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Closing the gap on institutional delivery in northern India: a case study of how integrated machine learning approaches can enable precision public health

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ABSTRACT

Introduction Meeting ambitious global health goals with limited resources requires a precision public health (PxPH) approach. Here we describe how integrating data collection optimisation, traditional analytics and causal artificial intelligence/machine learning (ML) can be used in a use case for increasing hospital deliveries of newborns in Uttar Pradesh, India.

Methods Using a systematic behavioural framework we designed a large-scale survey on perceptual, interpersonal and structural drivers of women's behaviour around childbirth (n=5613). Multivariate logistic regression identified factors associated with institutional delivery (ID). Causal ML determined the cause-and-effect ordering of these factors. Variance decomposition was used to parse sources of variation in delivery location, and a supervised learning algorithm was used to distinguish population subgroups.

Results Among the factors found associated with ID, the causal model showed that having a delivery plan (OR=6.1, 95% CI 6.0 to 6.3), believing the hospital is safer than home (OR=5.4, 95% CI 5.1 to 5.6) and awareness of financial incentives were direct causes of ID (OR=3.4, 95% CI 3.3 to 3.5). Distance to the hospital, borrowing delivery money and the primary decision-maker were not causal. Individual-level factors contributed 69% of variance in delivery location. The segmentation analysis showed four distinct subgroups differentiated by ID risk perception, parity and planning.

Conclusion These findings generate a holistic picture of the drivers and barriers to ID in Uttar Pradesh and suggest distinct intervention points for different women. This demonstrates data optimised to identify key behavioural drivers, coupled with traditional and ML analytics, can help design a PxPH approach that maximise the impact of limited resources.

Key questions

What is already known?

- ► Effective behaviour change interventions require targeted approaches that take into account the varying perceptual, interpersonal and structural drivers of behaviour.
- ► Singular approaches to behavioural analysis, including predictive models, are inadequate to uncover the precise causal links behind decisions such as whether to give birth at home or in a healthcare facility.

What are the new findings?

- ► A holistic, multi-pronged analysis using machine learning (ML) techniques showed that for women in Uttar Pradesh state, India, having a delivery plan, believing that hospital is safer than home and awareness of financial incentives were direct causes of institutional delivery (ID). But these were not the case for all women.
- ► We identified distinct segments of women that differed in what drove their reasons to deliver, or not, in a facility.
- ► Some factors previously thought to be causative of ID, such as the distance to the hospital, were found to be only an indirect cause.

What do the new findings imply?

- ► A precision public health approach that draws on optimised data collection techniques and integrated ML methods can uncover the drivers of behaviour, enabling targeted interventions and maximising the impact of limited resources.

INTRODUCTION

Improving the health and well-being of people in low-income settings is challenging, especially with limited resources. Taking a precision public health (PxPH) approach—getting the right intervention to the right person, at the right time and place—enables more targeted use of resources to bridge outcome gaps.[1–5]

Expanding global health data, novel and more comprehensive data sets, and advances in analytic methods are making a PxPH approach more feasible.[6–10] In particular, significant progress has been made in the capability and accessibility of artificial intelligence (AI) methods. These enhance the ability to acquire and organise data, and to identify patterns and underlying heterogeneity in data that would not be possible with traditional methods. Machine learning (ML), perhaps the most common subset of AI, uses algorithms and statistical models to perform tasks without explicit instruction by relying on patterns in data.[11 12]

To date, most studies taking a PxPH approach have focused on one aspect of a precision approach, or a single analytic method.[4 13–16] However, designing and evaluating interventions without a thorough understanding of the underlying causes of the target behaviour, which often include risk and incentive perceptions, for example, among others, can be an inefficient use of time and resources, and a single intervention is often insufficient to drive change.[17] The greatest potential for impact lies in an integrated intervention design for PxPH that can target multiple behavioural and structural aspects, using a range of analytic methods. Such an approach allows subgroups of people to be differentiated by the varying drivers behind their behaviours, for more precise targeting. Here, we demonstrate the feasibility of using multiple AI methodologies to inform a PxPH approach, with the example of promoting in-hospital births in Uttar Pradesh, India.

Use case of AI for PxPH: institutional delivery in Uttar Pradesh, India

Maternal and neonatal mortality remain stubbornly high in Uttar Pradesh, India's most populous state. For every 100 000 live births, it is estimated that 201 women and 4100 infants die.[18 19] Getting women to deliver in hospital facilities instead of at home is key to address this public health crisis.[20] The Indian government's programme providing women with a financial incentive to reduce out-of-pocket expenditure on institutional delivery (ID) succeeded in increasing the national ID rate from 43% to 83% in the 10 years since 2004.[21–24] Our current study finds that 18% of women in rural Uttar Pradesh continue to deliver at home. To persuade all women to choose ID, governments and policymakers need to better understand the remaining drivers and barriers to ID. This is the problem we aimed to address using a PxPH approach.

Standard data collection focuses on the *what* (ie, behaviour) instead of the *why* (ie, drivers of behaviour). Without *why* information, interventions are unlikely to result in impactful and sustainable behaviour change.[25] Several relevant variables are available in surveys such as the National Family Health Survey.[26] To collect data on a wider range of possible drivers of and barriers to women's behaviour before, during and after childbirth, we designed a comprehensive survey built on the CUBES (to Change behavior, Understand Barriers, Enablers, and Stages of change) framework.[27] The variables collected included not only demographic information but also beliefs, perceptions, knowledge, role of influencers, structural factors and health behaviour patterns collected from women, their household members and community health workers (Accredited Social Health Activists or ASHAs) that visit these women. Using a combination of predictive models, causal ML and segmentation methods, we developed a holistic picture of the factors driving ID, identified high-value intervention targets and developed insights for intervention prioritisation and targeting.

METHODS

Data

Household survey

We designed surveys using the CUBES framework[27] to enumerate the interpersonal, perceptual and contextual factors that may affect an individual's behaviour. For the purposes of this study, the primary sampling unit (PSU) was the ASHA's catchment area. Stratified random sampling of rural ASHA catchment areas was done across all 75 districts in Uttar Pradesh. The minimum required sample size was 1575 catchment areas, to support development of a stable statewide segmentation solution, as well as to generate valid and reliable inferential statistics on target maternal and newborn behaviours at state level. The sample included data from 600 blocks, with an oversampling of the 100 poorest-performing blocks on reproductive, maternal and child health outcomes. A census of all households in the catchment area was done to select all that met the screening criteria of having a woman (alive at the time of survey) who had given birth in the past 60 days (referred to as 'women' hereafter for simplicity).

