability of data on midlife, as surveys on ageing often include only individuals aged 50+, whereas surveys on reproductive health focus on those <45. It is crucial to examine the impact of reproductive histories on women's health at the end of the reproductive age too: this is usually the most neglected age group in (sexual and reproductive) health studies.

Indonesia was chosen for this empirical application for three main reasons: (1) the availability of good-quality data, including both reproductive histories and mid/later-life health information with biomarkers; (2) the timing and speed of Indonesia's fertility transition, which made it possible to compare the impact of reproductive histories on health in high-fertility vs declining-fertility contexts; and (3) a growing older-adult population. Indonesia is a 'lower middle income' country, which has experienced a steep fertility decline (from 5.7 births per woman in 1960 to 2.3 in 2016) and a considerable increase in contraceptive use (from 8.6 per cent in 1973 to 60.9 in 2017) (Figure 1) (World Bank 2020). The old-age dependency ratio is set to rise from 9.5 in 2019 to 24.5 in 2050, and 8.5 per cent of older adults (aged 60+) are living alone (United Nations Population Division 2019). Understanding the mechanisms through which later-life health is affected is fundamental in considering appropriate policymaking options.

The aim of this paper is to analyse the cumulative effect of reproductive histories (i.e. timing and quantum of fertility; number of pregnancies not ending in live birth) on Indonesian women's AL, from the end of their reproductive period up to older ages. Moreover, we aim to investigate the ability to use AL as a health outcome within an LMIC setting with secondary data. We chose AL as the outcome because it is a relatively stable and objective measure of health deterioration (McEwen 1998; Read and Grundy 2012) and it is also an understudied indicator in LMICs. We need a better understanding of the mechanisms through which AL functions in order to explore the potential to use it with current secondary data and provide suggestions for future primary data collection efforts.

Although the relationship between AL and fertility can be bidirectional, we analyse only the effects of fertility outcomes on AL due to data constraints. So far the literature on AL in LMICs has been very limited, and we lack evidence from studies based on representative household surveys. This study is therefore a unique application of existing methods to Indonesian data.

Background

Fertility and health: Possible mechanisms

There are positive and negative associations between childbearing and biological, physical, mental, and physiological health. Low fertility (one/two children) in HICs has a positive effect on long-term mental and physical health compared with having no children. This could be due to exposure to higher levels of progesterone and oestrogen during pregnancy and breastfeeding; these have been found to lower, for instance, the risk of certain types of cancer (Hurt et al. 2006; Dieterich et al. 2013). It could also be due to a stigma

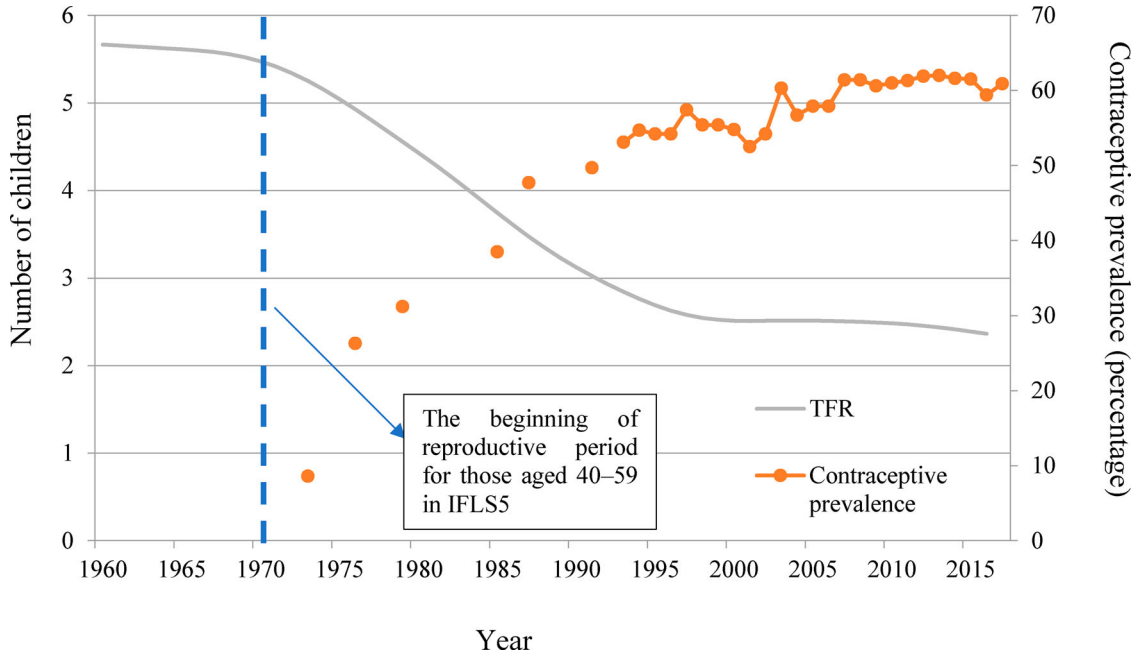


Figure 1 Total fertility and contraceptive prevalence (percentage): Indonesia 1960–2017
Source: World Bank (2020).

around childlessness, which could be even more damaging in some high-fertility settings (Tanaka and Johnson 2016).

On one hand, high parity can be associated with a higher risk of obesity and cardiovascular diseases, possibly due to intrapartum and post-partum complications (Hurt et al. 2006; Davis et al. 2012). On the other hand, high fertility can be positively associated with good mental health (Roth et al. 2012; van den Broek 2021) and healthier lifestyles. However, the evidence is mixed: the risk of depressive symptoms in women with two/three children does not differ from those with four or more in the UK (Grundy et al. 2019). In general, greater social support and fulfilment in life, including the social interaction that comes from having children, have been found to have a positive effect on health (Grundy and Read 2015).

Although we study the association from fertility to AL, there are many biosocial mediators and confounders, which make the actual direction of the relationship challenging to detect. Socio-economic status, genetic factors, timing and tempo of childbearing, and life satisfaction all affect both fertility and health (Grundy and Read 2015). In particular, early childhood experiences, such as neglect and trauma, have been found to be negatively associated with both fertility and health (McEwen 2002). In the other direction, physically and mentally healthier women are typically also more likely to be able to bear children (Soares and Melo 2008).

Allostatic load as a measure of health

AL is a composite measure of the body's wear and tear resulting from the psychological and physical impact of stressors on the body (McEwen 2002). Stress hormones can be protective in the short term but damaging in the long term (McEwen 1998, 2002; Read and Grundy 2012). The measurement of AL is usually based on two categories of biomarkers: primary mediators, which are substances the body releases as a result of stress (e.g. cortisol); and secondary effects that derive from the actions of the primary mediators (e.g. blood pressure, cholesterol) (McEwen 2002). The secondary biomarkers are categorized into immune (e.g. C-reactive protein), metabolic (e.g. cholesterol), cardiovascular and respiratory (e.g. blood pressure), and anthropometric (e.g. BMI) measures. AL is a synthetic indicator with between eight and 16 components, including ideally both primary and secondary markers, as these different types of markers represent acute (primary mediators) vs more long-term effects (secondary outcomes) (Geronimus et al. 2006; Read and Grundy 2012). Even if it is not possible to include both primary and secondary markers, the AL indicator should represent the interplay of different systems (e.g. inflammatory, neuroendocrine, and metabolic) (Read and Grundy 2012). While it is usually best to measure the primary measures earlier in life, secondary measures are often sufficient at older ages because the primary

indicators affect the secondary ones, which start to show later in life (Read and Grundy 2012).

AL measures the body's response to stress, which can cause long-term illnesses, such as cardiovascular diseases or depression (McEwen and Seeman 1999), with both acute and chronic impacts. Ageing, lower wealth (Seeman et al. 2014), cognitive decline (Juster et al. 2010), and stressful childhood events (McEwen 1998; Karlamangla et al. 2006) are all associated with higher AL, which in turn predicts higher mortality.

AL also fits the weathering hypothesis, which states that the health of individuals who have been exposed to socio-economic disadvantage and discrimination throughout their lives deteriorates more quickly than the health of those in more advantageous positions (Geronimus et al. 2006). This is particularly the case for secondary markers (Dowd et al. 2009). For instance, cumulative measures of socio-economic adversity across childhood and adulthood are stronger predictors of high inflammatory burden (Loucks et al. 2006) and weight gain (Baltrus et al. 2005) than measures from single points in the life course (Karlamangla et al. 2006). Thus, we assume that individuals living in settings with low or no access to good-quality healthcare, high poverty, and high stress—including Indonesia and many other LMICs—will be likely to experience early health deterioration.

