



# Infusion of Data Science and Computation into Introductory Statistics

Sayed Mostafa<sup>1</sup>, Tamer Elbayoumi, Seongtae Kim

Department of Mathematics & Statistics North Carolina A&T State University

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<sup>&</sup>lt;sup>1</sup>Assistant Professor & Coordinator of Introductory Statistics

### Outline

- ► Introduction
  - Background
  - Study Objectives
  - Study Setting
- ▶ Infusion of Data Science and Computation into Intro Stats
  - Guiding Literature
  - Proposed DS/Computationally-Infused Intro Stats Design
- Evaluating the DS-Infused Intro Stats Design
  - ▶ DS awareness, readiness & aspirations
  - Statistical learning gains
  - Overall course performance
- Resources for Teaching a DS-Infused Intro Stats Course

### Introduction

- Nolan and Temple Lang's (2010) paper on "Computing in the Statistics Curriculum" led many statistics educators to advocate integrating computing in statistics courses starting with the Introductory Statistics (Intro Stats) course.
- The need for computationally-infused statistics curriculum was further signified by the fast-growing demands on graduates with computational and data analytical skills who can work as data scientists.
- ► As a result, a significant body of literature on integrating computing in statistics courses emerged during the last decade
  - see the JSDSE Special Issue Horton and Hardin (2021): "Integrating computing in the statistics and data science curriculum: Creative structures, novel skills and habits, and ways to teach computational thinking".

# Study Objectives

### In this study, we aim to

- ▶ introduce an Intro Stats course design that integrates computing as a core component of the course and
- evaluate the effectiveness of such design for
  - enhancing students' statistical gains,
  - boosting students' levels of data science (DS) awareness, aspiration, and readiness, and
  - improving students' overall course performance.

# Study Setting



- ► The study took place at North Carolina A&T State University (NCA&T)
- ▶ NC A&T is a public, high-research activity land-grant university
- ► The largest Historically Black College and University (HBCU) in the United States
- ▶ Medium-sized university with Fall 2022 enrollment over 13,000
- Strong focus on STEM education

# Study Setting

- "Introduction to Probability & Statistics" (MATH224)
- Algebra-based 3.00 credits course
- Serves as one of the Gen Ed courses for Mathematical, Logical, and Analytical Reasoning (MLAR)
- ► Serves STEM (~46%) and non-STEM (~54%) majors
- Most students in the course are from groups underrepresented in Statistics/DS
  - ▶ ~82% are African Americans and ~69% are females
- ▶ About 7 sections each semester (~45 students in each section)

# The "Traditional" Intro Stats Course Design

- "Consensus" course content (see below)
- ▶ 3 hours of lecture per week
- ▶ Use of a calculator and/or excel for course computation
- ► All inference rely on distribution tables (e.g., z/t tables)
- ► This design prevailed at NCA&T until before Spring 2022

### Content and computation in the traditional Intro Stats course (before Spring 2022)

#### 1. Introduction (basic concepts)

- · Descriptive vs inferential statistics
- Types of data (quantitative vs qualitative)
- Sample vs population
- Data collection & Sampling methods

### 2. Descriptive statistics

- Describing data graphically (manually/using excel construct various types of univariate graphs)
- Numerical summaries (manually/using excel compute central tendency and variability measures, and standardized scores)
- Bivariate relationships: scatterplots, correlation, and simple linear regression\*

### 3. Introduction to probability

- Basic probability terminologies (sample spaces, events, complementary events, and unions and intersections of events)
- Additive rule, disjoint events, multiplicative rule, independence, and conditional probability

### 4. Probability distributions

- Use formulas to compute expectation and variance of a given discrete probability distribution
- Use binomial formula to compute probabilities about binary variables
- Use normal table to compute probabilities and percentiles for normal random variables

### 5. Sampling distribution of sample mean

- Central limit theorem
- Use normal table to compute probabilities about the sample mean/proportion

#### 6. Confidence intervals

- Use formula, calculator and normal table or excel to compute confidence interval for the population mean/proportion
- 7. Hypothesis testing
- Perform 5 systematic steps and use calculator and normal table or excel to compute p-value and reject/retain the null hypothesis about the population mean/proportion

<sup>\*</sup>Optional/time-permitting topic.