Women, their husbands or other male head of household (HOH), and the mother-in-law/matriarchs, as well as the ASHA, were interviewed after giving informed consent. Data were collected from 15 120 household members (5968 women, 4199 male HOH and 4953 matriarchs) between September 2017 and January 2018. For all analyses presented in this article, data from women who had given birth was used, unless otherwise noted. The survey included behaviour during pregnancy, such as frequency and location of antenatal care (ANC) checkups, taking iron and folic acid supplements, and frequency of visits from ASHAs. It also assessed birth planning, ID barriers, opinion of services and infrastructure, risk perception, financial planning for delivery and awareness of government financial incentives. Demographic variables—age, religion, caste, household composition, income and proxies for wealth (eg, electricity in the home)—were also collected. The resulting data set enabled us to apply several analytic approaches to the question of why some women continue to deliver at home.

Community Behaviour Tracking Survey

We also applied our analysis to the Community Behaviour Tracking Survey (CBTS), an independently collected data set with some variables similar to those in the household survey.[28] The CBTS is a periodic rolling survey covering women's demographics, ANC preparedness and ID. We used it primarily to validate the robustness of the causal model generated by the household survey, and to check the algorithm's robustness. To provide block-level estimates of key maternal and newborn health indicators across women who terminated pregnancy in the past 2 months, the required sample size per block was estimated based on the observed value of the behaviour/service utilisation indicators and expected magnitude of change in the indicators between rounds. Given the large inter-district variations in indicator levels, the sample size varied by district. In the CBTS, the catchment area of a rural ASHA is considered as the PSU. In each block, a systematic random sample of the required number of PSUs was selected from a sampling frame consisting of all ASHA areas in the block. We used data from round 1 (February 2014–February 2015, n=57788) women who terminated pregnancy within 60 days prior to interview in 100 blocks of 25 districts in Uttar Pradesh (see online supplemental material for full variable list).

Patient and public involvement

Those interviewed in the survey were not directly involved in its design, conduct, analysis or dissemination.

Analyses

Descriptive statistics

We examined descriptive statistics assessing possible correlates for home delivery among the subset of women who delivered at home. These variables were used to classify home deliveries as either elective (eg, preference for traditional village birth attendant; perceived as more convenient; belief that the hospital is not necessary) or non-elective (eg, the baby came too quickly; hospital too far; hospital fees were too high; ambulance no-show). Women could select more than one reason for home delivery; if at least one preference reason was given, the delivery was classified as elective. All analyses were weighted to account for the oversampling of the poorest-performing blocks. The primary outcome variable for all subsequent analyses was whether a mother delivered in a healthcare facility (public or private) or at home.

Predictive model

Predictive models indicate which variables are likely to be co-observed with the outcome variable. We constructed a predictive model using logistic regression to predict the delivery location. To determine which variables to include in the predictive model, we first identified a broad subset of variables that had a feasible relationship with ID (based on the temporal chain of events and expert knowledge of ID in Uttar Pradesh). We removed or combined correlated predictors, and removed predictors with little to no variance and those that were not assessed for the entire sample (due to skip patterns). This resulted in 41 predictors included in the predictive model (table 1).

Given the large number of predictor variables in the model, a p value of 0.01 (ie, 99% CI) was used as the threshold for statistical significance. Women who reported having a planned C-section were excluded from the analysis (n=131). Missing data were removed using listwise deletion, leaving a final analytic sample of 5613 women (see online supplemental figure 1 for full analytical sample flowchart). The model was weighted to account for the oversampling of poorest-performing blocks.

Causal ML

Causal models indicate variables in whose absence outcome variables are unlikely to be observed. We used causal Bayesian networks (BN) for causal ML, recognising that multiple intertwined pathways can give rise to a given outcome.[29 30] Causal BN are probabilistic graphical models that leverage the conditional dependencies underlying a set of variables to extract causation patterns, under the assumption that all potential causes are measured in the data set. The underlying idea is that causation can be distinguished from correlation if several independent causes can be observed. The causal model produces two outputs. First, a graph shows which variables are directly causal of the outcome of interest, which are causal through upstream pathways and which are outside the causal chain. Second, the model can be used to conduct intervention query or 'what-if' analyses.[31] This is equivalent to conducting a virtual randomised control trial that quantifies the change in the outcome variable that occurs when a specific intervention is made at a variable.

Since a causal BN relies on estimating conditional dependencies between all combinations of included variables, sample size often poses a de facto constraint on the number of variables that can be included.[32] Through synthetic data simulations, we estimated that only up to 20 variables could be supported by the household survey sample size; thus, we looked to the significance test results in the predictive model to inform inclusion. Caste, which was not a significant predictor in the predictive model but has previously been established as a variable associated with ID, was also included in the causal model. Since caste is correlated with another important variable, religion, we included caste as a compromise input in the causal modelling, to further reduce the number of variables. Income, which was not a significant predictor in the predictive model but has been argued to be an associated variable as well, was not included because there were already two other closely correlated variables commonly used to indicate socioeconomic status (ie, education and electricity).[33] To improve computational efficiency given our sample size, some variables were recoded from continuous to categorical, or were condensed to include three or fewer categories.[32] These decisions were consulted on with domain experts to ensure that the cutoffs remained relevant to programme policies. The variables selected are listed in table 1.

Table 1 Summary of variables used in predictive model, causal model and segmentation