Allostatic load and pregnancies

The long-term impact of pregnancies on health is challenging to gauge. AL can be both a cause (Premji 2014; Olson et al. 2015) and consequence (Kramer et al. 2009) of perinatal distress, preterm births, miscarriages, and stillbirths. Physiologically speaking, pregnancy itself is an inflammatory stressor, and the more complex and unhealthy a pregnancy is, the higher the level of inflammation (C-reactive protein) in the blood (Premji 2014). The processes of conception and maintaining a pregnancy cause physiological stress. Therefore, timings and outcomes of pregnancies over the life course may affect levels of both physiological and mental stress on the body.

Losing a pregnancy, whether through miscarriage, unsafe induced abortion, or stillbirth, constitutes a stressor on women's health that is usually studied only in the short term (Premji 2014; Câmara et al. 2015; Christiaens et al. 2015; Barrett et al. 2018). While research is emerging in the United States (US) on pregnancies not ending in live birth as a stressor for AL in the long term (Barrett et al. 2018), to date there is no consensus on the mechanisms. Importantly, there is no evidence on the issue in LMICs. In addition, the approach is often solely biomedical. There is a need to include socio-demographic and biosocial variables, which may be associated with the likelihood of experiencing a pregnancy not ending in live birth, and to use measurements outside the pregnancy period.

The Indonesian context

Indonesia is an archipelago with a very fragmented topography and great ethnic diversity (Ananta et al. 2015). Within the key ethnicities (Javanese, Sundanese, Batak) there is a trend of declining population growth and increasing population ageing (Ananta et al. 2015). The Javanese population (over 40 per cent of Indonesians) displays the lowest fertility and the steepest decline in growth. This is due to increasing efforts by the government to decentralize its activities and a consequent increase in in-country migration, as well as a heavy-handed family planning programme promoted on the islands (Ananta et al. 2015). The steepest fertility decline occurred between 1970 and 2000 (Figure 1), the period when contraceptive use started to increase. Around this time, the cohort of women who were aged 40–59 during Wave 5 of the Indonesian Family Life Survey (IFLS) reached reproductive age; this might help us understand some of the trends shown later in the modelling. Overall, despite this progress, Indonesian women have endured high fertility and high risks of birth injuries across the last half century (Nababan et al. 2017).

The burden of high fertility and low obstetric resources has been felt in Indonesia for the last few decades. Despite Indonesia's maternal mortality ratio declining from 450 deaths per 100,000 live births in the 1990s to around 313 in 2012 (World Bank 2020), problems persist where specialized obstetric care continues to be deficient, and there are wide inequalities in access to emergency intrapartum services across regions (Nababan et al. 2017). The high maternal mortality is likely partially due to Indonesia's very restrictive law on abortion, with unsafe abortion being common. Yet, 36 per cent of all pregnancies are unintended and of these around 63 per cent end in abortion (Giorgio et al. 2020). Abortion rates vary widely by region, with Jakarta reporting the highest rate (68 abortions per 1,000 women of fertile age) and East Java the lowest (30 per 1,000).

Health in Indonesia as a whole has been improving, with life expectancy for women rising from 48 years in 1960 to 73 in 2014 (United Nations Population Division 2019). Currently the population of older adults (aged 65+) is estimated at 21 million out of the population of 270 million. Indonesia's older-adult population is the fourth largest in Asia and in percentage terms the highest in Southeast Asia. It is estimated that the population aged 60+ will more than double between 2019 and 2050, with the old-age dependency ratio increasing from 9.2 to 24.5 (United Nations Population Division 2019).

Previous studies on social mobility in Indonesia, with its growing economy, have shown a considerable decline in poverty, while the middle class has expanded, due mainly to greater achievements in human capital and permanent employment (Dartanto et al. 2020). These socio-economic transitions have been heterogeneous across the archipelago and translate into inequalities in access to healthcare, in particular for secondary and tertiary care, which can be hard to access due to financial and geographical barriers (Mulyanto et al. 2019).

Although not analysed in this paper directly, internal migration could have played a significant role in Indonesia's health transition. Rural–urban migration has been reported to have a detrimental effect on mental and physical health due to family disruption and deterioration in lifestyle, showing a possible urban disadvantage (Lu 2010).

Within a setting of fertility decline and progressive ageing, Indonesia's key policy priority lies in health and social care for older individuals. This is important in a country where family networks are atypical of South Asia. Many older Indonesians live separately from their families, often due to very high mobility among the younger population (Kadar et al. 2013). In addition, a move towards nuclear families with fewer ties with the extended family has occurred over the last few decades (Kreager and Schröder-Butterfill 2008). Moreover, Indonesia's ethnic diversity means there is a diversity of kinship relationships: for example, Batak and Bali are more patrilineal, West Sumatra is home to one of the biggest matrilineal populations in the world, and Java has a bilateral kinship system (Guilmoto 2015; Kunto and Bras 2019). Thus, while the social care system is very weak, the social network, which could support the ageing population, is also weak and varies by ethnicity and region.

In summary, Indonesia until only recently displayed high fertility, high maternal morbidity and mortality, and an unmet need for safe maternal healthcare (Nababan et al. 2017). It is also an ageing society, where the increasing prevalence of non-communicable diseases and disability is putting a burden on health and social care services (Mboi et al. 2018). Although the diversity within the country might present a challenge for researchers, the timing of its fertility transition and its kinship arrangements make Indonesia an excellent application for an analysis of the impact of fertility histories on health from an empirical as well as a policy perspective.

Data and methods

With a cross-sectional approach, we used data from the first five waves (1993, 1997, 2000, 2007, and 2014–15) of the IFLS, which is representative of 83 per cent of the Indonesian population. A sample of 7,730 households was selected in the first wave. Multiple individuals were selected within each household using the following criteria: all heads of households and their spouses, two randomly selected children aged 0–14, an individual aged 50+ randomly selected from the remaining members and their spouses. Households and household members were added in subsequent waves, to ensure IFLS households are always representative of the Wave 1 (IFLS1) households and their descendants. The strength of this survey lies in the wide range of topics included, the low attrition (92 per cent of IFLS1 households were re-contacted in Wave 5 (IFLS5)) (Strauss et al. 2016), and data on a range of life-course events and health indicators. The sample was increased at each wave to arrive at a total of 16,204 households in IFLS5.

Although the IFLS data are longitudinal, we used data mainly from the fifth wave, as many of the AL questions were included only in this wave. For the outcome variable we used only IFLS5 data, as we explain shortly. We did reconstruct some of the independent variables using more than one wave in cases with high item missingness or where some of the reproductive history questions were asked at certain ages (e.g. only women aged <60 were asked their age at first birth): these variables covered parity, miscarriages, employment, union status, age, hospitalization, and child death. We found higher missingness at older ages (90+), which is negligible given the very small size of this age group (less than 1 per cent of the sample); see also Tables 1 and 2 for further information on missingness. We used cross-sectional survey weights in all analyses.

Starting from a total sample of 19,401 women aged 15–101 who were interviewed in IFLS5 (2014–15)

Table 1 Allostatic load biomarkers: Missingness and cut-off points

	Percentage missing (*N*)	Percentile score for 25 per cent highest-risk population
Pulse rate	0.64 (18)	25.01
Systolic blood pressure	0.90 (18)	33.58
Diastolic blood pressure	0.64 (18)	28.15
Lung function	4.87 (94)	32.30
Waist-to-hip ratio	1.21 (26)	26.98
Body mass index	2.31 (36)	22.96
Haemoglobin	0.37 (7)	25.24
Glycosylated haemoglobin	0.00 (0)	25.90
C-reactive protein	0.00 (0)	28.68

Source: Authors' analysis of IFLS5.

(Herningtyas et al. 2018), we first selected all those with biomarkers measured (n = 4,153; a randomly selected sample of the overall survey population), then excluded those for whom waist-to-hip ratio (WHR) was not measured (n = 2,136; it was measured only for women aged 40+). Finally, we excluded those without at least five biomarkers measured (n = 16), ending up with a final analytic sample of 2,001 women aged 40–101 (Figure 2). Comparisons of socio-demographic characteristics between the entire sample and our analytic sample (available on request) showed that the latter was a representative sample of the wider survey population aged 40+ (i.e. women who are near completing or have finished childbearing). Although biomarkers that allow the construction of AL were collected in both Waves 4 and 5, we could not examine within-woman changes in AL between Waves 4 and 5 due to the differences in biomarker data collected; that would be beyond the scope of this study.

