

Never-use of long acting reversible contraception (LARC) among U.S. women aged 15-49 years

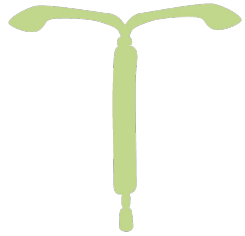
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Background

Why LARC?

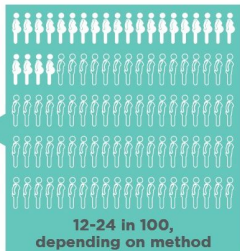
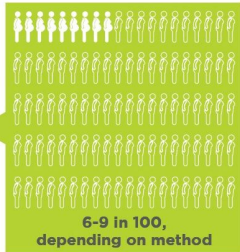
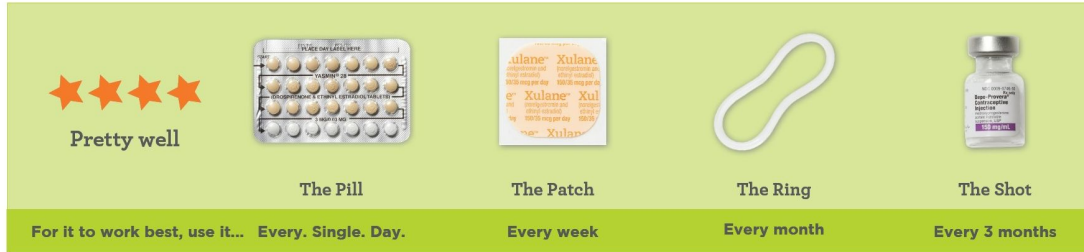
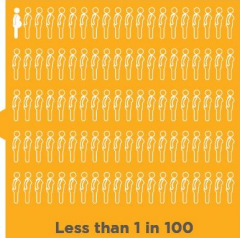


What is LARC?

HOW WELL DOES BIRTH CONTROL WORK?



What is your chance of getting pregnant?



FYI, without birth control, over 90 in 100 young people get pregnant in a year.



Contraception Use in the U.S.

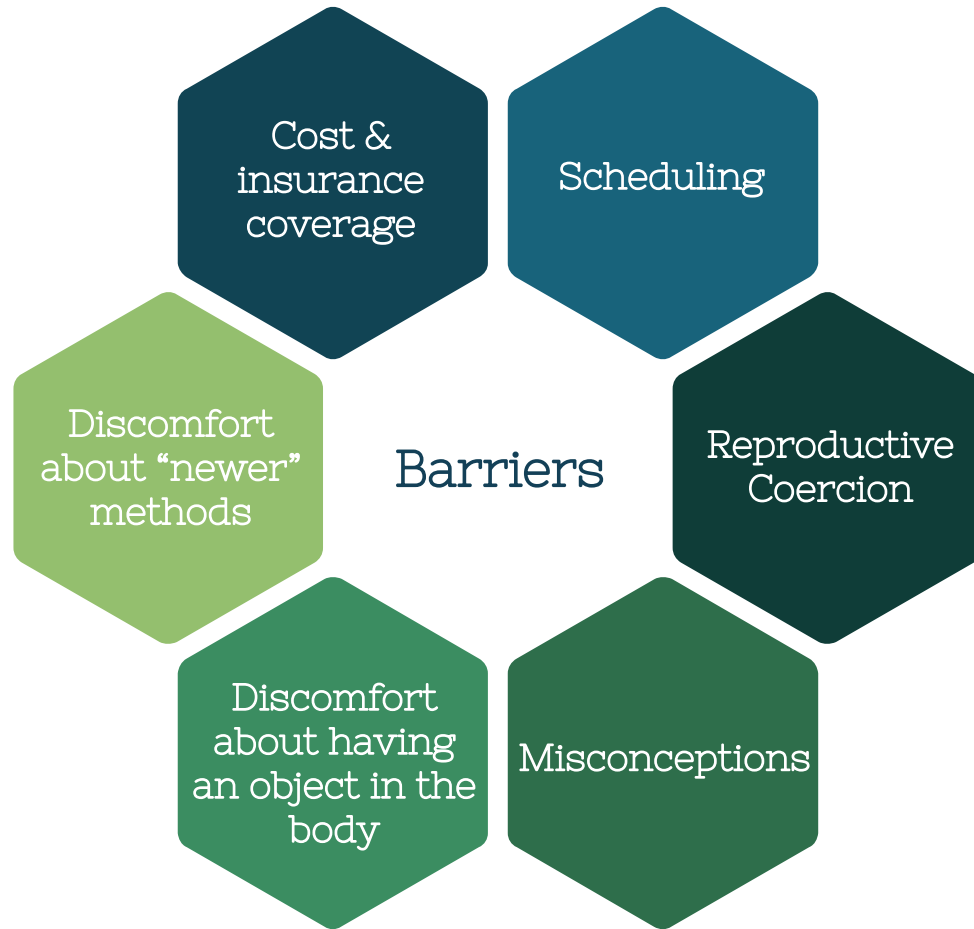
- Use of LARC has steadily increased
 - 6% in 2002
 - 14% in 2014
- Oral contraception continues to be most commonly used form of contraception