Variable	Response options	Predictive model	Causal machine learning	Segmentation (S) and profiling (P)
Demographics				
Education	0–4 years, 5–9 years, 10–12 years, 13+ years	X	X	P
Parity	1, 2, 3, 4+	X	X	S
Religion	Hindu versus other	X		P
Caste	ST, SC, OBC, none of these	X	X	P
Income*	Little versus lot	X		P
Financial insecurity	2-item composite; 1–5 Likert scale	X		P
Electricity in home	Yes versus no	X	X	P
Household type	Nuclear versus joint/other	X		P
Internal beliefs				
Opinion of hospital facilities	7-item composite; low versus high	X		P
Opinion of hospital services	6-item composite; low versus high	X	X	P
Rank importance of hospital delivery	Important versus unimportant	X	X	P
Risk perception of childbirth	Low versus high	X		P
Worry about delivery problems	Little versus lot	X		P
Perception of hospital safety	Hospital safer versus home safer	X	X	S
Nurse gives injection to make delivery easier	Agree versus disagree	X		P
Hospital is not necessary if birth attendant is good	Agree versus disagree	X		P
Hospital is not necessary if past home delivery	Agree versus disagree	X		P
Pregnant women attract evil spirits	Agree versus disagree	X		P
False beliefs about ANC checkups	3-item composite; few versus many	X		P
Barriers to ANC checkups	5-item composite; few versus many	X		P
Knowledge of IFA	Percent correct recall (0–100)	X		P
Agency	10-item composite; 1–5 Likert scale	X		P
Insecurity	2-item composite; 1–5 Likert scale	X		P
Conscientiousness	3-item composite; 1–5 Likert scale	X		P
Empathy	1–5 Likert scale	X		P
Openness	2-item composite; 1–5 Likert scale	X		P
Optimism	1–5 Likert scale	X		P
Neuroticism	1–5 Likert scale	X		P
Structural				
Social norms	Low versus high	X	X	P
Hospital distance	0–20 min versus 21–40 min versus 40+ min	X	X	P
Labour start time	Middle of the night versus day versus evening	X	X	P
Money borrowed*	None versus some	X	X	P
Incentive awareness	Yes versus no	X	X	P
Influencers				
Discussed delivery location with ASHA	True versus false	X		P

Continued

Table 1 Continued

Variable	Response options	Predictive model	Causal machine learning	Segmentation (S) and profiling (P)
Primary decision maker	Self versus husband versus mother-in-law versus other	X	X	P
People for social support	Few versus many	X		P
Number of ASHA home visits	None versus 1–2 versus 3–4 versus 5+	X	X	P
Behaviour				
Pregnancy registration	Not registered versus first trimester versus second trimester versus third trimester	X		P
Delivery plan	Planned ahead of time versus last minute decision	X	X	S
Number of ANC checkups	0–9	X	X	P
Take IFA during pregnancy	None versus less than recommended amount versus recommended amount or more	X	X	P

Some variables were constructed from several items in the questionnaire. X indicates variables as inputs.
*Variables that were only assessed for male head of household (HOH); for women who did not have a male HOH interviewed, a median imputation method was used to generate these estimates. Relevant survey questions are listed in online supplemental information.
ANC, antenatal care; ASHA, Accredited Social Health Activists; IFA, iron and folic acid.

To generate our causal BNs we used GNS Healthcare's proprietary Reverse Engineering and Forward Simulation platform,[34 35] which uses the Markov Chain Monte Carlo algorithm to search for the best causal structure. For all variables, we conducted a series of what-if analyses for the ID outcome. The results are plotted as odds ratios (ORs) for ID. The population attributable fractions (PAFs)[36] for variables in the causal model were also estimated using what-if analysis. The PAF of a variable from a causal model is interpreted as the proportion of home deliveries that is preventable with an intervention on that variable.

Duplicate entries (n=650), women who reported they had an abortion (n=5116), women who reported they had a stillbirth (n=1176), women whose babies did not survive at least 1 day (n=618) and women whose babies at the time of survey were less than 1 day old (n=388) were excluded from the analysis, leaving a final analytic sample of 49 840 women (see online supplemental figure 2 for full analytical sample flowchart).

Variance decomposition

Our data set had two main sources of heterogeneity—geographical variables (ie, districts and blocks), and individuals' characteristics (eg, behaviours and perceptions). We conducted variance decomposition to better understand the relative proportion of variance in delivery location attributable to these two sources before the segmentation analysis. We used mixed-effect logistic regression to fit a null (intercept-only) model, with the geographical units of block and district included as random effects.[37] This generates the proportion of variance attributed to both the district and block level, with the residual variance representing all other sources of variance contribution, including individual-level factors. For completeness, we also checked the variance attributable to ASHAs in addition to geographical variables.

Segmentation

To segment women into subgroups, we used a χ^2 automatic interaction detection analysis (CHAID) decision tree algorithm on the full set of 41 variables used in the predictive model (table 1).[38] Decision tree algorithms are particularly well-suited to data in which the target outcome is defined (eg, ID) and are advantageous in their ability to handle categorical and continuous variables simultaneously. They are also easy to understand, visualise and interpret, making them highly actionable.

We employed a top-down pruning approach by sequentially modifying the stopping criteria (ie, minimum number of cases per node, maximum tree depth and alpha threshold) to be more stringent. We used a 10-fold cross-validation method to evaluate generalisation error; the tree with the simplest structure and lowest prediction error and generalisation error was chosen as the final model.

After the final tree was constructed, that final data subset with no further splits defined one segment. Each of these segments was profiled to determine how they differed from each other. All variables in the predictor set were profiled using χ^2 and one-way analyses of variance. Additionally, we examined home delivery classification (elective versus non-elective) and reasons for home delivery. In some cases, the continuous version of the measure was used to allow for greater sensitivity in detecting differences between segments. The final profiles generated for each segment were based on a combination of the interpretation of practically meaningful differences between segments.

RESULTS

Most home deliveries are non-elective

Eighteen per cent of women reported delivering their baby at home. The majority (59.6%, 95% CI 56.4% to 62.8%) of at-home deliveries were non-elective, 29.8% (95% CI 26.8% to 32.8%) were elective and 10.6% (95% CI 9.6% to 11.6%) were classified as 'other'. The most common reason given for non-elective home deliveries was that the baby came too quickly (40.0%, 95% CI 36.8% to 43.2%); 13.9% (95% CI 11.7% to 16.1%) of women also reported delivering at home because labour started in the middle of the night (see online supplemental table 1 for full descriptive statistics). The most common reasons for elective at-home delivery were the perception that it was more convenient (21.8%, 95% CI 19.0% to 24.6%), followed by a preference for the village birth attendant (7.0%, 95% CI 5.4% to 8.6%).