# Consequences of the "Traditional" Intro Stats Design

- ► Low statistical learning gains
  - ▶ In Fall 2019, we measured students' learning gains from the course by the improvement in their scores on the Comprehensive Assessment of Outcomes in a First Statistics Course (CAOS) scale
  - ▶ the average learning gain (posttest pretest) was 5.4% compared to a 9.1% national average (delMas et al., 2007)
- High overall course repeat rate
  - ► The course DFW rate was 24.4%

# Opportunities for Intro Stats

- Intro Stats can (and should) help us attract and prepare a large diverse pool of undergraduates for further Statistics and Data Science (DS) education
- ► Intro Stats students are likely unaware of Statistics/DS educational/career opportunities
  - In Fall 2019, we survey our Intro Stats students (n = 181) about their awareness and interest in DS
  - ▶ Only 33.15% of students surveyed had heard about DS
  - Of those, only 27.12% knew NCA&T offers DS courses and only 18.64% knew NCA&T offers an undergrad DS certificate

# Infusion of Data Science and Computation into Intro Stats

### **Guiding Literature**:

- The Intro Stats course should
  - introduce students to the entire data analysis cycle rather than pieces of it (**Cobb**, **2015**),
  - expose students to multivariable thinking (GAISE #1),
  - leverage the use of technology for exploring concepts with simulations (GAISE #2),
  - help students learn statistics actively while analyzing real data using technology (GAISE #3, 4 & 5),
  - ► train students to think structurally with data and become data-savvy (Horton et al., 2015), and
  - expose students, early and frequently, to the elements of the DS workflow and the data scientist's toolbox (Horton et al., 2015)

# Infusion of Data Science and Computation into Intro Stats

Revised course content adopted in Spring 2022:

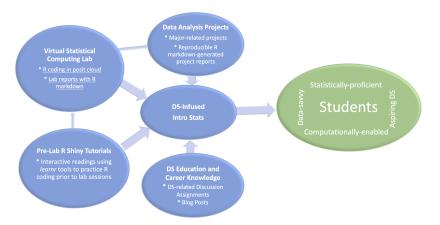
### Content of the redesigned Intro Stats course.

- Introduction to elements of data analysis
   Data analysis workflow (research question.
  - data acquisition, cleaning, wrangling, visualization, modeling, and interpretation)
- 2. Data collection/acquisition
  - · Target population vs sample
  - · Sampling variation and generalization
  - · Sampling and resampling
  - Data from designed experiments
- 3. Univariate descriptive statistics
  - Graphics (bar charts, dot plots, histograms, boxplots, and density plots)
  - Numerical summaries (five-number summary, mean, standard deviation, and standardized scores) and detect outliers
- 4. Bivariate relations
  - · Scatterplots, correlation, and causation
  - · Contingency tables for categorical variables
  - Faceted plots for displaying relations across different levels of categorical variables

- Simple linear regression
- 5. Probability, chance models and sampling distributions
  - Basic probability rules, conditional probability, and independence
  - · Binomial and normal probability models
  - Sampling distribution of sample mean/proportion with simulations
- 6. Inference for one population mean/proportion
  - · Construction and interpretation of confidence intervals
  - Classical t-tests and resampling tests for one mean/proportion
  - . How large is the evidence (effect size)?
- Statistical versus practical significance
   Inference for two population means/proportions
  - Construction and interpretation of confidence intervals for difference bet, two means/proportions
  - · Classical t-tests and permutation tests for two groups
- Using plots to check assumptions
- 8. Multivariate relations
  - Multiple linear regression & analysis of variance

# DS/Computationally-Infused Intro Stats

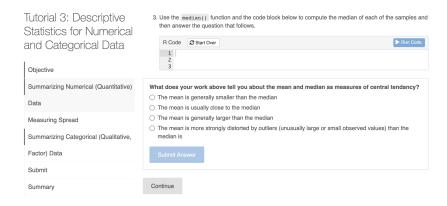
► Redesigned Intro Stats Course – Phase I (Fall 2022)



▶ Implementation: 2 treatment sections and 2 control sections

# DS/Computationally-Infused Intro Stats: Phase I-FA22

### ► Interactive Shiny Pre-Lab Tutorial



## DS/Computationally-Infused Intro Stats: Phase I-FA22

## ► Computing Lab Description (Static)

# Getting started Analysis R as a big calculator Adding a new variable to the data frame Departure delays

You can also obtain numerical summaries for these flights:

Note that in the summariae function you created a list of three different numerical summaries that you were interested in. The names of these elements are user defined, like mean\_dd, median\_dd, n, and you can customize these names as you like (suit odn't use spaces in your names). Calculating these summary statistics also requires that you know the function calls. Note that not, yeroprofit has example size.