Disconnect between high typical use effectiveness of LARC and low use



Increasing LARC Access

- LARC has shown to have high efficacy, benefits, and acceptability among users
- Anyone who wants a LARC method should be able to get one (but there are so many barriers!).



Goal: Increase accessibility of LARC for those who would most benefit from it and want it.



Objectives

1 Identify important features

What are the most important predictors of ever-use of LARC among ever-contraception users?

2 Predict LARC never-use

Among ever-contraception users, who might benefit most from LARC and from targeted outreach for LARC use?

Indicator of lifetime use may be informative for targeting strategies with contraceptive counseling

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Data Set

The National Survey of Family Growth



The National Survey of Family Growth (NSFG)

- Family life
- Marriage and divorce
- Pregnancy
- Infertility
- Use of contraception
- General and reproductive health



**CENTERS FOR DISEASE
CONTROL AND PREVENTION**



The National Survey of Family Growth (NSFG)

Sample

- Starting in 2015, representative of women aged 15-49 in US
- Response rate: ~69%

Administration of Survey

- Voluntary participation
- In-person interviews at participants' homes



2015-2017

Survey of interest for this project



5,554 women

Total participants of the 2015-2017 survey



4,904 women

Ever-users of contraception

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Analysis



Primary Outcome

Ever-use of LARC

- Binary variable
- Derived from ever use of IUD and ever use of implant
- Never used in NSFG data set



Predictors

Demographics

Age, education, race, income, rural/urban residence, etc.

Substance use

Alcohol use, drug use

Health care access

Health insurance status, having a regular provider, etc.

Relationship history

Marital status, number of sexual partners, sex education, etc.

Housing insecurity status

Homelessness, inability to pay rent, etc.

Religious characteristics

Religious affiliation, frequency of attending religious services now/past



Preprocessing Steps

Data cleaning

Imputation for missing data

Dummy variable encoding for categorical variables

Min-max scaling for continuous variables



Analysis

Neural Network

PCA and f-score method to reduce dimensions

Imbalance data: class weights or resampling (SMOTE or undersampling)

Tuning: input features, nodes, layers, dropout, learning rate

Ensemble Learning

K-fold cross validation ensemble

Bootstrap aggregation ensemble

Meta classifier: logistic regression

Comparison with Other Classifiers

Logistic regression

Random forest classifier

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Results



Neural Network Model: Deeper or Wider?

Best Deep Model

PCA to get 40 best features.

SMOTE resampling to deal with imbalance.

4 hidden layers with 32, 16, 8 and 4 nodes.

Result: higher accuracy and high specificity, very low sensitivity.

Best Wide Model

All features included.

Class weighting to deal with imbalance.

1 hidden layer with 80 nodes.

Result: more balanced sensitivity and specificity.



