

Analysis of Eyewitness Accuracy

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1 Executive Summary

Eyewitnesses to a crime are frequently called upon to participate in a police lineup during a criminal investigation. To ensure that witness identifications aid in the conviction of actual offenders rather than innocent people, authorities must know how accurate a given witness should be. To learn more about this issue, Dr. Chad Dodson, our client, conducted an experiment. Participants were initially instructed to watch a brief movie portraying a simulated robbery. Then, participants were shown a lineup that may or may not have the robber in it and were asked to identify the robber in the video. The video, lineup type, presence of weapon, and duration between watching the video and choosing from the lineup were all randomized among the participants.

This report provides sufficient answers to all three of the client's questions. First, Delay, Robber Race, Actor, Confidence, Face Recognition Test Score, Gender, and Age are likely to be significant factors that determine how likely an eyewitness is to correctly identifying the suspect in a lineup overall. Second, Delay, Robber Race, Actor, Weapon, Confidence, Face Recognition Test Score, Gender, and Age are likely to be significant factors that determine how likely an eyewitness is to correctly identifying the suspect in a lineup given that they chose someone. Third, Delay and Confidence are likely to be significant factors that determine how likely an eyewitness is to correctly identifying the suspect in a lineup given that they did not chose someone.

2 Introduction

2.1 General Background

Eyewitnesses to a crime are frequently called upon to participate in a police lineup during a criminal investigation. In a police lineup, a suspect is placed among a group of other people (“fillers”) who have nothing to do with the crime. The eyewitness is then asked to identify the suspect. To ensure that witness identifications aid in the conviction of actual offenders rather than innocent people, authorities must know how accurate a given witness should be.

To learn more about this issue, Dr. Chad Dodson, our client, conducted an experiment. Participants were initially instructed to watch a brief movie portraying a simulated robbery. Then, participants were shown a lineup that may or may not have the robber in it and were asked to identify the robber in the video. The video, lineup type, presence of weapon, and duration between watching the video and choosing from the lineup were all randomized among the participants.

2.2 Objectives

The primary goal of this consultation is to provide answers to the following three questions:

1. Which factors determine how likely an eyewitness is to correctly identifying the suspect in a lineup overall?
2. Which factors determine how likely an eyewitness is to correctly identifying the suspect in a lineup given that they chose someone?
3. Which factors determine how likely an eyewitness is to correctly identifying the suspect in a lineup given that they did not choose someone?

2.3 Variable Description

Variable Name	Description
Participant	Unique ID for participant
Delay	Assigned delay time (Immediate, 2 days, 4 days, 8 days)
Robber Race	Race of robber in video
Actor	Actor A or B
Weapon	Weapon (if gun present) or Unarmed (no gun present)
Lineup Type	TA (Target Absent) or TP (Target Present)
Participant Response	Not Present, Target (correct choice), Foil (incorrect choice)
Confidence	% confidence of participant's response (0, 20, 40, 60, 80, 100)
Chooser	Yes (chose someone) or No (did not choose someone)
Decision Time	Seconds between being shown lineup and choosing
Face Recognition Test Score	Score between 25 and 75 on Face Recognition Test
Race	Race of participant
Gender	Gender of participant
Age	Age of participant

3 Project Approach

3.1 Data Cleaning

Processing the raw data involved the following four actions:

1. The columns Delay, Robber Race, Actor, Weapon, Lineup Type, Participant Response, Confidence, Chooser, Race, Gender, and Age were converted to a factor data type.
2. The column Age was converted to a numeric data type.
3. Missing values in the Age column were imputed with the median because Age has a right-skewed distribution, as seen in Figure 1.