Summary statistics: Some useful function calls for summary statistics for a single numerical variable are as follows:

- mean() The arithmetic mean is found by adding the numbers and dividing the sum by the number of numbers in the list
   median() The middle number in a sorted, ascending or descending, list of numbers and can be more descriptive of that data set than the mean.
- . sd() The measure of the amount of variation or dispersion of a set of values.
- · var() the expectation of the squared deviation of a random variable from its population mean or sample mean.
- IQR() the interquartile range is a measure of statistical dispersion, which is the spread of the data. The IQR may also be
- called the midspread, middle 50%.
- min() The smallest value in the data set.
   max() The largest value in the data set.

Note that each of these functions takes a single vector as an argument and returns a single value.

You can also filter based on multiple criteria. Suppose you are interested in flights headed to San Francisco (SFO) in February:

```
sfo_feb_flights <- nyoflights %>%
filter(dest == "SFO", month == 2)
```

Note that you can separate the conditions using commas if you want flights that are both headed to SFO and in February. If you are interested in either flights headed to SFO or in February, you can use the | | instead of the comma.

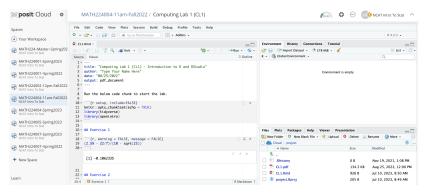
Exercise 2 Create a new data frame that includes flights headed to SFO in February, and save this data frame as sfo\_feb\_flights. How many flights meet these criteria?

Exercise 3

Describe the distribution of the arrival delays of these flights using a histogram and appropriate summary statistics. Hint: The summary statistics you use should depend on the shape of the distribution.

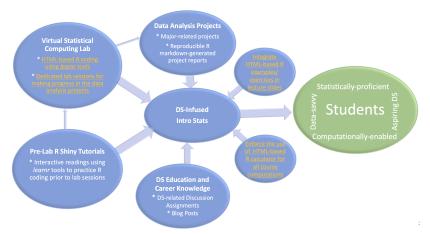
# DS/Computationally-Infused Intro Stats: Phase I-FA22

Computing Lab R Markdown Template



## DS/Computationally-Infused Intro Stats

Redesigned Intro Stats Course – Phase II (Spring 2023)



▶ Implementation: 4 treatment sections and 2 control sections

# DS/Computationally-Infused Intro Stats: Phase II-SP23

Interactive Computing Lab (using the learnr package)

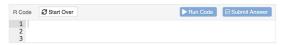
### Exploratory Data Analysis Part I

Start Over

Recall that the five number summary includes the min, first quantile (Q1), median, third quantile (Q3), and max. Using the mpg dataset, we can compute the five number summary of the vehicle's highway mileage hwy as follows.

Notice how the quantile() function is used to obtain quantiles by setting the proportion of data below the quantile (i.e., 0.25 or 0.75)

Use the code chunk below to calculate the measures of center (mean and median) for the vehicle's city mileage cty.



Use the code chunk below to calculate the variation measures (standard deviation and interquartile range) for the vehicle's city mileage cty.

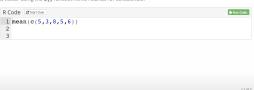


# DS/Computationally-Infused Intro Stats: Phase II-SP23

Slides with Interactive Coding

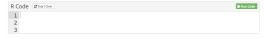
# Example 1. Calculate the mean of a sample with five observations: 5, 3, 8, 5, 6. $\bar{x} = \frac{\sum_{i=1}^n x_i}{n} = \frac{5+3+8+5+6}{5} = \frac{27}{5} = 5.4$

Using R, we can calculate the mean using the **mean()** command. Notice that we need to put the values in a vector using the **c()** function which stands for *concatenate*.



### Discussions

- 1. If the data set has 5 observations, with  $\bar{x} = 5.4$ , find  $\sum_{i=1}^{5} x_i$ .
- 2. Continue discussion in 1, if add one more observation 10, will the mean  $\bar{x}$  increase or decrease? What is the new  $\bar{x}$ ?
- 3. Compare data sets 5, 3, 8, 5, 6 and 5, 3, 80, 5, 6, which one has the higher mean?



# DS/Computationally-Infused Intro Stats: Phase II-SP23

### Interactive R Calculator

### Using R as a calculator

R can be used as an calculator as we already saw in the tutorial. So let's get a refresher on this.

Let's say we want to calculate  $\frac{36}{29(15-9)}$ . Then we would do the following:

R also has built-in constants such as pi and mathematical functions such as e and log.