Hospital delivery is associated with a broad set of factors

Sixteen variables were significantly associated with ID. In addition to previously established demographic correlates of hospital delivery in India,[20 39–42] we found that beliefs, perceptions and behaviour were key predictors of delivery location. For example, one of the strongest predictors of ID was having a delivery plan. Having a delivery plan means that the woman reported that her household had planned ahead of time to deliver the baby in the place (a particular health facility or at home) where the baby was in fact eventually delivered. Women who said they delivered in their planned location were far more likely to have delivered in a hospital than those who said it was a last-minute decision (OR=4.91, 95% CI 3.84 to 6.28). Women who believed home is safer than the hospital were much less likely to deliver in a hospital (OR=0.23, 95% CI 0.18 to 0.31) and those who were unaware of ID incentives were less likely to have delivered there (OR=0.46, 95% CI 0.34 to 0.63). While the significant increase in ID thus far has been attributed to financial incentives, which were also found to be a significant predictor (OR=2.18, 95% CI 1.59 to 2.99), a minority of women (13.8%) were not aware of it in our survey. The perception that ID is the social norm in a woman's community increased the odds that she would deliver there (OR=1.76, 95% CI 1.38 to 2.25). While previous studies have shown that income, education and proxy for wealth (eg, electricity) are associated with delivery locations,[43] our analysis showed only the latter two to be significant. We speculate that this is because these factors are very much correlated with each other.[44] Full results for the regression model are available in online supplemental material.

BN identify causal factors driving ID

Figure 1 shows the causal BN learnt from the household survey. Several variables are directly causal to (ie, one edge away from) delivery location: having a perception that ID is safer than home, having a predetermined delivery plan, being aware of ID incentives, education level of the mother and being a first-time parent. The number of ASHA home visits plays a key role in promoting incentive awareness and delivery planning.

Perception of ID being a safer option, and further upstream, the amount of ANC checkups, are two important 'gateway' variables that are central to many causal pathways in the network. Perception of ID being a safer option also factors into delivery planning. The number of ANC checkups is particularly interesting: even just 1–2 checkups lead to positive opinions about ID, knowledge and awareness of the health services (and incentives), and committed behaviours (eg, delivery plan), all of which contribute to the location of delivery.

Upstream, the mother's educational level—itself closely related to her caste—and perceiving ID as the social norm appear to be important internal and external causes, respectively, that modulate other downstream behaviours and opinions.

Several variables that were associated with delivery location in the predictive model—such as distance to the nearest hospital and the time of labour onset—were not found to be causal factors. Similarly, the primary decision-maker of delivery location, whether the family borrowed money, and general opinions about hospital services were associated with ID but not causal of it. They appear to be conflated with ID in the predictive model due to some common upstream causes (such as delivery planning). Finally, we observed that a higher number of ANC checkups leads to more ASHA home visits, rather than the other way around.

The what-if analyses (figure 2) showed that having a delivery plan is by far the most influential cause of ID; women had six times the odds of delivering in public facilities if there was a delivery plan than if there was not. Almost just as causal (greater than five times the odds) is perceiving that ID is safe. This result suggests key intervention areas for focusing programme resources. Incentive awareness and mother's education are also important (greater than three times odds), followed by whether the woman is a first-time parent (two times). The number of ANC checkups, home visits and perceptions of ID being a social norm are significant causes with more moderate ORs.

The PAFs show that delivery planning and perceptions of safety are high-value targets (for the full table, see online supplemental material). For delivery planning, 46% of home delivery can be converted to ID by having a delivery plan. For perceptions of hospital safety, 26% of home deliveries can be converted by convincing women the hospital is safer. Though awareness of financial incentives is directly causal of delivery location, the PAF is low

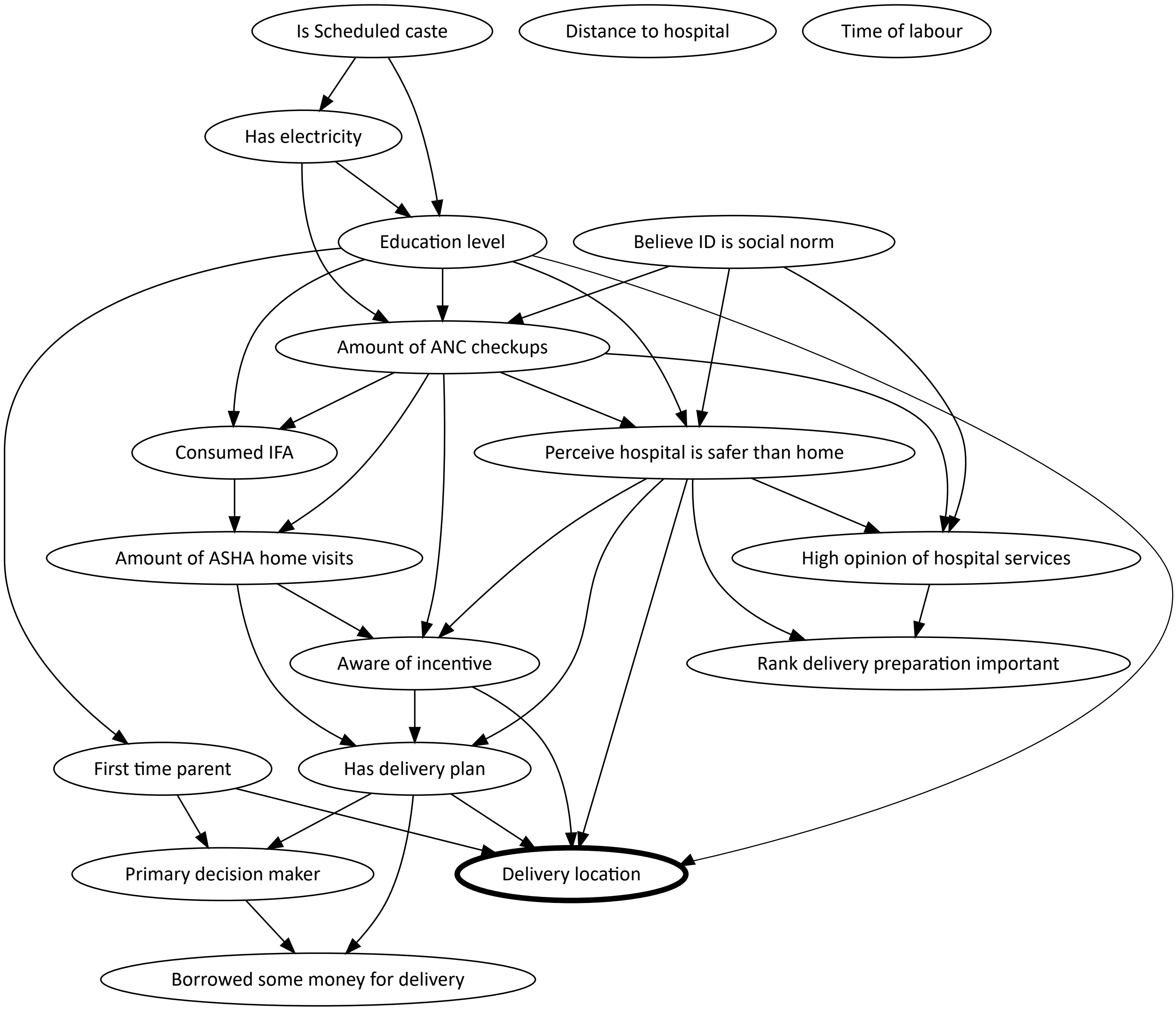

Figure 1 Causal graph depicting causal relationships. ANC, antenatal care; ASHA, Accredited Social Health Activists; ID, institutional delivery; IFA, iron and folic acid.