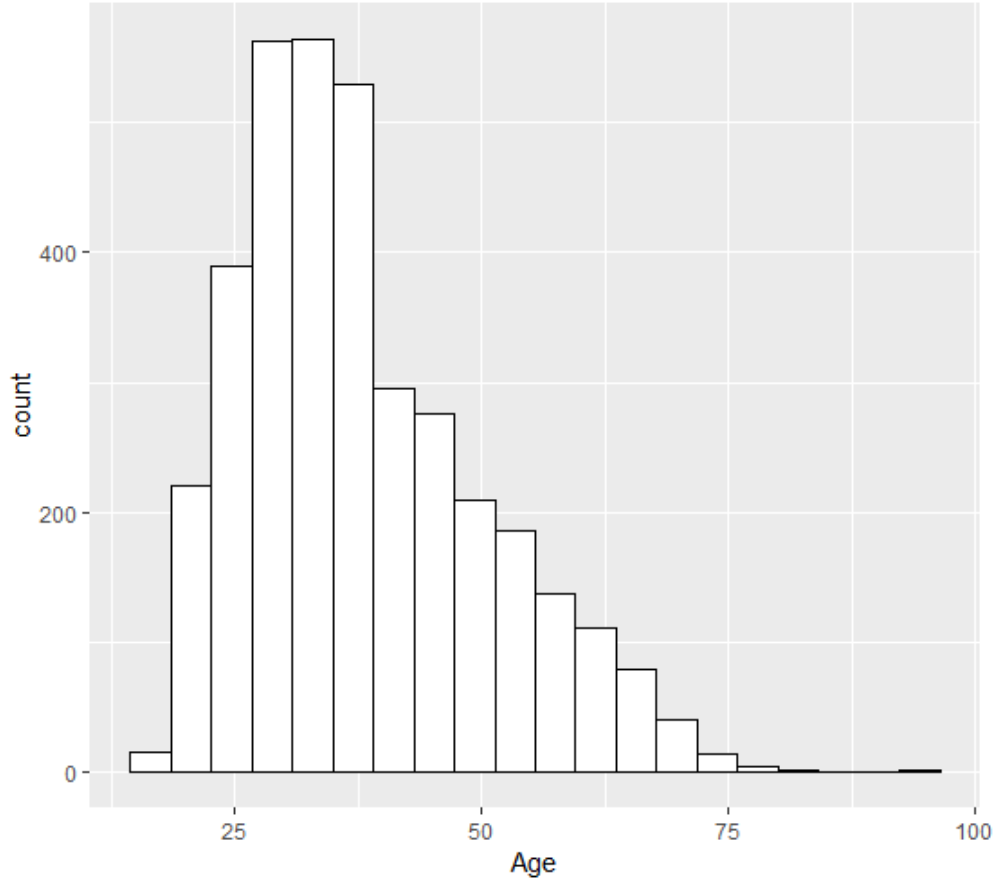


Figure 1: Distribution of Age

4. Observations with missing values in the Gender column were omitted because we believe we cannot ethically impute a gender for a participant.

3.2 Methodology

We implemented logistic regression, a supervised machine learning model, to answer all three questions. Based on a given data set of independent variables, logistic regression calculates the likelihood that an event will occur. A logit transformation is applied on the odds, the probability of success divided by the probability of failure, in logistic regression. The transformed odds are often referred to as log odds. In this model, the beta parameters, or coefficients, are often estimated via maximum likelihood estimation. This algorithm evaluates various beta values over a number of iterations to get the best match for the log odds. To determine the most accurate parameter estimate, logistic regression aims to maximize the log likelihood function, which is produced by all of these iterations. Following the identification of the best coefficients, the conditional probabilities for each observation

can be computed, logged, and summed to provide a predicted probability.

4 Results

First, we fitted the following logistic regression model, with Accuracy as the response, using the `glm()` function with the argument `family = "binomial"`:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 Delay + \hat{\beta}_2 RobberRace + \hat{\beta}_3 Actor + \hat{\beta}_4 Weapon + \hat{\beta}_5 Confidence \\ + \hat{\beta}_6 DecisionTime + \hat{\beta}_7 FaceRecognitionTestScore + \hat{\beta}_8 Race + \hat{\beta}_9 Gender + \hat{\beta}_{10} Age$$

We can view our model's summary statistics by using the `summary()` function. Figure 2 shows Delay4day, DelayImmediate, Robber_RaceWM, ActoractorB, Confidence80, Confidence100, Face.Recognition.Test.Score, GenderMale, and Age are statistically significant at $\alpha = 0.05$.

