Coding Bootcamps - Perceptions and Outcomes

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CODING BOOTCAMPS - PERCEPTIONS AND OUTCOMES

by

Logan L. Hendricks

A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Computer Science

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ABSTRACT

Coding Bootcamps - Perceptions and Outcomes

by

Logan L. Hendricks, Master of Science
Utah State University, 2023

Major Professor: John Edwards, Ph.D.
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This thesis is focused on gathering, aggregating and analysing data related to software development coding bootcamps. It comprises of three major research initiatives: A coding bootcamp outcomes meta-analysis, a study on perspectives regarding white-label coding bootcamps, and the data analysis of a survey gathering long-term outcomes of coding bootcamp and certificate program graduates.

The first study aggregates graduate outcome data from the three main organizations that review coding bootcamp outcomes: CourseReport.com, SwitchUp.com and the Council on Integrity in Results Reporting (CIRR). The purpose of this meta-review is to establish a baseline dataset which is immediately utilized in my further research. It also acts as a baseline for future research.

The second study is designed to gather opinions on White-label coding bootcamps from currently employed software engineers and software engineering managers. White-label coding bootcamps are a newer business model that has developed in the last decade and are coding bootcamp education providers who provide out of the box bootcamp solutions for existing education institutions. This study proposes that white-label coding bootcamps are a risk for all parties involved in the transaction. Namely, the white-label provider, the partnering education institution, and the students. The data potentially indicated that
the public maintains neutral to positive opinions on the white-label programs when they unaware of the particular business model. However, when an individual becomes aware of the relationship, their opinion demonstrates a negativity to the program.

The third study is focused on gathering long-term outcome data from graduates of coding bootcamps and certificate programs. This gathered data will fill a gap in the currently collected outcome data available to the public. It is also being utilized to determine the potential factors that impact long-term salary growth and software engineering transition for these graduates.
To all of my personal mentors and teachers. Whether they were online, on the job, at a bootcamp or a university
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• Third, my companions who started their similar review of Computer Education Research together with Dr. Edwards.

• Fourth, the seven partner programs that collaborated with me as I began my first study.

• Fifth, the many, many people who put up with my constant commentary about these topics as I refined my ideas on the topic.

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Logan L. Hendricks
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CHAPTER 1
INTRODUCTION

Coding bootcamps are a modern computer science education paradigm that came into popularity in 2011 [1]. In 2020, coding bootcamps educated 24,975 students [2]. This is almost half as many as the 59,565 graduates that were awarded computer science degrees for the 2020-2021 school year [3]. As such, coding bootcamps stand as the foremost competitor to traditional computer science education.

Coding bootcamps are also a largely unregulated education sphere. This is partially due to the lack of empirical research to help empower the next generation of accreditation that will be necessary to support this growing industry.

Some of the people attending these programs come from unprotected and vulnerable demographics. Unless organizations with higher power focus on these institutions, these individuals may be taken advantage of by bad actors in an unregulated industry.

In short, coding bootcamps and codeschools within the US are a topic that deserves academic investigation, and it stands as the main focus of this thesis.

1.1 Main sections of thesis

This thesis is divided into four main sections.

- An overview of the related studies that focus on coding bootcamps
- A brief taxonomy of the coding bootcamps that will be focused on in this study
- Three chapters related to independent research conducted for this thesis
- A summary of the outcomes that should be pursued based on the results of the research

For readers purely interested in the academic research, it is recommended to start at chapter four. Chapters two and three are optional reading to help the reader come up to speed on the topic of coding bootcamps as a whole.
1.2 Overview of research conducted

The research for this thesis was completed in partnership with Dr. John Edwards, and focuses on the following three topics:

- A Meta-review study of the current student outcome data that is publicly available
- A survey study to gather industry perspectives on White-label bootcamps
- A survey study to gather data on the long term outcomes for graduates of coding bootcamp and certificate programs

Each of these studies has been broken into an individual chapter the study methods, results and discussion items are presented. They are the contents for chapters four through six correspondingly.
CHAPTER 2
RELATED WORKS

2.0.1 Overview

Publications regarding coding bootcamps are limited. However, it is worth reviewing some of the current related studies on coding bootcamps. The three main areas of prior research include the following: student success, women in coding bootcamps, and coding bootcamps in higher education.