(15%) because of the existing high awareness of the incentives.

General conclusions of the causal model of the household data are consistent with the causal model of another independently collected data set

To confirm our results and explore the role of additional variables, we built another causal model on the CBTS data. We obtained similar results for variables that overlapped with the household survey: having a delivery plan, checkups and education level were all directly causal of public-hospital delivery. Most of the indirect causes for ID found in the household model were also found to be indirectly causal in the CBTS model (online supplemental material). These results suggest that the causal relationships we found are robust in the Uttar Pradesh region.

The CBTS did not include perception and other variables present in the household survey. For example, haemoglobin check in the third trimester was found to be causal in the CBTS, presumably being a proxy of the quality of prenatal checkups. While distance to hospital was not causal in the household model, identification of transportation vehicle was a causal variable in the CBTS model.

Individual heterogeneity matters the most in determining delivery location

In the variance decomposition analysis, we found that 20% of the variance in delivery location can be attributed to geography (10% to the district level, 10% to the block level). The residual variance—including (potentially) lower geographic and individual-level factors—accounted for 80% of the variance in delivery location.

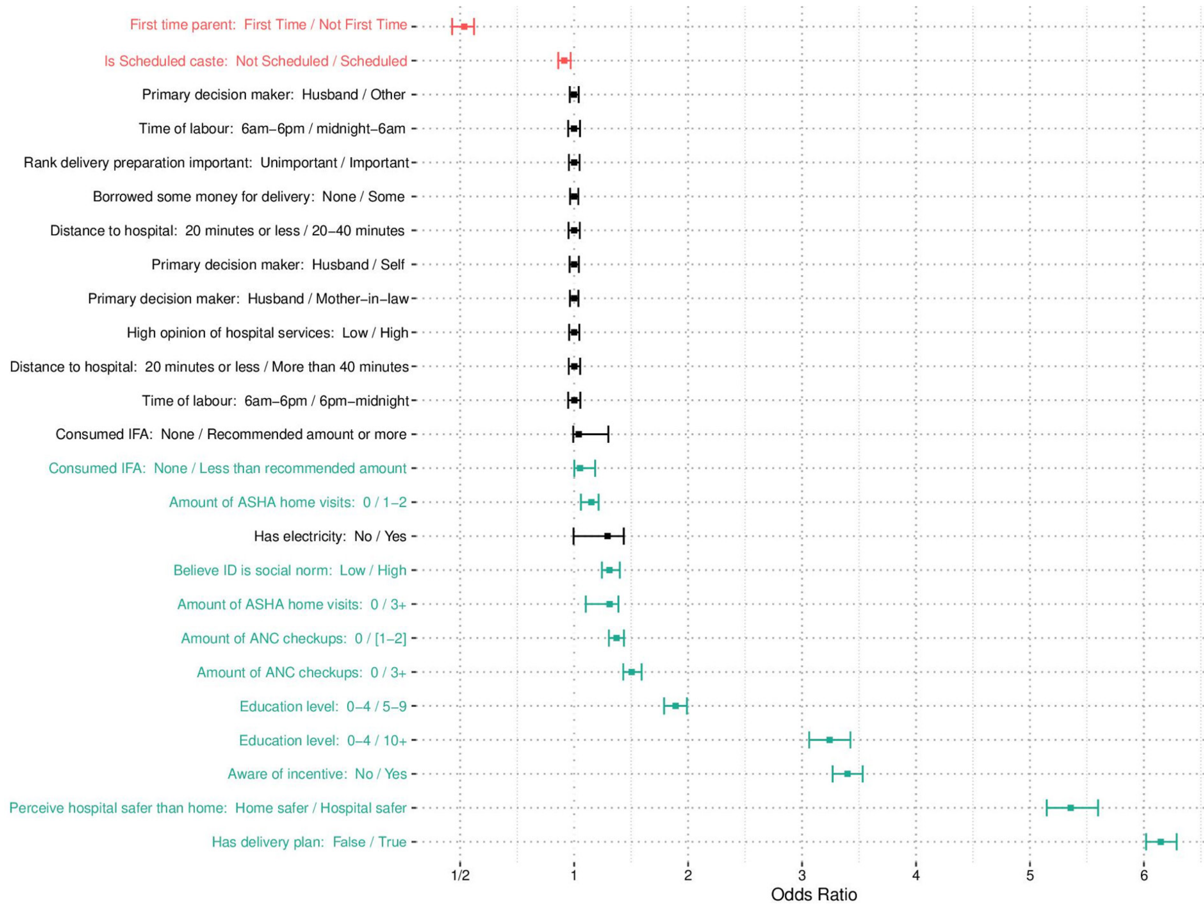

Figure 2 What-if analysis (reference vs intervention); interventional OR of institutional versus home delivery with 95% CIs on the simulation. ORs significantly greater than 1 (green) indicate higher odds of delivering in a facility; ORs significantly less than 1 (red) indicate higher odds at delivering at home. ANC, antenatal care; ASHA, Accredited Social Health Activists; ID, institutional delivery; IFA, iron and folic acid.

When we reanalysed to include variance attributable to ASHAs, we found that 17% of the variance in delivery location can be attributed to geographic levels (8% to district, 9% to block) and 14% to ASHAs, with residual variance accounting for 69% of the variance in delivery location.

These results indicate that, although geographic features and specific ASHAs do contribute to the likelihood of a mother delivering in a hospital, individual-level factors are far more important in determining delivery location.

Four segments can explain individual-level heterogeneity

The decision tree analysis segmented women into four groups based on demographics, behaviours and behaviour correlates (figure 3). All branches in the decision tree were made based on a p value of <0.0001. The first branch was made on perceptions of hospital safety. Among women who believe the hospital is safer, the next branch was made on delivery planning. Among women who believe the home is safer than the hospital, the tree branched based on parity (first-time births vs two or more past deliveries).