Coefficients:				
	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-1.8240	0.3337	-5.5	5e-08 ***
Delay4day	-0.2075	0.1003	-2.1	0.038 *
Delay8day	-0.1589	0.0998	-1.6	0.111
DelayImmediate	0.5850	0.1001	5.8	5e-09 ***
Robber_RaceWM	0.1683	0.0701	2.4	0.016 *
ActoractorB	-0.1875	0.0700	-2.7	0.007 **
WeaponWeapon	-0.0559	0.0698	-0.8	0.424
Confidence20	0.1286	0.2384	0.5	0.590
Confidence40	0.3281	0.2249	1.5	0.145
Confidence60	0.3477	0.2221	1.6	0.117
Confidence80	0.5817	0.2256	2.6	0.010 **
Confidence100	1.0083	0.2456	4.1	4e-05 ***
Decision_Time	0.0020	0.0024	0.8	0.409
Face_Recognition_Test_Score	0.0206	0.0035	5.8	6e-09 ***
RaceBlack/African American,American Indian or Alaska Native	-13.7688	882.7434	0.0	0.988
RaceBlack/African American,Asian	1.2118	0.8966	1.4	0.177
RaceBlack/African American,Hispanic/Latino	0.2184	1.0708	0.2	0.838
RaceBlack/African American,Native Hawaiian or Pacific Islander	14.3676	882.7434	0.0	0.987
RaceBlack/African American,Other	-14.3464	882.7434	0.0	0.987
RaceWhite/Caucasian	0.1124	0.1227	0.9	0.360
RaceWhite/Caucasian,American Indian or Alaska Native	0.3358	0.7401	0.5	0.650
RaceWhite/Caucasian,American Indian or Alaska Native,Asian,Native Hawaiian or Pacific Islander,Hispanic/Latino	14.7379	882.7434	0.0	0.987
RaceWhite/Caucasian,American Indian or Alaska Native,Hispanic/Latino	14.5450	624.0914	0.0	0.981
RaceWhite/Caucasian,American Indian or Alaska Native,Native Hawaiian or Pacific Islander	-14.3904	882.7434	0.0	0.987
RaceWhite/Caucasian,Asian	0.1448	0.4381	0.3	0.741
RaceWhite/Caucasian,Asian,Hispanic/Latino	0.7698	1.4217	0.5	0.588
RaceWhite/Caucasian,Asian,Native Hawaiian or Pacific Islander	16.1254	882.7434	0.0	0.985
RaceWhite/Caucasian,Asian,Other	-13.2644	882.7434	0.0	0.988
RaceWhite/Caucasian,Hispanic/Latino	-0.2030	0.3495	-0.6	0.561
RaceWhite/Caucasian,Hispanic/Latino,Other	-14.0800	882.7434	0.0	0.987
RaceWhite/Caucasian,Native Hawaiian or Pacific Islander	-13.7345	623.6791	0.0	0.982
RaceWhite/Caucasian,Other	1.5304	1.1952	1.3	0.200
GenderMale	0.1636	0.0709	2.3	0.021 *
Age	-0.0090	0.0030	-3.1	0.002 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Figure 2: Summary Statistics for Overall Logistic Regression Model

Then, we subsetting the data set into two smaller data sets. The **Chooser** data set contains only participants who chose someone, and the **Non-Chooser** data set contains only participants who did not choose someone. Afterwards, using the same model as before, we fitted two logistic regression models with the **Chooser** and **Non-Chooser** data sets.

We can view our models' summary statistics by using the `summary()` function. Figure 3 shows Delay8day, DelayImmediate, Robber_RaceWM, ActoractorB, WeaponWeapon, Confidence60, Confidence80, Confidence100, Face.Recognition.Test.Score, GenderMale, and Age

are statistically significant at $\alpha = 0.05$. Furthermore, Figure 4 shows DelayImmediate, Confidence40, and Confidence100 are statistically significant at $\alpha = 0.05$.

Coefficients:				
	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-3.4734	0.6562	-5.3	1e-07 ***
Delay4day	-0.1921	0.1498	-1.3	0.200
Delay8day	-0.4014	0.1573	-2.6	0.011 *
DelayImmediate	0.7695	0.1512	5.1	4e-07 ***
Robber_RaceWM	0.2966	0.1080	2.7	0.006 **
ActoractorB	-0.4563	0.1087	-4.2	3e-05 ***
WeaponWeapon	-0.2412	0.1070	-2.3	0.024 *
Confidence20	0.8928	0.5551	1.6	0.108
Confidence40	1.0504	0.5393	1.9	0.051 .
Confidence60	1.2888	0.5359	2.4	0.016 *
Confidence80	1.6252	0.5391	3.0	0.003 **
Confidence100	2.2088	0.5714	3.9	1e-04 ***
Decision_Time	0.0053	0.0036	1.4	0.149
Face_Recognition_Test_Score	0.0288	0.0054	5.3	1e-07 ***
RaceBlack/African American,American Indian or Alaska Native	-13.2083	882.7434	0.0	0.988
RaceBlack/African American,Asian	0.2969	1.3149	0.2	0.821
RaceBlack/African American,Hispanic/Latino	-12.9220	623.9247	0.0	0.983
RaceWhite/Caucasian	0.0124	0.1878	0.1	0.947
RaceWhite/Caucasian,American Indian or Alaska Native	1.0704	0.8319	1.3	0.198
RaceWhite/Caucasian,American Indian or Alaska Native,Asian,Native Hawaiian or Pacific Islander,Hispanic/Latino	14.8857	882.7434	0.0	0.987
RaceWhite/Caucasian,American Indian or Alaska Native,Hispanic/Latino	14.6020	882.7434	0.0	0.987
RaceWhite/Caucasian,Asian	0.1962	0.6825	0.3	0.774
RaceWhite/Caucasian,Asian,Hispanic/Latino	-13.1713	882.7434	0.0	0.988
RaceWhite/Caucasian,Asian,Other	-12.4315	882.7434	0.0	0.989
RaceWhite/Caucasian,Hispanic/Latino	-0.2445	0.5534	-0.4	0.659
RaceWhite/Caucasian,Hispanic/Latino,Other	-13.7950	882.7434	0.0	0.988
RaceWhite/Caucasian,Native Hawaiian or Pacific Islander	-12.9993	882.7434	0.0	0.988
RaceWhite/Caucasian,Other	-13.0562	882.7434	0.0	0.988
GenderMale	0.2541	0.1083	2.3	0.019 *
Age	-0.0126	0.0046	-2.7	0.007 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Figure 3: Summary Statistics for Chooser Logistic Regression Model