Outcome: Allostatic load

We used a total of nine biomarkers to calculate AL: two from the anthropometric system (WHR and body mass index (BMI)); two from the metabolic system (haemoglobin (to test for anaemia) and glycosylated haemoglobin (A1C blood sugar test for diabetes)); one from the immune system (mean C-

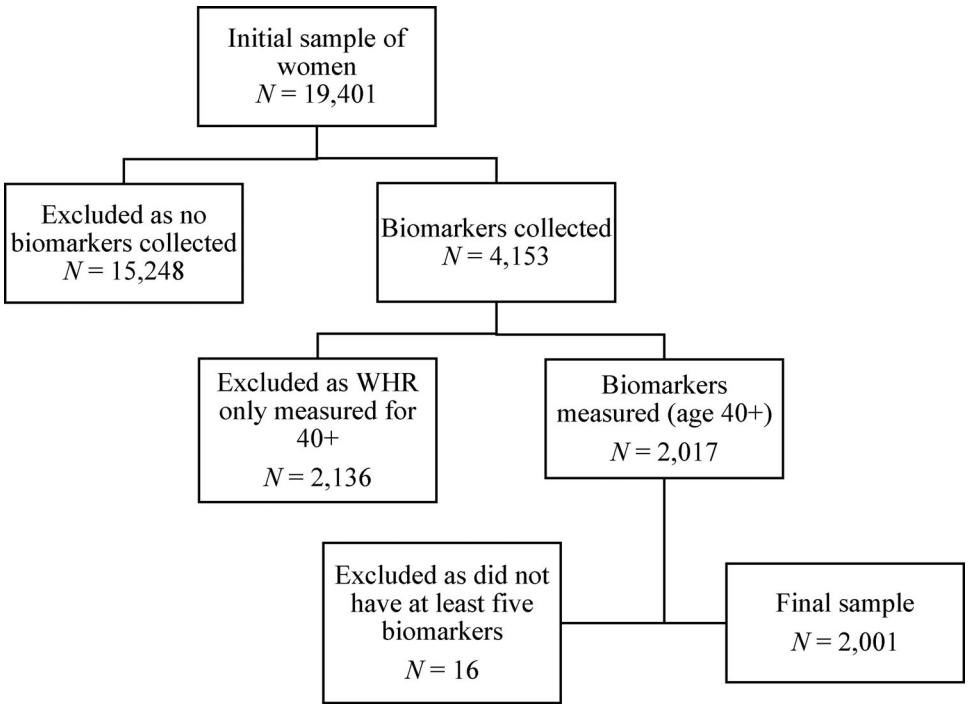


Figure 2 Sample selection: Indonesian women
Note: WHR = Waist-to-hip ratio.
Source: Authors' analysis of IFLS5 data.

reactive protein concentration, measuring the level of inflammation in the body); and four from the cardiovascular and respiratory system (pulse rate, systolic and diastolic blood pressure, and lung function). Table 1 reports the level of missingness for each item.

Our measure therefore included all the main groups within the secondary biomarkers mentioned earlier but did not include any primary biomarkers. This is also common in other data sets widely used to study AL in HICs, for example the English Longitudinal Study of Ageing (ELSA) and Health and Lifestyle Survey in England. This may be a minor limitation for the younger cohorts in our sample (those aged <60). For the older cohorts, the secondary markers are likely to be enough. This is because health deterioration is a process in which the primary markers deteriorate first, followed by the secondary ones. Thus, secondary markers are more important when considering an older population (Dowd et al. 2009; Read and Grundy 2012). A strength of the composite AL measure is that despite the limitations of single biometrics, such as BMI, in assessing health risks (Ashwell et al. 2012), AL considers an array of measures, each identifying a different health subsystem, all of which are represented within the selection of markers used to construct the AL measure in this study.

Beyond the type and number of biomarkers, a comparison of the range of methods used to calculate AL has shown that a count-based method is straightforward and slightly better at accounting for high and low values than modelling-based methods (Seplaki et al. 2005). Thus, we gave each participant a score of one for a variable if they were deemed 'high risk', otherwise a score of zero, and we computed AL as a count of high-risk scores for each measure. For example, if an individual was in the highest quartile for BMI and WHR but not for the other measures they would score two out of nine.

Using the sample distributions for women, 25th percentile high-risk cut-off points were chosen to identify individuals falling into the highest-risk quartile of each measure's sample distribution (Geronimus et al. 2006; Read and Grundy 2012). We report the distribution of these cut-off points and missingness in Table 1. In addition, for diastolic and systolic blood pressure, we interpreted current use of hypertension medication to mean individuals had the condition and thus were at high risk. If the participant used medicine for anaemia we counted them as high risk for low haemoglobin, and if they used medicine for diabetes, they were assigned to the high-risk group for glycosylated haemoglobin. The values of C-reactive protein can be reduced by 25–30 per cent when medication is taken to control blood pressure, diabetes, or cholesterol (Grundy and Read 2015), so we gave individuals with values in the second highest quartile a value of one on the C-reactive protein indicator if they took any of the above-mentioned medications.

Explanatory variables

Explanatory variables for our path analysis were selected based on previous literature and hypotheses constructed within the model.

Fertility variables. These included childbirths, pregnancies not ending in live birth, and age at first pregnancy (for parous women). We grouped *parity* into 0, 1–2, 3–4, and 5+ in line with previous studies and to reflect low, medium, and high fertility (Grundy and Read 2015; Barrett et al. 2016).

Pregnancies not ending in live birth were calculated based on information available in all IFLS waves, where women were asked to report any spontaneous and induced abortions. This variable was included as continuous because we wanted to test its cumulative impact on AL. We did not distinguish between miscarriages, induced abortions, and stillbirths because induced abortions are typically under-reported and can be reported as miscarriages (Jones and Kost 2007; Lindberg and Scott 2018). Stillbirths are likely under-reported due to the challenge in distinguishing them from neonatal deaths (Jones and Kost 2007; Lawn et al. 2011).

For women aged <60, we constructed a binary variable *age at first pregnancy*, showing whether the respondent first became pregnant before age 18 or aged 18+. The majority of these pregnancies (94 per cent) resulted in live births and thus the variable indicates early childbearing. These data were largely unavailable for women aged 60+ in the IFLS. This variable has previously been found to be significantly associated with later-life health (Grundy and Read 2015).

To measure significant stressors, we included whether the woman had ever *experienced child death*. Child deaths negatively impact the mental and physical health of parents and their ageing process (Rogers et al. 2008; Alburez-Gutierrez et al. 2021). They can also affect childbearing patterns, for example via replacement fertility. After the 2004 tsunami in Indonesia, women were found

to be more likely to give birth after losing one or two children (Nobles et al. 2015). Our variable records whether any biological or adopted children either living in or outside the woman's household died.

Health stressors and health behaviours. We included two measures of health, which account for information in Waves 1–5: childhood illness and hospitalizations during adulthood, used as proxies for health experiences throughout the life course. Respondents' *childhood illness* classifies respondents according to whether they have suffered from serious childhood illness, defined as having taken time off school, stayed in bed, or been hospitalized, in each case for more than a month during their childhood. Childhood illnesses are associated with poor later-life health and in general a greater risk of chronic diseases (Case and Paxson 2010), as well as with lower education and wealth outcomes (Case et al. 2005). Although there is a selection effect (poorer individuals are more likely to experience poor health), childhood illnesses may lead to lower investments in human capital and, in general, to higher dropout rates.

For adulthood health, we calculated whether the respondent had been *hospitalized in the last 21/22 years*, that is, for more than a week at least once since 1993 (Wave 1) due to an illness or accident (not pregnancy). This variable is an indicator of underlying risk factors and poor health but could also indicate different health-seeking behaviours. Evidence suggests that wealthier individuals are far more likely to seek healthcare and therefore to report episodes of hospitalization in a setting with financial barriers to healthcare access (Mulyanto et al. 2019). Given the missing values and gaps across these variables, we considered this as a cross-sectional value meaning ever having been hospitalized as a result of being sick. This is a limitation of the study but one that allows the inclusion of even partial information on adult health status history.