Segment profiling

The results of the profiling analysis, including the significance testing of all profiled variables, are presented in table 2. Here, we highlight a few key variables that are not predictive of the target outcome, but differentiate the segments and so could be used to identify segment members for targeted interventions.

Segment 1 are the disempowered first-timers. These are women giving birth for the first time who believe the home is safer than the hospital. They tend to be younger, have more years of education, and fewer financial barriers (ie, indicators of poverty). They tend to live in joint family households and report more often than women in the other segments that their mother-in-law is responsible for making the decision about where they deliver. They have some false beliefs about pregnancy and delivery. These women do not perceive ID to be the social norm in their community. They account for 7% of all home deliveries.

Segment 2 are the traditional home deliverers. They are experienced women who believe the home is safer for delivery. They tend to be older, less educated and have many financial barriers. They tend to live in nuclear family households, and are more likely to decide

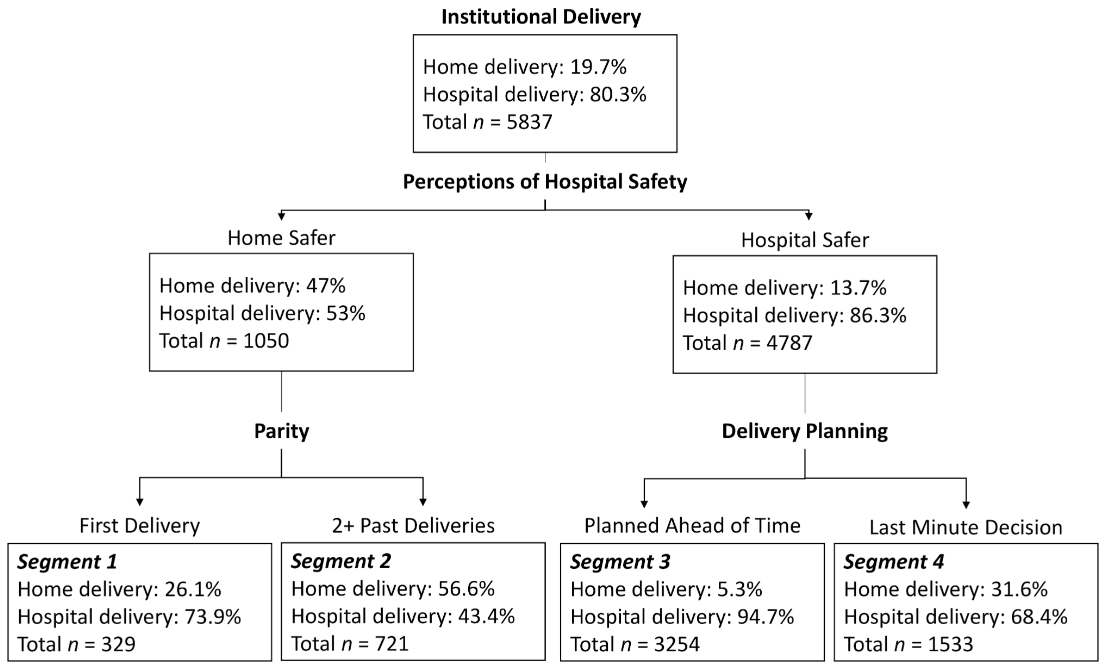

Figure 3 Final decision tree; values within nodes indicate the proportion of each subgroup delivering at home or at a hospital facility and the total sample represented within the node. The model correctly classified 81.9% of cases; sensitivity (ie, correct classification of institutional delivery) was 93.3% and specificity (ie, correct classification of home delivery) was 35.4%. The generalisation risk estimate was .181 (SE=0.005), indicating the model performed comparably on the validation samples. Values are based on the cross-validated model.

themselves where to deliver. They have many false beliefs about pregnancy and delivery, and poor and infrequent contact with the ASHA. These women do not perceive ID to be the social norm in their community. They account for 35% of all home deliveries.

Segment 3 are the hospital seekers. They believe the hospital is safer for delivery and plan ahead to deliver there. They are more educated, have fewer financial barriers to ID and are aware of the ID incentive. They have low rates of false beliefs about pregnancy and delivery. These women believe that ID is the social norm in their community. They have good ANC practices, frequent and positive contact with the ASHA, and report a high level of social support. They account for 15% of all home deliveries.

Segment 4 are the informed poor planners. These women believe the hospital is safer but lack a delivery plan. In terms of education and financial barriers they are better off than segment 2 but worse off than segments 1 and 3. They tend to have positive perceptions of hospitals and fewer false beliefs. They perceive ID to be the social norm in their community. These women have less frequent and positive contact with the ASHA. They account for 42% of all home deliveries across the four segments.

We also examined the subset of home deliveries within each segment and found that home delivery risk is well differentiated. Seventy-seven per cent of all home deliveries occur just in segments 2 and 4, but for very different reasons between segments. The home deliveries that occurred among the informed poor planners (segment 4) were almost entirely non-elective (83.6%), the most common reason given being that the baby came too quickly (54.9%). In contrast, more than half (56.2%) of all elective home deliveries are accounted for by traditional home deliverers (segment 2), who most commonly reported that it was more convenient (36.3%).

DISCUSSION

By applying a PxPH approach, using novel data and integrating multiple ML methodologies, we were able to generate more nuanced insights into why 18% of women in Uttar Pradesh continue to deliver at home. Insights from any single method would have provided only a piece of the picture, potentially misdirecting intervention strategies.

First, by focusing on collecting the *why* data,[27] we enabled findings that ran counter to some of the conventional wisdom. Respondents reported that most home deliveries were not a matter of preference, but occurred for non-elective reasons. Factors outside of a mother's perceived control—for example, labour progressing too quickly to get to the hospital in time—are associated with home delivery. Those who delivered at home because it was the preferred location accounted for a much smaller subset of women. Had the data not included this critical aspect, we would have missed highly associative factors to be included in subsequent analyses.