Let's find the radius of a circle with radius 4. Then using R we can get the area and the circumference.

```
RCode & Stant Over

1 radius = 4
2
3 area = pi * radius^2
4
5 circumference = 2 * pi * radius
6
7 c("Area" = area, "Circumference" = circumference)
```

We can also use R to calculate probabilities under the normal distribution. The following code returns the probability that a normal variable with mean 25 and standard deviation 15 is less than 50.

As you work on your homework assignments, feel free to use the below code chunks to perfom your calculations.

```
R Code Stant Over Prun Code

1 |
2 |
3 |
```

# Evaluating the DS-Infused Intro Stats Design

- ▶ DS awareness, readiness & aspirations
  - Students completed a DS awareness, readiness, and aspirations survey in Qualtrics
  - Pre-survey was completed during 1st week of semester; post-survey was completed during second-to-last week in semester
- Statistical learning gains
  - ► Students completed a revised version of the CAOS scale (e.g., Tintle et al., 2018)
  - Pre-test was completed during 1st week of semester; post-test was completed during second-to-last week in semester
- Overall performance
  - Measured by final course grade (focus on DFW rate)

# Evaluating the DS-Infused Intro Stats Design

### ▶ DS awareness, readiness & aspirations: EFA results

	Pre-s	urvey	Post-s	urvey	
Item	Awareness	Aspiration	Awareness	Aspiration	
<ol> <li>Are you aware that NCA&amp;T offers courses in Data Science?§</li> </ol>	0.71		0.87	_	
<ol> <li>Are you aware that NCA&amp;T offers an undergraduate certificate in Data Science?§</li> </ol>	0.85		0.94		
<ol> <li>Are you aware that NCA&amp;T offers degrees with concentration in in Data Science?§</li> </ol>	0.89		0.85		
<ol> <li>Do you plan to take Data Science course(s) during your undergraduate program or during your graduate study (if you plan to do graduate studies)?<sup>‡</sup></li> </ol>		0.54		0.76	
<ol> <li>Do you plan to complete a certificate in Data Science during your undergraduate program or during your graduate study (if you plan to do graduate studies)?<sup>‡</sup></li> </ol>		0.78		0.85	
<ol> <li>Do you plan to complete a minor in Data Science during your undergraduate program or during your graduate study (if you plan to do graduate studies)?<sup>‡</sup></li> </ol>		0.85		0.87	
<ol> <li>Do you plan to complete a degree in Data Science during your undergraduate program or during your graduate study (if you plan to do graduate studies)?<sup>‡</sup></li> </ol>		0.81		0.86	
Cronbach Alpha	0.85	0.82	0.92	0.90	
Lewis-Tucker Index of Factoring Reliability	0.	89	0.87		
RMSR (RMSEA)	0.042	(0.131)	0.034 (0.174)		

\$Possible responses were coded as "Yes=1" and "No=0". Possible responses were coded as "Yes=2", "Not sure=1", and "No=0". The correlation between the two factors is 0.02 and 0.07 for pre-survey and post-survey, respectively.

# Evaluating the DS-Infused Intro Stats Design

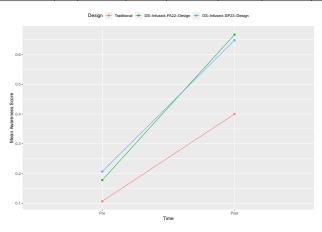
### ▶ DS awareness, readiness & aspirations: EFA results

	Pre-survey		Post-s	survey
	Readiness	Readiness	Readiness	Readiness
Item	(General)	(R)	(General)	(R)
1. I feel confident summarizing data sets using summary statistics and				
graphics in RStudio.§	0.93		0.94	
<ol> <li>I feel confident performing basic statistical inference in RStudio.§</li> </ol>	0.98		0.97	
<ol> <li>I feel confident performing basic modeling (linear and/or logistics regression).</li> </ol>		0.80		0.90
4. I feel confident creating reproducible data analysis reports in RStudio using R Markdown.§	0.84		0.79	
<ol> <li>I feel adequately prepared to apply statistical and data-analytical techniques and/or tools to study a given topic.§</li> </ol>		0.73		0.70
Cronbach Alpha	0.95	0.75	0.94	0.82
Lewis-Tucker Index of Factoring Reliability	1.	00	0.	97
RMSR (RMSEA)	0.004	(0.000)	0.008	(0.115)

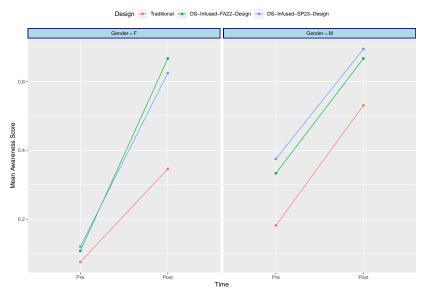
§Possible responses were reported on a 6-point Likert scale and coded as "Strongly disagree=1" to "Strongly agree=6". The Correlation between the two readiness sub-scales is 0.71 and 0.67 for pre-survey and post-survey, respectively.