To account for behavioural health risk factors, we included *ever smoked* as a binary variable, because smoking at the time of the survey alone would not have been as meaningful as we wanted to test long-term health effects. Smoking affects cardio-circulatory functions, which directly affect AL (McEwen 1998) as well as fecundity via their effect on ovarian functions (Soares and Melo 2008). In the first iteration of the modelling, we included information on husband/partner's smoking to control for passive smoking due to high prevalence of smoking among Indonesian men (80 per cent of the population exposed) (WHO 2012). These variables were later removed due to high missingness. We did not include alcohol consumption, as data were unavailable.

Socio-demographics. We created a range of variables measuring respondents' current socio-demographic characteristics. *Education* was measured in IFLS5 (2014–15) as an ordinal variable for highest grade achieved (no schooling, up to elementary, up to junior high, up to high school / junior college, and university). If educational level was missing at Wave 5 but available for Wave 4, we used the latter value (n = 127) as, given the age of those in our sample, we would not expect it to change between the waves.

Wealth in adulthood was measured as an index variable constructed with principal component analysis using assets (e.g. electricity, type of floor and wall material, ownership of various household goods) at residence level in the respondent's household. This type of variable has long been used in LMICs as a proxy for wealth and despite its limitations has been proven to be robust for detecting rural and urban differences as well as wealth within the informal sector (Filmer and Pritchett 2001). We also considered childhood wealth, but this variable had too many missing cases to be included (>50 per cent). *Employment status* was divided into three categories: working, housekeeping (of own home), and not working. Unfortunately, we could not distinguish between more specific types of employment due to the high level of missingness in more detailed employment variables (41 per cent). This variable needs to be interpreted with caution, as work status itself could be both a cause and a consequence of health outcomes (Hoven et al. 2015).

In addition to *age* (measured in single years at the time of IFLS5), we measured respondents' current *residence* (rural/urban), marital status, and ethnicity. *Marital status* is a binary variable (currently in a union or not) due to lack of variation in the non-union categories (e.g. widow, divorced, separated). Being in a union can have both negative and positive impacts on women. For instance, widowhood can be beneficial for women's health in the long term, but the loss of a partner is a key stressor in the short term (Wu and Hart 2002). *Ethnicity* was recoded into: Javanese, Sundanese, Malay, Batak, Madurese, and 'Other', in line with previous research (Ananta et al. 2005, 2015). Given the scope of this paper and the size of the sample, we considered this variable only as a control factor and did not conduct more in-depth analysis of ethnic differences.

Analytic strategy

After descriptive analyses, we ran various maximum likelihood linear regression models exploring the association between our explanatory variables and AL, including in turn the entire sample, women aged 40–59, and women aged 60+, to distinguish between cohorts who were of prime childbearing age before/after the rapid fertility decline in Indonesia discussed earlier. We decided to separate these cohorts because: (1) their fertility experiences differed (see also Figure 1); (2) AL without primary markers is better for older populations, so it is better to analyse those aged <60 separately to see if the results differ; (3) the path models would not have converged in the overall sample due to the associations being so different across the different cohorts; and (4) using the two cohorts, we could see if the impact differed (relatively) soon after the end of the reproductive period vs in older adulthood.

Some of the youngest cohorts of women in our study might not yet have completed their reproductive histories. However, we expected only a few of them to experience more pregnancies, given the low median age at childbearing in Indonesia (22.4 years) and the low age-specific fertility rates for ages 40+ (20 per 1,000 women for ages 40–44; 4 per 1,000 for ages 45–49) (BKKBN 2018).

In order to include a wider range of fertility-related variables (i.e. age at first pregnancy and death of child), we conducted some models separately for parous women only.

Finally, we analysed these data using path analysis within a structural equation framework using Mplus software (version 8) (Muthén and Muthén 1998–2017). The advantage of path models is their detailed information about the direct and indirect pathways both from and via fertility events to AL. Indirect pathways can sometimes be more prominent than direct pathways when the association between fertility events and health/well-being is examined (e.g. Grundy et al. 2019). We used the full information maximum likelihood (FIML) method to address missingness (Acock 2005). This enabled inclusion of cases with missing values for any dependent variable in the path models. FIML produces estimates for means and the variance–covariance matrix and uses these to obtain model parameters (Enders and Bandalos 2001; Acock 2005). The assumption behind the algorithm is that by using all variables in the model that potentially contribute to the missingness, we can obtain a robust estimate for all individuals included, even if some information for them is missing. We tested models both with and without missing values, and the results were not significantly different.

We constructed paths reflecting plausible chains of association, based on previous literature, data availability, timing (when the variables were recorded in the IFLS), and the endogeneity of the variables. We created four models mirroring the regression modelling strategy: two including all women (for cohorts aged 40–59 and 60 + at IFLS5); and two including only parous women in each cohort but with a wider range of fertility variables. Models for both cohorts together were also conducted but not reported here (available on request), as they failed to converge or reach a good model fit due to the pathways being quite different for the two cohorts. We calculated direct, indirect, and total effects of key variables on AL based on the results of the path models. We report standardized coefficients, allowing us to compare the magnitude of the impact of each variable on the outcome.

In Figure 3 we report the full pathway analysis strategy. We express the fertility pathways with dashed lines, while the other pathways are solid lines. Pathways can be direct (e.g. from education to AL) or indirect (mediated by other behavioural factors), for example from education to AL, mediated by smoking or residence. Dotted lines refer to the models restricted to younger samples, where variables such as age at first birth were available.

Results

Descriptive statistics

Table 2 reports the distribution of the sample for the two cohorts. On average, AL for women in the sample was 2.4 (out of nine; higher values indicating poorer health), with the younger cohort reporting significantly lower values than the older (2.2 and 2.8, respectively).

The older cohort's fertility was higher than the younger cohort's, and they experienced a higher number of pregnancies not ending in live birth (0.4 on average for the older and 0.3 for the younger cohort). There were no large differences in age at first pregnancy (31.4 per cent were <18 in the younger cohort and 33.8 per cent in the older), but the variable was missing for 50 per cent of the older cohort and thus not included in further models for them (Table 2).

Childhood illnesses were more common among the younger cohort, where 17.1 per cent had been

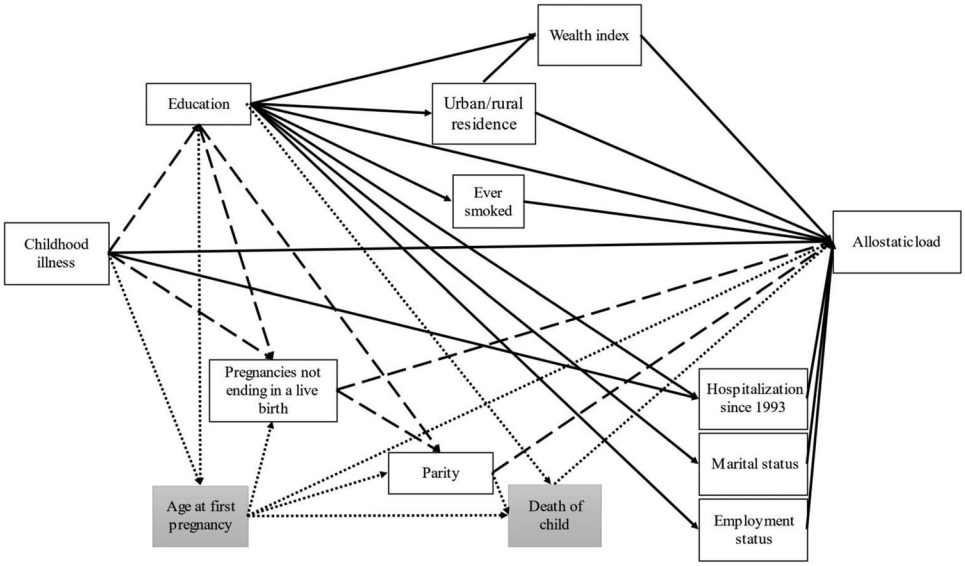


Figure 3 Path analysis strategy
Notes: Dashed lines = fertility pathways; solid lines = other pathways; dotted lines and greyed boxes refer to variables used for younger samples only. Age is associated with all variables but not shown here for clarity.
Source: Authors' own.

ill for at least a month compared with 11.4 per cent in the older cohort (Table 2). This could be for several reasons: younger cohorts might have been more likely to survive the illnesses, they might have recalled the events more clearly, and they might have had better access to hospitals than the older cohort. For the other health/stress indicators, the younger cohort showed smaller proportions having been hospitalized, ever smoked, or experienced the death of a child than the older one.