We used traditional methods to construct a predictive model of ID using the broad set of drivers and barriers; this analysis confirmed past research showing,

Table 2 Decision tree profiling

Variable	Segment 1: disempowered first-timers	Segment 2: traditional home deliverers	Segment 3: hospital seekers	Segment 4: informed poor planners
Variables in segmentation				
Believes home is safer (%)	100_{a}	100_{a}	0_{b}	0_{b}
Has a delivery plan (%)	52.9_{a}	57_{a}	100_{b}	0_{c}
Average parity	$1.00\ (0.00)_{a}$	$3.44\ (1.67)_{b}$	$2.43\ (1.59)_{c}$	$2.46\ (1.68)_{c}$
Demographics				
Years of education	$6.24\ (5.40)_{a,c}$	$3.06\ (4.56)_{b}$	$6.07\ (5.43)_{c}$	$5.72\ (5.43)_{a}$
Age	$22.19\ (2.68)_{a}$	$26.66\ (4.16)_{b}$	$25.12\ (3.85)_{c}$	$25.16\ (4.00)_{c}$
Hindu religion (%)	$85.4_{a,b}$	73.5_{c}	86_{b}	82.5_{a}
Muslim religion (%)	$14.3_{a,b}$	26.2_{c}	13.9_{b}	17.1_{a}
Scheduled tribe (%)	4.9_{a}	4.0_{a}	3.4_{a}	4.4_{a}
Scheduled caste (%)	27.4_{a}	29.0_{a}	29.2_{a}	27.3_{a}
Other backward class (%)	55.6_{a}	57.6_{a}	55.6_{a}	56.1_{a}
Upper caste (%)	12.2_{a}	9.4_{a}	11.7_{a}	12.2_{a}
Low income (%)	70.2_{a}	76.6_{b}	75.3_{b}	$74.7_{a,b}$
No electricity in home (%)	$21.3_{a,b}$	29.3_{c}	21.5_{b}	24.6_{a}
Financial insecurity	$2.76\ (1.10)_{a}$	$3.12\ (1.00)_{b}$	$2.99\ (1.05)_{c}$	$3.01\ (1.06)_{c}$
Joint family household (%)	79_{a}	51_{b}	67.5_{c}	63_{d}
Internal/beliefs				
High opinion of hospital facilities (%)	37.7_{a}	35.1_{a}	46.3_{b}	46.8_{b}
High opinion of hospital services (%)	39.2_{a}	42.9_{a}	54.9_{b}	55.3_{b}
Ranks hospital delivery as important (%)	30.4_{a}	$33.8_{a,b}$	39.8_{c}	$38.1_{b,c}$
High risk perception of childbirth (%)	$63.8_{a,b}$	63.7_{b}	67.7_{a}	$66.4_{a,b}$
High worry about delivery problems (%)	$62.3_{a,b}$	66.9_{b}	62.3_{a}	61.5_{a}
Believes nurse can give injections to make delivery easier (%)	75.1_{a}	66.4_{b}	72.2_{a}	74.5_{a}
Believes hospital is not necessary if there is a skilled Dai (%)	68.1_{a}	69.3_{a}	35.6_{b}	41.4_{c}
Believes hospital is not necessary if delivered at home in the past (%)	67.2_{a}	68.5_{a}	38.9_{b}	40.5_{b}
Believes pregnant women going out attract evil spirits (%)	$60.8_{a,b}$	65.9_{b}	59.4_{a}	60.3_{a}
False beliefs about ANC checkups (%)	51.7_{a}	54.4_{a}	43.5_{b}	42.8_{b}
High opinion of ANC checkups (%)	43.8_{a}	40.5_{a}	50_{b}	51_{b}
Agency	$2.93\ (0.47)_{a}$	$2.95\ (0.46)_{a}$	$3.01\ (0.47)_{b}$	$2.99\ (0.48)_{b}$
Insecurity	$3.74\ (0.94)_{a}$	$3.78\ (0.84)_{a}$	$3.81\ (0.90)_{a}$	$3.88\ (0.87)_{b}$
Conscientiousness	$3.63\ (0.64)_{a,b}$	$3.56\ (0.64)_{b}$	$3.69\ (0.62)_{a}$	$3.69\ (0.63)_{a}$
Empathy	$3.36\ (1.24)_{a,b}$	$3.23\ (1.20)_{a}$	$3.36\ (1.16)_{b}$	$3.33\ (1.16)_{a,b}$
Openness	$3.99\ (0.85)_{a}$	$3.76\ (0.91)_{b}$	$3.99\ (0.85)_{a}$	$3.97\ (0.83)_{a}$
Optimism	$3.80\ (1.00)_{a,b}$	$3.75\ (1.01)_{b}$	$3.85\ (1.00)_{a}$	$3.88\ (0.96)_{a}$
Neuroticism	$3.51\ (1.15)_{a}$	$3.56\ (1.15)_{a}$	$3.53\ (1.12)_{a}$	$3.45\ (1.12)_{a}$
Structural				
Perceives ID as social norm (%)	47.7_{a}	45.1_{a}	69.5_{b}	63.5_{c}
Lives 40+ min from hospital (%)	15.9_{a}	18.6_{a}	19.1_{a}	19.8_{a}
Labour starts in the middle of the night (%)	$24.8_{a,b}$	29_{b}	25.4_{a}	$25.4_{a,b}$

Continued

 Huang VS, *et al. BMJ Global Health* 2020;**5**:e002340. doi:10.1136/bmjgh-2020-002340

Table 2 Continued

Variable	Segment 1: disempowered first-timers	Segment 2: traditional home deliverers	Segment 3: hospital seekers	Segment 4: informed poor planners
Borrows no money for delivery (%)	76_{a}	$81.7_{b,c}$	84_{c}	$79.8_{a,b}$
Aware of ID incentive (%)	80.9_{a}	79.8_{a}	89.8_{b}	82.8_{a}
Influencers				
Discusses delivery location with ASHA (%)	30.7_{a}	23.4_{b}	42.5_{c}	32_{a}
Mother is primary decision maker (%)	$25.9_{a,b,c}$	31.6_{c}	26.8_{b}	21.3_{a}
Mother-in-Law is primary decision maker (%)	18.3_{a}	11.2_{b}	$15.7_{a,c}$	$13.7_{b,c}$
High social support (%)	61.4_{a}	$65.6_{a,b}$	72.5_{c}	67.7_{b}
Number of ASHA visits	$3.49\ (2.80)_{a,c}$	$3.15\ (2.75)_{a}$	$4.02\ (2.65)_{b}$	$3.29\ (2.64)_{c}$
Behaviour				
Did not take any IFA (%)	23.1_{a}	31.8_{b}	14_{c}	20.8_{a}
Took recommended amount of IFA (%)	16.1_{a}	9.8_{b}	16_{a}	11.4_{b}
Number of ANC checkups	$2.23\ (1.76)_{a}$	$1.73\ (1.52)_{b}$	$2.58\ (1.70)_{c}$	$2.39\ (1.70)_{a}$
Pregnancy registered in first trimester (%)	53.8_{a}	45.2_{b}	59.8_{c}	54.4_{a}