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Coefficients:
(Intercept) -7.6e-01 4.6e-01 -1.7 0.09 .
Delay4day -1.5e-01 1.5e-01 -1.0 0.30
Delay8day 2.3e-02 1.5e-01 0.2 0.87
DelayImmediate 3.4e-01 1.4e-01 2.4 0.02 *
Robber_RaceWM 1.1e-01 1.0e-01 1.1 0.28
ActoractorB 7.9e-02 1.0e-01 0.8 0.44
WeaponWeapon -2.4e-02 1.0e-01 -0.2 0.81
Confidence20 3.4e-01 3.0e-01 1.1 0.27
Confidence40 6.4e-01 2.8e-01 2.3 0.02 *
Confidence60 4.5e-01 2.8e-01 1.6 0.11
Confidence80 4.6e-01 2.8e-01 1.6 0.10
Confidence100 6.1e-01 3.0e-01 2.0 0.04 *
Decision_Time 9.8e-04 3.6e-03 0.3 0.79
Face_Recognition_Test_Score 7.5e-03 5.2e-03 1.4 0.15
RaceBlack/African American,Asian 1.6e+01 8.4e+02 0.0 0.99
RaceBlack/African American,Hispanic/Latino 1.5e+01 1.0e+03 0.0 0.99
RaceBlack/African American,Native Hawaiian or Pacific Islander 1.5e+01 1.5e+03 0.0 0.99
RaceBlack/African American,Other -1.6e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian 2.6e-01 1.7e-01 1.5 0.13
RaceWhite/Caucasian,American Indian or Alaska Native -1.6e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian,American Indian or Alaska Native,Hispanic/Latino 1.5e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian,American Indian or Alaska Native,Native Hawaiian or Pacific Islander -1.6e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian,Asian 1.8e-02 5.9e-01 0.0 0.98
RaceWhite/Caucasian,Asian,Hispanic/Latino 1.6e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian,Asian,Native Hawaiian or Pacific Islander 1.6e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian,Hispanic/Latino -1.1e-01 4.9e-01 -0.2 0.82
RaceWhite/Caucasian,Native Hawaiian or Pacific Islander -1.6e+01 1.5e+03 0.0 0.99
RaceWhite/Caucasian,Other 1.5e+01 8.3e+02 0.0 0.99
GenderMale 6.2e-03 1.0e-01 0.1 0.95
Age -6.0e-03 4.2e-03 -1.4 0.15
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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Figure 4: Summary Statistics for Non-Chooser Logistic Regression Model

5 Conclusions

In this report, we feel we have appropriately addressed all three of the client’s questions. In response to the first question, Delay, Robber Race, Actor, Confidence, Face Recognition Test Score, Gender, and Age are likely to be significant factors that determine how likely an eyewitness is to correctly identifying the suspect in a lineup overall. In response to the second question, Delay, Robber Race, Actor, Weapon, Confidence, Face Recognition Test Score, Gender, and Age are likely to be significant factors that determine how likely an eyewitness is to correctly identifying the suspect in a lineup given that they chose someone. In response to the third question, Delay and Confidence are likely to be significant factors that determine how likely an eyewitness is to correctly identifying the suspect in a lineup given that they did not chose someone.