The socio-economic indicators showed poorer socio-economic status (SES) for the older than the younger cohort. The older cohort were more likely to be in the poorest strata of the population, more likely to be less educated, and less likely to be working (Table 2).

On average, the younger cohort were 49.7 years old, and the older cohort 68.7. The younger cohort were more likely to be married or cohabiting and to belong to the Javanese ethnic group than the older cohort, while the older cohort were more likely to live in urban areas and to not be working.

Finally, the relationship between pregnancies in general and AL (not shown here) was an inverted U-shape, with the highest AL around parity three.

Results of the path analyses

The results of the ordinary least squares regression are reported in the Appendix (Table A1) for information. The final path models with the highest model fit values (as measured by Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) (Muthén and Muthén 2006) and with variables and paths with $p > 0.1$ excluded in most cases) are presented in Figures 4(a,b) and 5(a,b) separately by cohort and fertility status (all women vs parous only). Table 3 summarizes the effects of direct and indirect pathways via the fertility variables of interest. In our interpretation of Figures 4 and 5, we focus on the pathways via the fertility variables (dashed lines).

For all women in the younger cohort (Figure 4(a) and Table 3 panel (a)), there was a positive direct effect from pregnancies not ending in live birth to AL (0.080), which indicates that such pregnancies were associated with worse health (higher AL). Parity had no direct or indirect association with AL. The largest direct impacts on AL were observed for education (−0.170), rural residence (−0.275), and not working (0.159) (Figure 4(a)). It is worth noting that as education had many indirect associations with AL, some positive and others negative, its total effect was more modest than the direct effect alone (−0.082, not shown).

In the older cohort (Figure 4(b) and Table 3, panel (b)), fewer paths were significantly associated with AL. Pregnancies not ending in live birth had a positive direct impact on AL (0.083) and one of the indirect positive pathways from education was also mediated by this variable (0.007). Parity was again

Table 2 Demographic characteristics of analytic sample of Indonesian women: percentage or mean (SD) and *N*

		Younger cohort (aged 40–59)	Older cohort (aged 60+)	All women	*N* (unweighted, all women)	Missing, *N* (unweighted, all women)
Outcome	*Allostatic load, mean (SD)*	2.20 (1.63)	2.79 (1.61)	2.44 (1.65)	2,001	0
Fertility	*Parity, percentage*				2,001	0
	0	18.71	4.46	4.55	91	–
	1–2	31.69	18.92	27.73	755	–
	3–4	32.04	26.17	37.78	756	–
	5+	17.56	50.45	19.94	399	–
	Pregnancies not ending in live birth, mean (SD)	0.28 (0.61)	0.39 (0.79)	0.33 (0.71)	1,674	327
	No such pregnancies, percentage	79.57	73.73	76.62	1,217	–
	One such pregnancy, percentage	14.20	18.13	16.19	279	–
	Two or more such pregnancies, percentage	6.23	8.14	7.19	178	–
	Age at first pregnancy, percentage				1,399	602
	<18	31.41	33.79	32.07	436	–
	18+	68.59	66.21	67.93	963	–
Health	*Childhood illness, percentage*	17.07	11.43	15.02	272	265
	Hospitalized in the last 21/22 years, percentage	7.05	9.25	7.97	151	0
	Ever smoked, percentage	5.84	12.54	8.62	173	2
	Experienced child death, percentage	20.56	61.55	38.65	613	457
SES	*Education, percentage*				1,861	140
	No schooling	10.86	34.03	20.28	377	–
	Elementary school	55.83	51.69	54.15	989	–
	Junior high	12.42	7.35	10.36	200	–
	High school and Junior College	16.87	6.19	12.53	242	–
	University	4.02	0.73	2.68	53	–
	Wealth quintiles, percentage				1,995	6
	Poorest	22.36	32.93	26.74	501	–
	Poorer	22.00	23.18	22.49	465	–
	Middle	18.86	16.19	17.75	356	–
	Richer	21.63	17.45	19.9	397	–
	Richest	15.14	10.25	13.12	276	–
	Employment status, percentage				2,001	0
	Working	48.97	31.62	41.77	828	–
	Housekeeping	46.84	41.98	44.82	888	–
	Not working	4.19	26.40	13.40	285	–

(*Continued*)

Table 2 Continued.

		Younger cohort (aged 40–59)	Older cohort (aged 60+)	All women	*N* (unweighted, all women)	Missing, *N* (unweighted, all women)
Demographic characteristics	*Age (mean, SD)*	49.74 (5.94)	68.69 (7.63)	57.61 (11.49)	2,001	0
	Place of residence, percentage				2,001	0
	Urban	50.27	60.58	48.37	1,106	–
	Rural	49.73	39.42	51.63	895	–
	Marital status, percentage				2,001	0
	Not in union	26.63	61.10	40.11	839	–
	Union	73.37	38.90	59.89	1,162	–
	Ethnicity, percentage				2,001	0
	Javanese	53.08	49.91	51.76	863	–
	Sundanese	14.06	16.96	15.26	249	–
	Malay	1.39	2.75	1.96	8	–
	Batak	3.82	2.61	3.32	53	–
	Madurese	2.07	1.76	1.94	71	–
	Other	25.58	26.00	25.75	757	–
	Total N (unweighted)	1,133	868	2,001		2,001

Notes: Percentage of non-missing cases. SD refers to the standard deviation.
Source: Authors' analysis of IFLS data.

Table 3 Standardized direct and indirect effects (from path models) of fertility variables on allostatic load for Indonesian women: all women and parous women only by cohort

	Direct effect	[*SE*]	Indirect effect	[*SE*]
(a) All women, younger cohort				
Parity five or more children	0	–	0	–
Pregnancies not ending in live birth	0.080*	[0.039]	0	–
Childhood illness via pregnancies not ending in live birth	−0.084†	[0.046]	0.008	[0.006]
(b) All women, older cohort				
Parity five or more children	0	–	0	–
Pregnancies not ending in live birth	0.083*	[0.035]	0	–
Education via pregnancies not ending in live birth	0	–	0.007†	[0.004]
(c) Parous women, younger cohort				
Parity five or more children	0	–	0	–
Pregnancies not ending in live birth	0	–	0	–
Early first pregnancy	0.177**	[0.055]	0	–
Education via early first pregnancy	0	–	−0.084**	[0.028]
(d) Parous women, older cohort				
Parity five or more children	0	–	0	–
Pregnancies not ending in live birth	0.167*	[0.036]	0	–
Childhood illness via pregnancies not ending in live birth	0	–	0.010	[0.006]
Education via pregnancies not ending in live birth	0	–	0.005	[0.004]

$^{\dagger}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
Note: SE refers to the standard error.
Source: As for Table 2.

not associated with AL directly or indirectly. The strongest direct associations were observed for rural residence (−0.105), not working (0.189), and hospitalization (0.132).

The results of the path model for the younger parous cohort are shown in Figure 5(a) and Table 3, panel (c). The only fertility variable directly associated with AL was young age at first pregnancy (0.177), but it also had a negative indirect effect mediated by education (−0.084, Table 3 panel (c)). Parity was not associated with AL and neither was child death. Rural residence (−0.304), not working (0.179), and education (−0.113) had the strongest direct associations with AL.