Neural Network Model: Wider = Better

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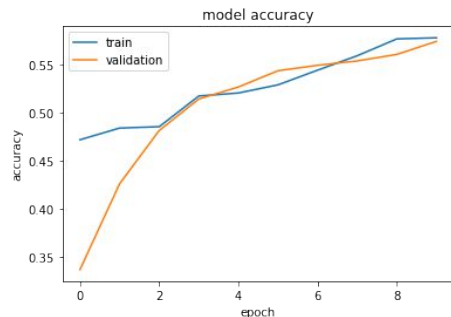
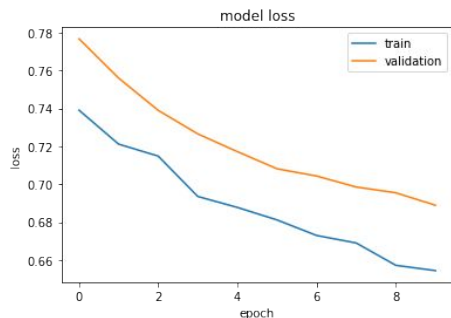
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Neural Network Model: Wider = Better

Metrics

Accuracy: 0.6

Mis-Classification: 0.4

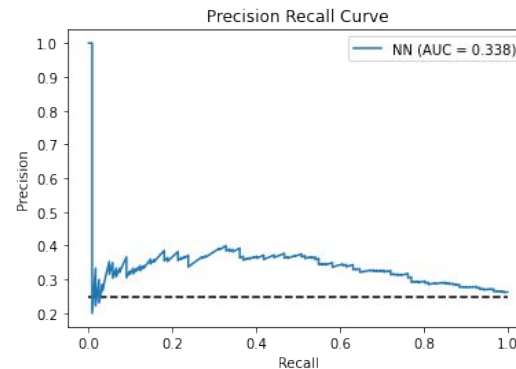
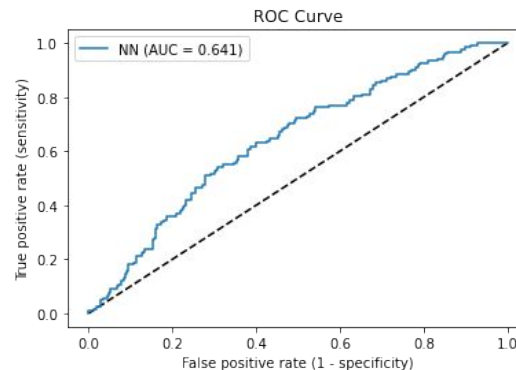
Sensitivity (Recall): 0.63

Specificity: 0.59

Precision: 0.34

f₁ Score: 0.44

	Predicted Negative	Predicted Positive
Actual Negative	217	152
Actual Positive	45	77





Ensemble Learning: K-Fold CV Ensemble

Metrics

Accuracy: 0.65

Mis-Classification: 0.35

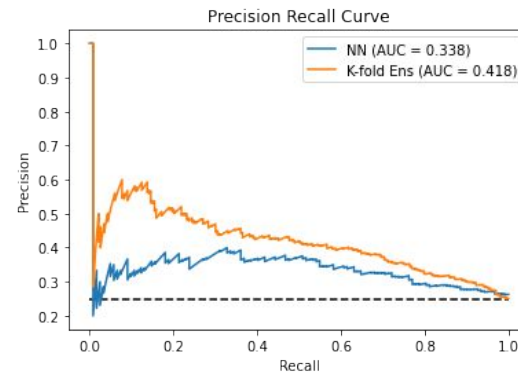
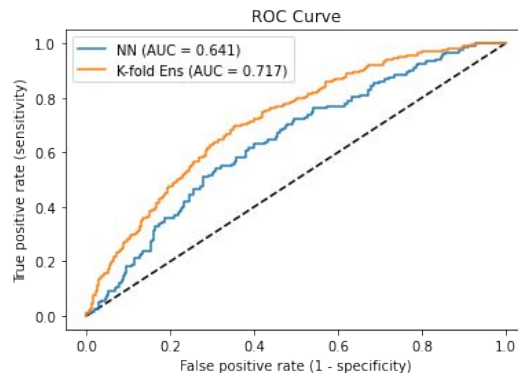
Sensitivity (Recall): 0.72

Specificity: 0.63

Precision: 0.38

f₁ Score: 0.5

	Predicted Negative	Predicted Positive
Actual Negative	471	276
Actual Positive	65	168