### ► DS awareness gains by course design

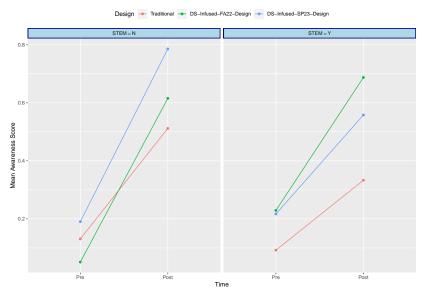
Course Type	n	Mean_Pre	SD_Pre	Mean_Post	SD_Post	Mean_Diff	SD_Diff
Traditional	75	0.11	0.27	0.40	0.46	0.29	0.43
DS-Infused-FA22-Design	45	0.18	0.33	0.67	0.46	0.49	0.44
DS-Infused-SP23-Design	71	0.21	0.37	0.65	0.46	0.44	0.46



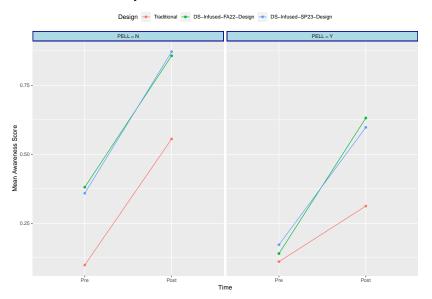
► DS awareness by gender



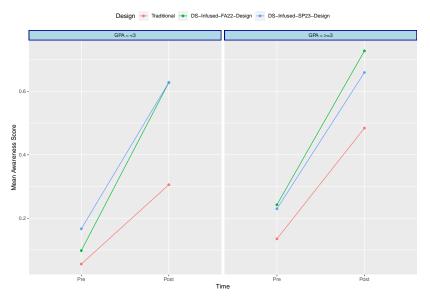
▶ DS awareness by STEM status



▶ DS awareness by PELL status



▶ DS awareness by pre-course GPA

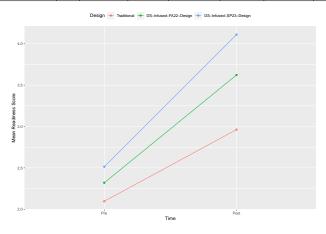


### ► Gains in DS awareness: regression on course design

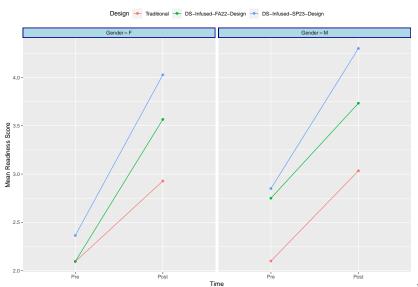
Regression Term	Estimate	LCL	UCL	p.value	Sig.
Intercept	0.43	-0.13	0.99	0.1301	Not Sig.
Type: DS-Infused-FA22-Design	0.26	0.08	0.44	0.0050	**
Type: DS-Infused-SP23-Design	0.18	0.02	0.33	0.0230	_*
Sex: Male	-0.09	-0.24	0.06	0.2439	Not Sig.
Race: Not Black	-0.14	-0.32	0.04	0.1225	Not Sig.
PELL Recepient: Yes	-0.21	-0.40	-0.02	0.0290	_*
Rural: Yes	0.11	-0.10	0.32	0.3135	Not Sig.
Residency: Out-of-State	0.05	-0.11	0.21	0.5109	Not Sig.
STEM: Yes	-0.15	-0.29	0.00	0.0431	_*
AP Stat: Yes	0.09	-0.07	0.25	0.2813	Not Sig.
Pre-Course Cum GPA	0.00	-0.14	0.14	0.9858	Not Sig.
Attendance	0.00	0.00	0.01	0.6380	Not Sig.