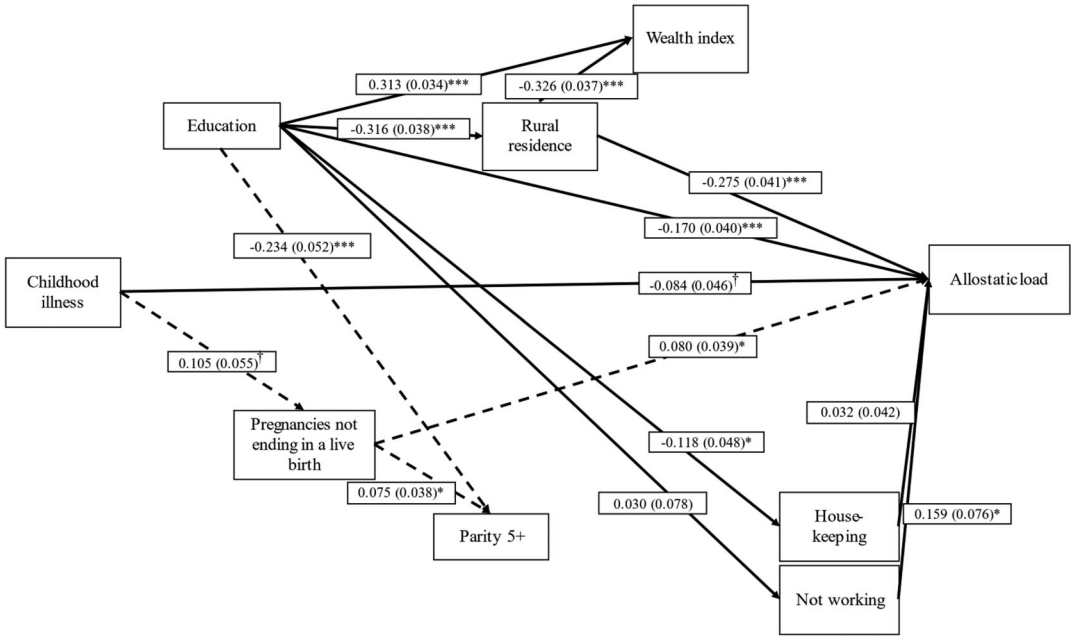
The results for the older parous cohort are shown in Figure 5(b) and Table 3, panel (d). Pregnancies not ending in live birth again had a positive direct impact on AL (0.167) and small positive indirect associations through it from childhood illness (0.010) and education (0.005, Table 3, panel (d)). Neither of the indirect pathways were significant, though. For this group, the strongest direct association occurred through the mediating effect of the not working category (0.268).

Discussion

This paper has shown the feasibility of a study on AL in a low-resource setting with secondary data. The data set used has many strengths including the wide range of biomarkers and the low missingness and attrition. This is particularly significant in relation to the biomarkers, where usually in a HIC setting we would see low response due to refusal to undergo these measurements. For instance, in France only 7.3 per cent of people invited to take part in a health panel study sample agreed to attend the health visit needed for the study (Goldberg et al. 2017), which is similar to the 5.5 per cent response in the UK Biobank (Batty et al. 2020). Beyond this, the limitations of this analysis are similar to those in many other longitudinal studies (e.g. ELSA), which collect a subsection of the full sample of mediators that are ideal but not essential for the calculation of AL.

There are several lessons to be learned from this analysis of limited data on AL in an LMIC setting. First, the paper demonstrated the suitability of the Indonesian data for analysis in a study on AL among midlife and older adults. Certainly, the caveats regarding many of the variables are similar to those in HIC studies: for example, the unavailability of reproductive histories for older cohorts and the absence of primary mediators among the biomarkers. Second, the low attrition in the panel allowed us to be creative when tackling missing data by constructing some explanatory variables from longitudinal information. Third, the inclusion of midlife cohorts allowed the comparison of different generations, an opportunity which has been absent in LMIC settings and unusual in HIC ones.

(a) 40–59 cohort



(b) 60+ cohort

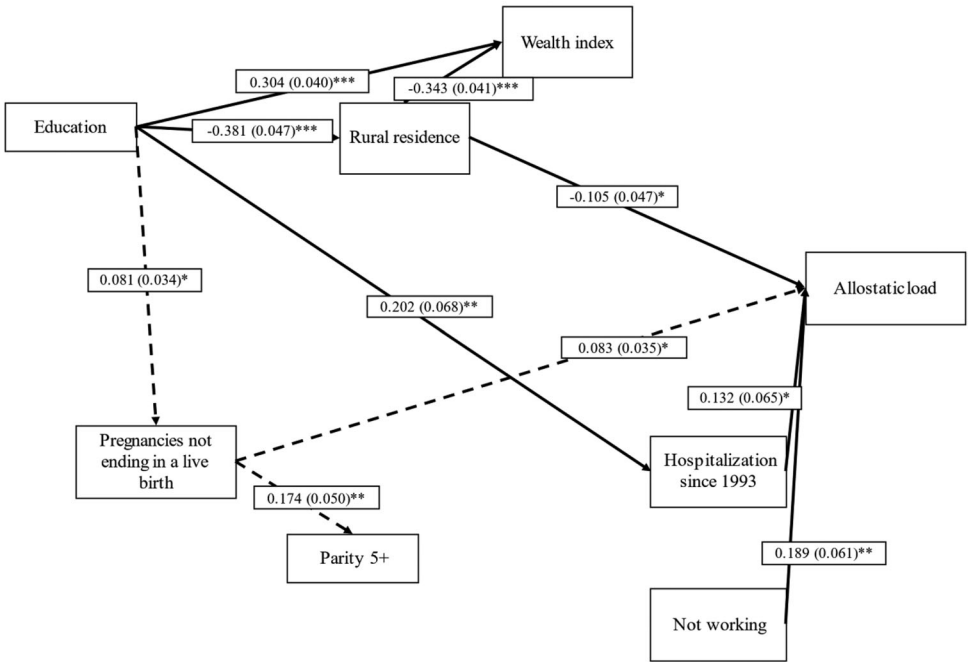
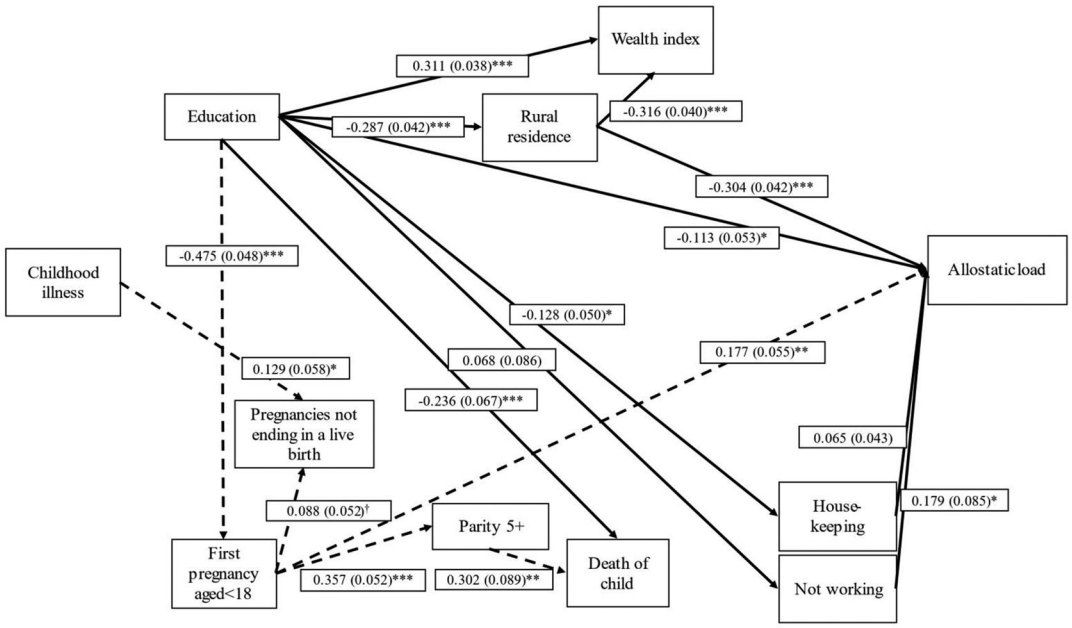


Figure 4 Path analysis of all women, by cohort
†$p < 0.10$, *p 0.05, **$p<0.01$, ***$p<0.001$.
Notes: Dashed lines = fertility pathways; solid lines = other pathways. Numbers in parentheses are standard errors. Age is associated with all variables but not shown here for clarity. (a) Model fit: CFI = 0.958; TU = 0.905; RMSEA = 0.996. (b) Model fit: CFI = 0.983; TU = 0.960; RMSEA = 0.990.
Source: As for Figure 2.

Lastly, conclusions on the full extent of the diverse impacts of AL from a rather small sample like ours need to be treated with caution, and generalizations to national level should be made with care, in particular as the IFLS represents only 83 per cent of the population.