Logistic Regression

Metrics

Accuracy: 0.64

Mis-Classification: 0.36

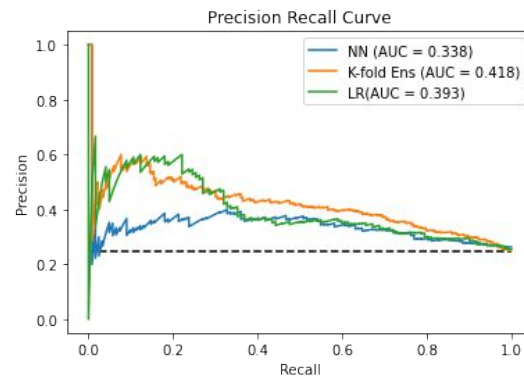
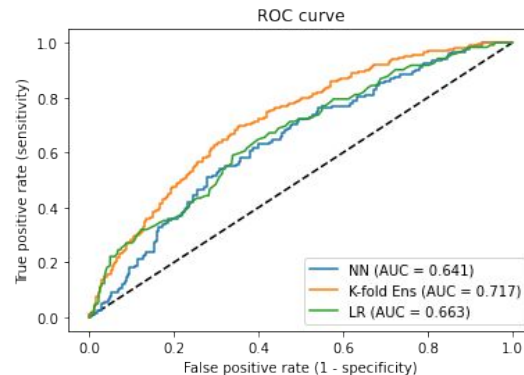
Sensitivity (Recall): 0.59

Specificity: 0.65

Precision: 0.36

f₁ Score: 0.45

	Predicted Negative	Predicted Positive
Actual Negative	240	129
Actual Positive	50	72





Random Forest Classifier

Metrics

Accuracy: 0.6

Mis-Classification: 0.4

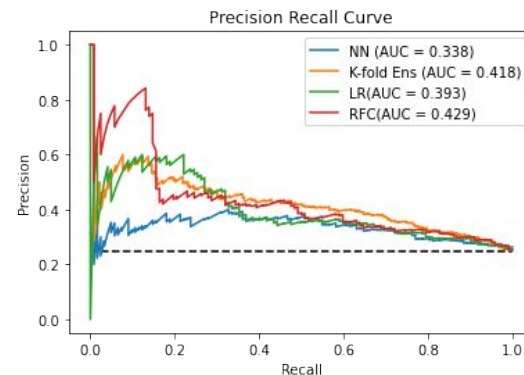
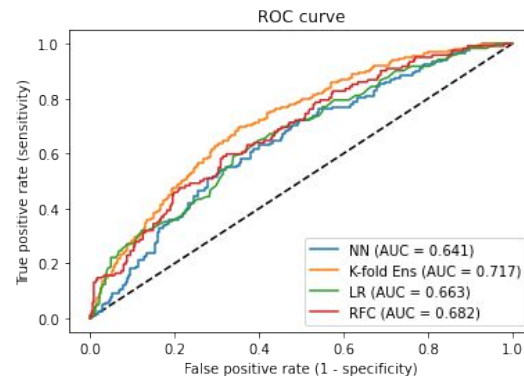
Sensitivity (Recall): 0.67

Specificity: 0.57

Precision: 0.34

f₁ Score: 0.45

	Predicted Negative	Predicted Positive
Actual Negative	211	158
Actual Positive	40	82





K-fold CV Ensemble: The Best Model

Metrics

Accuracy: 0.65

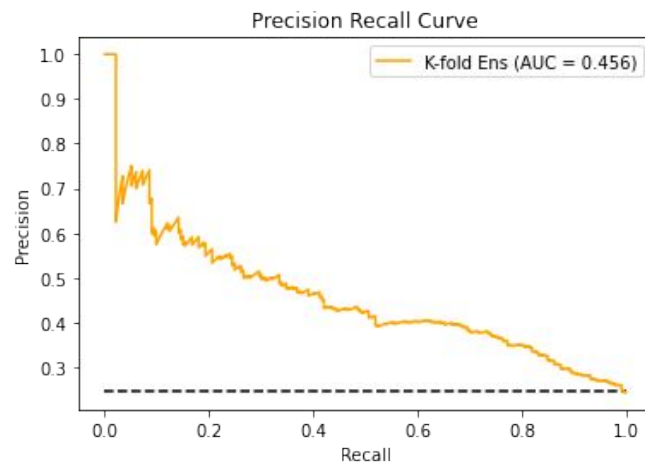
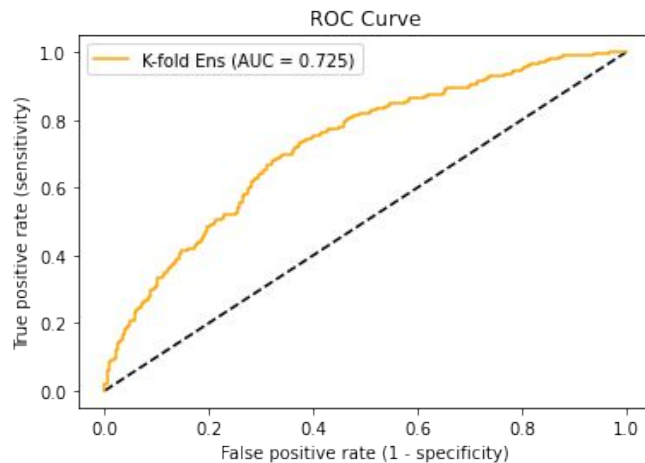
Mis-Classification: 0.35