### ► Gains in DS readiness by course design

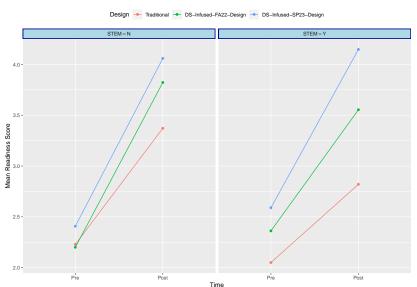
Course Type	n	Mean_Pre	SD_Pre	Mean_Post	SD_Post	Mean_Diff	SD_Diff
Traditional	54	2.10	0.88	2.96	1.10	0.87	0.92
DS-Infused-FA22-Design	35	2.32	0.80	3.62	1.08	1.30	1.06
DS-Infused-SP23-Design	65	2.51	1.05	4.11	0.87	1.60	1.11



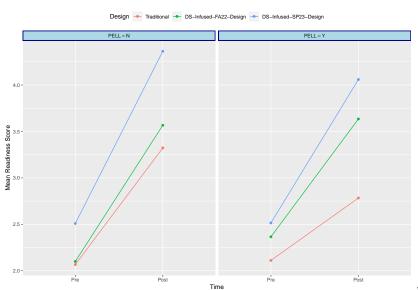
▶ DS readiness by course design & gender



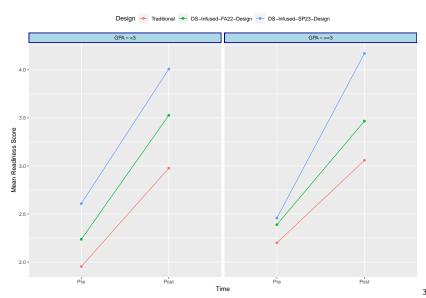
▶ DS readiness by course design & STEM status



▶ DS readiness by course design & PELL status



▶ DS readiness by course design & pre-course GPA



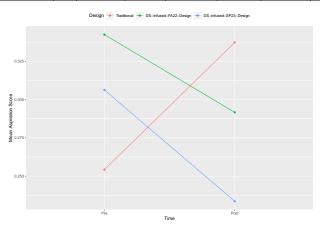
► Gains in DS readiness: regression on course design

Regression Term	Estimate	LCL	UCL	p.value	Sig.
Intercept	0.94	-0.53	2.42	0.2087	Not Sig.
Type: DS-Infused-FA22-Design	0.43	-0.04	0.90	0.0740	Not Sig.
Type: DS-Infused-SP23-Design	0.84	0.46	1.22	0.0000	****
Sex: Male	-0.16	-0.54	0.22	0.4079	Not Sig.
Race: Not Black	-0.21	-0.67	0.25	0.3687	Not Sig.
PELL Recepient: Yes	-0.62	-1.11	-0.13	0.0130	_*
Rural: Yes	-0.58	-1.10	-0.06	0.0296	_*
Residency: Out-of-State	0.30	-0.09	0.70	0.1300	Not Sig.
STEM: Yes	-0.06	-0.44	0.32	0.7428	Not Sig.
AP Stat: Yes	-0.27	-0.68	0.14	0.1934	Not Sig.
Pre-Course Cum GPA	0.15	-0.19	0.49	0.3932	Not Sig.
Attendance	0.00	-0.01	0.01	0.9119	Not Sig.

# **Data Science Aspirations**

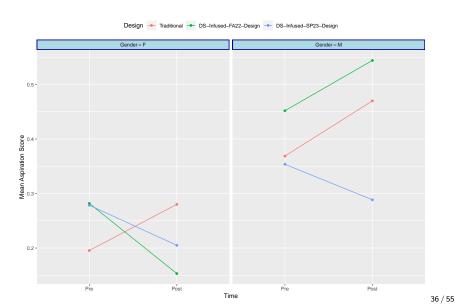
### ► Level of DS aspiration by course design

Course Type	n	Mean_Pre	SD_Pre	Mean_Post	SD_Post	Mean_Diff	SD_Diff
Traditional	81	0.22	0.36	0.33	0.50	0.11	0.50
DS-Infused-FA22-Design	47	0.37	0.51	0.30	0.50	-0.07	0.55
DS-Infused-SP23-Design	72	0.22	0.36	0.23	0.39	0.01	0.37