(a) 40–59 cohort



(b) 60+ cohort

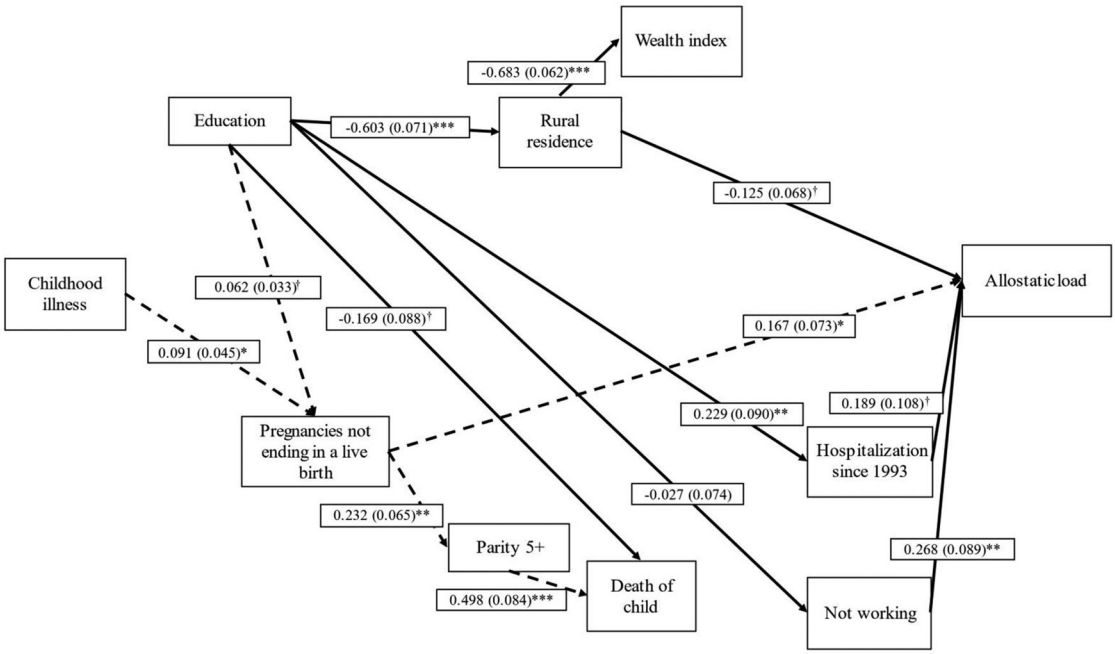


Figure 5 Path analysis of parous women, by cohort
†$p < 0.10$, *p 0.05, **$p < 0.01$, ***$p < 0.001$.
Notes: Dashed lines = fertility pathways; solid lines = other pathways. Numbers in parentheses are standard errors. Age is associated with all variables but not shown here for clarity. (a) Model fit: CFI = 0.944; TU = 0.888; RMSEA = 0.997. (b) Model fit: CFI = 0.953; TU = 0.911; RMSEA = 0.995.
Source: As for Figure 2.

Beyond the analytical merits of the AL analysis, the relationship between reproductive histories and AL emerged as complex, multifaceted, and possibly weaker than expected at higher parities. This result is in line with previous literature on HICs (Grundy and Read 2015; Read and Grundy 2016; Grundy et al.

2019) and on LMIC settings with relatively low fertility, such as Brazil (Câmara et al. 2015).

Interestingly, low parity was not associated with AL. Previous studies have suggested (Grundy and Read 2015; Grundy et al. 2019) that a small number of children can provide a protective effect on health, possibly through providing support/companionship and via breastfeeding and other biological factors. This result is key for several reasons. First, this is a rare study in a high-fertility LMIC setting, showing the lack of impact of high or low fertility on later-life health. Second, it is possible that the beneficial effect of having children as emotional support at low parities might be neutralized by the cumulative deleterious effect that childbearing has on women's bodies and health. In addition, in the Indonesian context we might find that low fertility is not beneficial to health at older ages due to the tendency for individuals to live in nuclear families (Hugo 1998; Ananta et al. 2015). This needs to be studied further with longitudinal AL data and tested at various stages of the reproductive history. Lastly, there could be an underlying selection effect, where only the 'fittest' manage to have more children and/or survive childbearing. Despite improvements, maternal mortality is still high in Indonesia, and this effect is particularly relevant for the older cohort (Nababan et al. 2017).

Further, our results suggest that timing of reproduction could be more relevant for health than quantity. For instance, pregnancy before age 18 had a positive relationship with AL in the path model, in line with previous studies (Grundy and Read 2015; Gurven et al. 2016; Read and Grundy 2016; Grundy et al. 2019). This could be due to a cumulative impact of early childbearing (usually more common among women of lower SES) and a higher risk of pregnancy complications among young mothers (Câmara et al. 2015).

A key result of this study was the positive relationship between pregnancies not ending in live birth and AL. A high number of pregnancies not ending in live birth could be an indicator of multiple induced abortions, which in a restricted setting, such as Indonesia, are likely unsafe. This may cause the association with poor health. Although no study has so far tested the impact of unsafe abortion on AL, we could speculate a short- to long-term physical and mental impact. There was also a selection effect, which should not be neglected. On the one hand, women who are prone to miscarriage could have more health problems in general, for example because chronic and autoimmune conditions increase the risk of miscarriage (Quenby et al. 2021). On the other hand, the burden of an unsafe abortion and/or miscarriage can take its toll on physical as well as mental health (Utomo et al. 2001; Barrett et al. 2018). Ideally, we would have liked to separate the analysis between abortions and miscarriages, but this was not possible due to data limitations. Nevertheless, such data are rare in longitudinal studies and both these pregnancy outcomes are under-reported in surveys (Lindberg and Scott 2018). Perhaps surprisingly, death of a child did not affect AL. This could occur if AL were less sensitive to mental than physical stressors (McEwen and Seeman 1999).

The Indonesian data showed a clear difference in pathways according to the demographic and socio-economic transition that cohorts experienced. In our regression models, rural residence had an effect only for the younger cohort, whereas wealth was only associated with the health of older women. These latter results could be due to a cohort effect linked to a socio-economic transition across generations in Indonesia, as discussed in the Indonesian context section (Witoelar et al. 2012; Dartanto et al. 2020).

Interestingly, the only SES variable which was significantly linked to AL either directly or indirectly was education. In models for younger cohorts, there was a clear negative effect (i.e. lower AL, better health), both directly and for parous women mediated by early age at first birth. In contrast, for older cohorts it had a slightly positive effect via pregnancies not ending in live birth (0.007, Table 3, panel (b)) for all women but was not significant for parous women (panel (d)). The fact that education showed a negative association with AL for younger women, whereas wealth showed no association, is another interesting result, as in the US, health gradient is strongest by income, but in Europe, education is what matters. This could most likely be due to a 'class' effect in the unequal Indonesian context (Kreager and Schröder-Butterfill 2008; Nababan et al. 2017; Dartanto et al. 2020). Within this setting, educated women may have benefited from better nutrition, better access to health services, and more accurate knowledge of health in general, which may explain education's negative association with AL.

There were several other empirical noteworthy results which call for further analysis. We recommend further exploration of the effect of variables such as education or smoking behaviours, as both the linear and the path models need testing to investigate the *pathways* to AL rather than just

calculating adjusted effects of each variable in a regression model if we are to understand fully how these events and characteristics are associated with health in the longer term.

Although urban/rural residence is not able to capture the longitudinal nature of individuals' movements, our results highlighted in particular for younger cohorts a possible urban disadvantage for Indonesian women. This result is in line with previous findings from many countries in the Global South and from Indonesia (Lu 2010). Despite its lack of interaction with reproductive outcomes, residence requires further investigation to understand the speed of ageing in rural vs urban areas and how this might differ across different ethnic groups.

Experiences earlier in life, such as childhood illnesses, did not seem to have a significant effect on AL aside from a negative impact in the younger cohort. Although unexpected, this could be due to a selection effect (i.e. those who survived the childhood illnesses could expect better later-life health).

Strengths and limitations

This study's strengths and limitations relate mainly to the data used, in terms of both timing and availability of information. The inclusion of nine biomarkers, including all the key secondary marker groups, provided a wealth of information which allowed the calculation of AL with very low missingness compared with HIC settings. On the limitations side, we could not explore in depth the full life-course information, including childhood wealth, age at menarche, and breastfeeding among others. Nor could we include more information on adverse childhood experiences, which can, for example, increase the risk of preterm births and miscarriages (Christiaens et al. 2015). However, the IFLS provides five waves of data for a wider-than-usual age group (40–101), allowing the analysis of adults at both midlife and older ages.

Despite these limitations, we constructed a number of synthetic variables which helped to bring out the potential importance of what IFLS data can show and what problems remain: for instance, in the way we reconstructed past stressors such as hospitalizations and childhood illnesses. Above all, a significant strength of our study was the provision of a template on how to analyse limited data in an LMIC context in a thorough and robust manner.