Sensitivity (Recall): 0.72

Specificity: 0.63

Precision: 0.38

f₁ Score: 0.5





Important Features

Top Features

Parity

Age

Sex Education

Ever having HPV test

Number of pregnancies

Lifetime sexual partners

Weight	Feature
0.0081 ± 0.0031	PARITY
0.0069 ± 0.0017	AGE_R
0.0041 ± 0.0027	SEDSTD_1.0
0.0032 ± 0.0007	EVHPVTST_1.0
0.0029 ± 0.0009	NUMPREGS
0.0029 ± 0.0004	LIFPRTNR
0.0026 ± 0.0009	USLPLACE_20.0
0.0025 ± 0.0012	ROSCNT
0.0023 ± 0.0009	AGEFSTSX
0.0023 ± 0.0010	RELDLIFE_3.0
0.0020 ± 0.0006	CHSUPPOR_R_4.0
0.0020 ± 0.0009	EVRMARRY_1
0.0019 ± 0.0014	ATTNDNOW_3.0
0.0019 ± 0.0005	ATTND14_7.0
0.0019 ± 0.0017	ATTRACT_5.0
0.0019 ± 0.0012	RELCURR_7.0
0.0017 ± 0.0011	SAMESEX_R_2.0
0.0017 ± 0.0010	TEMPSAFE_1.0
0.0017 ± 0.0009	EDUCAT_18
0.0017 ± 0.0010	POVERTY
... 94 more ...	

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Discussion

Impact & Limitations



Discussion

65% accuracy, 72% sensitivity, 63% specificity is informative

- Importance of parity and age are often emphasized a lot in the literature
- Suggests that there are other factors that are more informative for LARC use, e.g. hearing anecdotes
- Behavioral factors not captured in the survey

Behavioral Frameworks: Health Belief Model / Theory of Planned Behavior

Perceived susceptibility	How likely a participant believed it was that she would become pregnant
Perceived severity	Would becoming pregnant be a positive or negative thing?
Perceived benefits	Perceived positive benefits of using LARC
Perceived barriers	Embarrassment to ask and fear of using LARC
Health motivation	How important not becoming pregnant was to the participant
Cues to action	How influential a healthcare worker was in contraception choice
Attitude	Degree to which attitude towards LARC is viewed positively or negatively
Subjective norm	How partners approve or disapprove of LARC use
Perceived behavioral control	Ease or difficulty of using LARC in terms of internal factors (e.g. it's my choice) and external factors (it's out of my control)
Self-efficacy	Confidence in their own ability to use LARC



Future Research

- Understand most important drivers of LARC & contraception decision making
- Add questions to NSFG

Limitations

1

Self-reported data

2

Limited by the variables included in the NSFG survey

3

Class imbalance

Impact

Highlights gaps in
current understanding
of factors driving
LARC use

1

Address lack of
access to LARC in
a novel way

2

Nationally
representative
analysis

3

First application of
ML in contraception
research

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Acknowledgements

Shibani Chettri, Division of Epidemiology, College of Public Health, OSU

Moniba Keymanesh, Department of Computer Science and Engineering, OSU

Cankun Wang, Department of Biomedical Informatics, OSU

Ren Qi, Department of Biomedical Informatics, OSU

THANKS!

Any questions?