Values with the same subscript in the same row do not significantly differ. Values with different subscripts in the same row are significantly different, $p<0.05$.
ANC, antenatal care; ASHA, Accredited Social Health Activists; ID, institutional delivery; IFA, iron and folic acid.

for example, that higher education, lower parity, more ANC checkups and contact with the ASHA all are associated with increased odds of hospital delivery.[45 46] We also found that perceptual factors are correlated with delivery location. For example, one of the strongest predictors of ID was the perception of safety. Additionally, we found that the normative behaviour of a woman's community was strongly associated with ID. These findings are consistent with previous research in Uttar Pradesh done on a smaller scale and relying on qualitative interviews.[20]

The results of the causal ML analysis confirmed that perceptions of hospital safety and delivery planning had a direct causal effect on delivery location. Additionally, several variables shown to be associated with ID in the predictive model were ruled out as causal. For example, we saw that distance to the nearest hospital—a structural factor associated with ID in our predictive model—was not causally linked to location of delivery. Similarly, while respondents indicated that the time of onset of labour was an important reason for home delivery, it was not causal in the causal model. Although other research has shown that distance is associated with ID,[41 47 48] the lack of causal influence in our study may be due to the success of the financial incentive programme and other initiatives specifically designed to reduce this barrier to ID.[49] In the CBTS causal model, we found that identifying a vehicle for hospital transport was causally related to ID. While we cannot directly compare the two models, this suggests that the ability to access a healthcare facility, rather than absolute distance or the labour onset time, may be important in getting women to deliver there.[41]

In contrast to other research,[50] we found that the primary decision-maker of delivery location was not a direct cause of delivery location. In other words, changing the decision-maker does not influence whether a mother delivers at home or in the hospital. However, in other work we show that ASHAs were more effective when counselling husbands (who are most often the primary decision-maker) than when they counsel women, suggesting that the ASHA is a more effective channel for promoting behaviour change than the specific household dynamics.[51]

Together, these analyses point to several key areas for intervention efforts. Since resource constraints and other factors may not make it practical to design fully precision interventions customised to each individual, we need instead to exploit any underlying heterogeneity in the population to target distinct groups of women.[52] The results of our variance decomposition analysis indicate that although some variation in ID is attributable to geographic levels (district and block) or the ASHA, most of the variance (69%) is attributable to individual-level differences. It is possible that heterogeneity exists at a lower geographic level—for example, between ASHA areas or villages. However, we were unable to examine this due to sample size constraints. We used an ML algorithm to segment the sample population of women into four types with just three predictors—perceptions of safety, delivery planning and parity.

We then profiled these segments across several other variables to understand, descriptively, how they differed and to identify possible channels for interventions. For example, a key differentiator of the informed poor planners segment is that they did not have a delivery plan; based on the predictive and causal model, promoting delivery planning is likely to be a high-value intervention target, and better leveraging the ASHA could be the channel through which to deliver this intervention to these women. In contrast, traditional home deliverers are more likely to be persuaded to deliver in a facility by targeting false beliefs (eg, the perception that the home is safer for delivery than the hospital).

These findings have actionable implications for current intervention design. In Uttar Pradesh, many interventions to encourage women to deliver in hospitals have targeted specific factors (ie, financial barriers) that were assumed to be the same for everyone. This programme was successful in increasing ID for most women, but not all responded in the hoped-for way. Our analysis helps to explain why, and offers a viable path forward for developing and deploying targeted interventions. These should focus on a few key areas—improving delivery planning, behaviour change communications and counselling around hospital and home safety, and transport accessibility. Using public health principles, another potential intervention could be to equip ASHAs with tools to understand which segment a mother falls into and train her to provide targeted support. For some women, this could mean counselling the mother and mother-in-law about ID and emphasising the risk of delivery at home. For others, it could be helping develop a delivery plan and identifying transport to the hospital well in advance of her due date.

We have shown that predictive models, causal models, variance decomposition and decision trees are complementary tools. Traditional methods cannot identify causal relationships in the absence of long, expensive randomised control trials, but a predictive model is useful to narrow down the variables of interest to enable causal ML. However, our study has several limitations. The data requirements for causal ML are more stringent than for predictive models, including the need for a much bigger sample size to produce reliable estimates.[32] To be computationally feasible, the data are often converted to categorical rather than gradual numerical values.[53] Non-causal methods trade explanatory power for more relaxed restrictions. While BN excels in modelling observed confounding, in limited circumstances the true causal direction of connected variables may be challenging to recover if the training data lacks variables that are causal to the variables we are interested in (ie, latent common confounder).[54] It is therefore crucial that prior to causal modelling, domain experts and modellers make sure that all relevant variables are included in the training data, as far as possible. This 'causal sufficiency' requirement is an area of active research in causal discovery. Many traditional statistical models such as regression have accepted performance (goodness of fit) measures. Our causal ML performance is inferred using synthetic datasets with characteristics similar to the empirical input that is modelled.[32] However, this evaluation step is itself innovative and not typically done in causal ML.

Decision tree algorithms also have limitations. One of the key disadvantages is instability across training samples.[55] Given that CHAID is based on correlation rather than causation, there is no theoretical basis on which the resultant segments should respond to interventions. Here we were able to verify whether segmenting predictors were also causal by using a causal analysis, which revealed that they indeed were. In future work, we plan to use different methods for incorporating causal and classification algorithms, such as recursive partitioning for heterogeneous causal effects.[56] Finally, although we can offer recommendations based on our insights, the real test will be when an actual intervention is implemented on the ground and its long-term outcomes evaluated.

CONCLUSION

Many current studies focus on single methods and singular study outcomes, and it is often difficult to piece together a holistic picture to design field programmes in a more efficient and systematic way. Using ID in Uttar Pradesh as a use case, we have demonstrated how integrating multiple traditional and ML methodologies can inform a PxPH approach. By collecting better data and employing smarter analytic methods, we developed a holistic picture of why 18% of women continue to deliver at home. This approach can be applied to myriad global health problems, allowing programmes to leverage limited resources most efficiently to tailor interventions.

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