Conclusions

This paper is the first to estimate the effect of reproductive burden on AL in a high-fertility LMIC setting. It is also the first to explore AL data in an older population in such a context. On the application side, the study highlighted the following points: (1) AL should be a major research agenda topic; (2) existing sources such as the IFLS can, with many technical adjustments and further assumptions, be used to outline why and what is at issue; and (3) there are still several limitations that need to be overcome, and for this reason we call for further research.

Studies in LMICs have often been apologetic about the limitations of the data. However, a closer look at the biomarkers showed that response was particularly high and attrition relatively low. The challenges of the data when analysing AL in LMICs are therefore similar to those in HICs. A key issue is the lack of reproductive histories when collecting data on health longitudinally. There is a need to include such information in ageing studies more widely, as it forms an important part of the life course.

While the study pushed the potential of the data, the analysis could only be taken as far as the sample could go. The level of aggregation in the data meant that we could not explore the Indonesian context in detail. The study highlighted the need, in order to understand AL fully, to find ways to identify lower levels of aggregation that show distinctive combinations of AL problems and trends at more regional levels.

On the substantive side, we are the first to show a possible detrimental effect of miscarriages, stillbirths, and unsafe induced abortions on longer-term health. This paper calls for more support for ageing women that have endured a higher-than-average burden of such reproductive events. Furthermore, future research needs to investigate whether the associations differ if considering unsafe abortions, miscarriages, and stillbirths separately.

In addition, we found no association between number of children and AL. The timing of fertility might be more relevant for health than quantum is, or any possible harmful effects might be mitigated by other life events and/or selection. Parity might conflate an overall beneficial impact of childbearing on health in the long term with the impact of repeated pregnancies and complications. Future studies need to examine in more detail the burden of reproductive health, for example by exploring

modes of delivery, birth intervals, and pregnancy complications.

We need to consider more fully the pathways to ageing in order to assess the possible implications for health and social care systems in years to come. We also call for the inclusion of at least one primary mediator (e.g. cortisol) in future data collections, to enable checking of appropriate biomarkers across cohorts and more reliable analysis of younger age groups, who are more affected by primary mediators. Finally, biomarkers are relatively underused in LMICs, even when collected. Given the resources spent in collecting and analysing, as well as the ethics of putting individuals through measurements, there needs to be greater emphasis on and encouragement for the use of such data in studies in this field.

Notes and acknowledgements

1 Tiziana Leone is based at the London School of Economics and Political Sciences, UK. Heini Väisänen is based at INED, France, and also the University of Southampton, UK. Firman Witoelar is based at the Australian National University, Australia.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1 The associations between AL and the explanatory variables: ordinary least squares regression

		Model 1: all women						Model 2: parous women only					
		1(a): both cohorts		*1(b): younger cohort*		*1(c): older cohort*		*2(a): both cohorts*		*2(b): younger cohort*		*2(c): older cohort*	
Outcome		*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*
Fertility	*Parity*	–	0.202	–	0.112	–	0.835	–	0.363	–	0.454	–	0.621
	0	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	N/A		N/A		N/A	
	1–2	−0.45	0.044	−0.60	0.020	0.25	0.545	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)
	3–4	−0.31	0.173	−0.40	0.140	0.11	0.777	0.20	0.167	0.19	0.286	−0.26	0.346
	5+	−0.28	0.231	−0.37	0.217	0.23	0.565	0.17	0.326	0.27	0.337	−0.14	0.607
	Pregnancies not ending in live birth	0.20	0.003	0.21	0.096	0.21	0.012	0.16	0.044	0.18	0.223	0.14	0.138
	Age at first pregnancy	N/A	–	N/A	–	N/A	–	N/A	–		–	N/A	–
	<18	N/A	–	N/A	–	N/A	–	N/A	–	0.00	–	N/A	–
	18+	N/A	–	N/A	–	N/A	–	N/A	–	−0.19	0.379	N/A	–
Health	*Childhood illness*	−0.19	0.191	−0.17	0.332	−0.18	0.439	−0.28	0.092	−0.24	0.222	−0.37	0.202
	Hospitalized in the last 21/22 years	0.21	0.213	0.06	0.787	0.34	0.138	0.42	0.025	0.31	0.232	0.56	0.029
	Ever smoked	0.02	0.900	0.24	0.393	−0.16	0.467	0.13	0.511	0.43	0.195	−0.01	0.958
	Experienced child death	N/A	–	N/A	–	N/A	–	−0.06	0.655	0.01	0.949	−0.20	0.266
SES	*Education*	–	0.002	–	0.002	–	0.105	–	0.008	–	0.004	–	0.862
	No schooling	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)
	Elementary school	0.03	0.830	−0.13	0.612	0.11	0.553	0.05	0.781	−0.17	0.564	0.08	0.708
	Junior high	−0.46	0.018	−0.74	0.009	−0.11	0.698	−0.34	0.137	−0.78	0.018	0.15	0.642
	High school and Junior College	−0.49	0.018	−0.66	0.022	−0.41	0.263	−0.35	0.162	−0.70	0.041	0.54	0.260
	University	−0.58	0.060	−1.02	0.008	0.91	0.054	−0.85	0.007	−1.19	0.003	0.13	0.833
	Wealth quintiles	–	0.123	–	0.185	–	0.544	–	0.059	–	0.253	–	0.317
	Poorest	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)
	Poorer	0.01	0.933	0.12	0.573	−0.07	0.736	−0.09	0.596	0.18	0.468	−0.30	0.196
	Middle	0.26	0.110	0.27	0.253	0.25	0.260	0.28	0.131	0.35	0.185	0.20	0.470
	Richer	0.33	0.052	0.55	0.020	0.03	0.904	0.36	0.064	0.59	0.029	−0.01	0.969
	Richest	0.32	0.076	0.33	0.170	0.30	0.317	0.30	0.140	0.32	0.236	0.24	0.474
	Employment status	–	0.088	–	0.841	–	0.062	–	0.197	–	0.756	–	0.105
	Work	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	–	0.00	–	0.00	–
	Housework	0.09	0.383	0.05	0.715	0.13	0.424	0.11	0.365	0.10	0.510	0.09	0.660
	Not working	0.45	0.028	0.30	0.616	0.53	0.019	0.42	0.076	−0.21	0.778	0.53	0.042

(*Continued*)

Table A1 Continued.

		Model 1: all women						Model 2: parous women only					
		1(a): both cohorts		*1(b): younger cohort*		*1(c): older cohort*		*2(a): both cohorts*		*2(b): younger cohort*		*2(c): older cohort*	
Outcome		*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*
Demographic characteristics	*Age*	0.02	<0.001	0.03	0.011	0.02	0.245	0.03	<0.001	0.03	0.119	0.00	0.957
	Place of residence												
	Urban	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)
	Rural	−0.40	<0.001	−0.50	0.001	−0.20	0.208	−0.45	<0.001	−0.65	<0.001	−0.23	0.211
	Marital status												
	Not in union	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)
	Union	0.02	0.833	−0.05	0.756	0.11	0.484	0.02	0.882	−0.10	0.594	0.13	0.485
	Ethnicity	–	0.033	–	0.005	–	0.212	–	0.035	–	0.027	–	0.184
	Javanese	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)	0.00	(ref.)
	Sundanese	0.17	0.261	0.48	0.032	−0.20	0.338	0.25	0.136	0.49	0.046	−0.10	0.680
	Malay	0.17	0.514	1.01	0.010	−0.36	0.266	0.04	0.877	1.02	0.035	−0.64	0.085
	Batak	−0.33	0.123	−0.37	0.179	−0.36	0.295	−0.35	0.154	−0.16	0.627	−0.64	0.112
	Madurese	−0.46	0.054	−0.15	0.637	−0.80	0.025	−0.20	0.490	0.28	0.466	−0.78	0.067
	Other	0.19	0.123	0.34	0.054	−0.02	0.912	0.35	0.017	0.53	0.012	−0.08	0.714
	Constant	1.39	0.005	1.25	0.102	1.38	0.180	0.66	0.209	1.10	0.281	3.01	0.008
	N	2,001		1,133		868		1,910		1,067		843	

Notes: p-values shown above dummy variable categories indicate the significance of the dummy as a whole in the model. Ref. is the reference category.
Source: Authors' analysis of IFLS data.