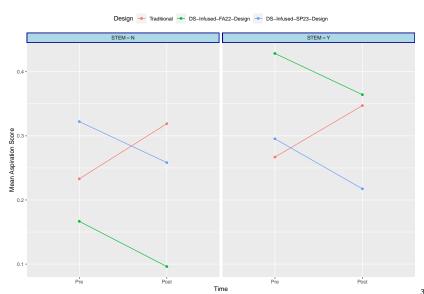


# **Data Science Aspirations**

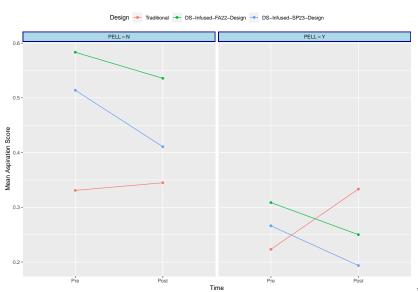
▶ Level of DS aspiration by course design & gender



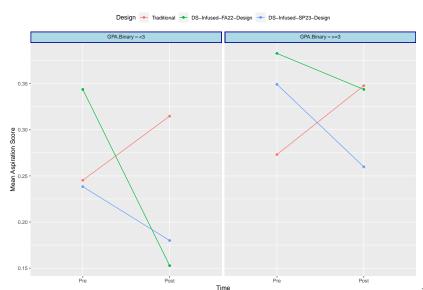
▶ Level of DS aspiration by course design & STEM status



▶ Level of DS aspiration by course design & PELL status



▶ Level of DS aspiration by course design & pre-course GPA

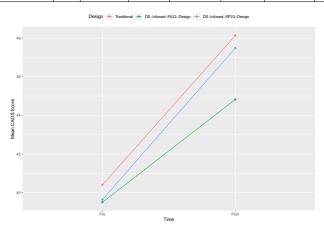


### ► Change in DS aspiration: regression on course design

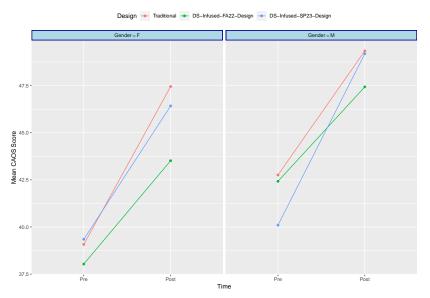
Regression Term	Estimate	LCL	UCL	p.value	Sig.
Intercept	0.05	-0.53	0.63	0.8688	Not Sig.
Type: DS-Infused-FA22-Design	-0.25	-0.44	-0.07	0.0074	**
Type: DS-Infused-SP23-Design	-0.10	-0.26	0.05	0.2030	Not Sig.
Sex: Male	0.04	-0.11	0.19	0.5946	Not Sig.
Race: Not Black	-0.03	-0.21	0.16	0.7821	Not Sig.
PELL Recepient: Yes	0.14	-0.06	0.33	0.1645	Not Sig.
Rural: Yes	-0.01	-0.22	0.20	0.9514	Not Sig.
Residency: Out-of-State	-0.04	-0.20	0.13	0.6532	Not Sig.
STEM: Yes	-0.04	-0.19	0.11	0.5902	Not Sig.
AP Stat: Yes	0.17	0.01	0.33	0.0426	_*
Pre-Course Cum GPA	-0.07	-0.22	0.07	0.3156	Not Sig.
Attendance	0.00	0.00	0.01	0.4408	Not Sig.

#### ► Statistical learning gains by course design

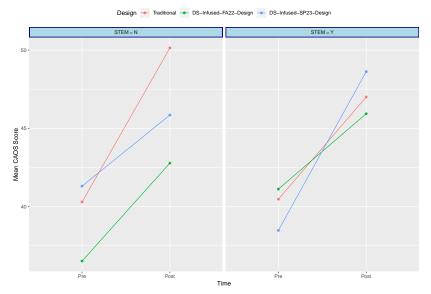
Course Type	n	Mean_Pre	SD_Pre	Mean_Post	SD_Post	Mean_Diff	SD_Diff
Traditional	75	40.40	10.90	48.13	14.84	7.73	16.75
DS-Infused-FA22-Design	57	39.50	11.24	44.82	12.20	5.32	12.86
DS-Infused-SP23-Design	112	39.64	12.43	47.48	14.77	7.85	18.54



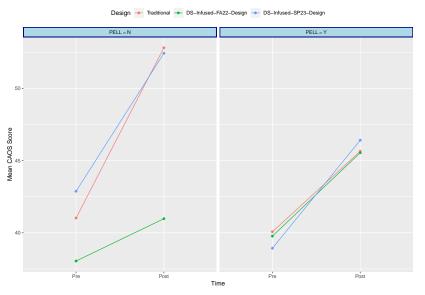
► Statistical learning gains by course design & gender:



▶ Statistical learning gains by course design & STEM status:



▶ Statistical learning gains by course design & PELL status:



▶ Statistical learning gains (Change): regression on course design

Regression Term	Estimate	LCL	UCL	p.value	Sig.
Intercept	0.25	-19.37	19.87	0.9800	Not Sig.
Type: DS-Infused-FA22-Design	-0.82	-7.34	5.70	0.8049	Not Sig.
Type: DS-Infused-SP23-Design	0.28	-5.08	5.65	0.9172	Not Sig.
Sex: Male	-1.54	-6.46	3.37	0.5373	Not Sig.
Race: Not Black	1.15	-5.53	7.84	0.7340	Not Sig.
PELL Recepient: Yes	0.69	-5.52	6.89	0.8277	Not Sig.
Rural: Yes	-5.74	-12.38	0.90	0.0901	Not Sig.
Residency: Out-of-State	-6.29	-11.71	-0.88	0.0229	_*
STEM: Yes	1.14	-3.68	5.95	0.6422	Not Sig.
Pre-Course Cum GPA	-1.96	-6.69	2.76	0.4139	Not Sig.
Attendance	0.18	0.01	0.36	0.0408	_*

Overall student performance by course design:

Course Type	Grade	n	percent
Traditional	ABC	99	72.26
Traditional	DFW	38	27.74
DS-Infused-FA22-Design	ABC	56	65.12
DS-Infused-FA22-Design	DFW	30	34.88
DS-Infused-SP23-Design	ABC	120	83.92
DS-Infused-SP23-Design	DFW	23	16.08

▶ Overall student performance by course design & gender:

Course Type	Gender	Grade	n	percent
Traditional	F	DFW	28	30.77
Traditional	М	DFW	10	21.74
DS-Infused-FA22-Design	F	DFW	13	24.07
DS-Infused-FA22-Design	М	DFW	17	53.12
DS-Infused-SP23-Design	F	DFW	13	14.77
DS-Infused-SP23-Design	М	DFW	10	18.18

▶ Overall student performance by course design & STEM status:

Course Type	STEM	Grade	n	percent
Traditional	N	DFW	16	32.00
Traditional	Y	DFW	22	25.29
DS-Infused-FA22-Design	N	DFW	9	29.03
DS-Infused-FA22-Design	Y	DFW	21	38.18
DS-Infused-SP23-Design	N	DFW	12	20.34
DS-Infused-SP23-Design	Y	DFW	11	13.10

▶ Overall student performance by course design & PELL status:

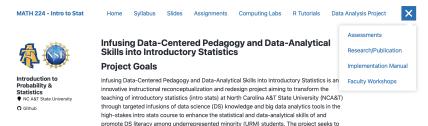
Course Type	PELL	Grade	n	percent
Traditional	N	DFW	6	15.38
Traditional	Y	DFW	32	32.65
DS-Infused-FA22-Design	N	DFW	4	36.36
DS-Infused-FA22-Design	Y	DFW	26	34.67
DS-Infused-SP23-Design	N	DFW	4	15.38
DS-Infused-SP23-Design	Y	DFW	19	16.24

# **Concluding Remarks**

- Infusing computation and DS tools/knowledge into Intro Stats was associated with
  - significant gains in students' levels of awareness of and readiness for Statistics/DS education opportunities
  - modest statistical learning gains (to be confirmed by further data collection)
  - substantial improvement in the course success rate
- Infusing computation and DS tools/knowledge into Intro Stats seemed to drive some students away from aspiring for further DS education
  - ► This is somewhat in line with other findings in the literature that hinted at the complexity of computing and the challenges of integrating computing into introductory courses (e.g., Woodard and Lee, 2021)

## Resources for Teaching a DS-Infused Intro Stats Course

▶ Project's Website on GitHub: https://introtostatncat.github.io



achieve three main goals: (1) Enhance students' statistical knowledge and data-analytical skills gained from the intro stats course; (2) Create a pipeline for the new DS programs offered at A&T; and (3) Build a faculty cadre capable of and committed to teaching intro stats using a data-centered pedagogy to promote data literacy among undergraduate students.

51 / 55

#### **Future Work**

- ▶ Continue to implement, evaluate, and refine the course design
- Evaluation of students' computational competency (e.g., competency in R coding)
  - We are not aware of an existing tool to assess computational competency

## Acknowledgments

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  - Project Title: Infusing Data-Centered Pedagogy and Data-Analytical Skills into Introductory Statistics
- ▶ We are grateful to our fellow Intro Stats faculty who helped with the implementation and data collection: Mingxiang Chen and Kossi Edoh.

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