2.0.2 Student Success

In 2013, Adam Lovallo and Liz Eggleston founded the online website “CourseReport.com”. This website allows students to submit reviews of the coding bootcamp they attend, and their current employment circumstances. Course Report has maintained this data since its inception, and publishes reports on coding bootcamp alumni outcomes and demographics. It published its latest report in 2020 [4].

SwitchUp.com was founded in 2014, following a business model similar to CourseReport.com. It collects student outcome data through a partnership with Burning Glass Technologies, a labor market analysis organization [5]. It has released student demographics and outcomes reports for the 2015, 2016 and 2018 calendar years [6].

The Council on Integrity in Results (CIRR) Reporting began in 2015 to provide a single reporting format that multiple institutions could follow [7]. CIRR attracted over a dozen different coding schools throughout the US to use its standard. Coding schools assemble the reports, and deliver them to CIRR for publication. In total, CIRR possesses over 300 published reports, with 277 from US-based institutions.

There have been four high-quality research publications on “student success”. The first stated that “many of the personal obstacles faced by bootcamp students in their soft-
ware industry trajectories overlap with those they faced in attending and succeeding in bootcamps, such as time, money, impostor syndrome, and location” [8]. A second study indicated that traditional CS graduates and coding bootcamp graduates have viable opportunities in the software industry [9]. A third study reported that graduates from both traditional CS programs and coding bootcamps would have chosen similar education paths if permitted to repeat their education [10]. Lastly, an “assessment test” for reviewing the quality of coding bootcamps was established, based on the student reviews submitted to CourseReport.com [11].

### 2.0.3 Women in coding bootcamps

Among the earliest pieces of data from CourseReport.com was the gender split for participants of coding bootcamps. Since their inception, coding bootcamps have featured a more gender-diverse student body, leading to two separate studies. The first reported that many “women attending bootcamps are career changers that develop an interest in software development too late to major in CS” [12]. The second study indicated that many women did not select computer science in their undergraduate programs, due to a lack of understanding of CS, and that coding bootcamps were an easier entry point for these students [13].

### 2.0.4 Coding bootcamps in higher education

The increase in coding bootcamp success has led researchers to consider how the bootcamp paradigm could feature in higher education settings. One study created a 7 week introductory course for a Computer Science master’s program [14]. A second study reviewed coding bootcamp curricula, evaluating the feasibility of counting it as University Credit toward an Information System degree [15].
3.1 Overview

For the benefit of those unfamiliar with the types of coding bootcamps available on the market, we will provide a history of coding bootcamps, as well as a classification of different types that can be found. The classification will be broken down into three main sections: Delivery Method, Subject Matter, and Type of Institution. It is important to note that these types of classifications are not mutually exclusive. For example, multiple types of delivery methods can be provided at the same institution, or the same subject matter can be delivered in multiple methods. We have broken these down into sub-sections for the benefit of contrasting types between each other.

3.2 History of Coding Bootcamps

In the early 1960’s, computer science emerged as an unprecedented concept and higher education institutions had no programs developed to educate the public. To solve this, many companies developed “in-house” programs to educate their staff and were a precursor to privately-owned Computer Science education programs [16]. In time, these “in-house” programs were often dropped with the formation of high-quality public education for computer scientists.

However, in 2011 [1], the United States saw the reemergence of the 1960’s concept of privately-owned Computer Science education programs. A growing dissatisfaction occurred as many computer scientists believed the core concepts of computer science needed to perform a job could efficiently be taught in a matter of months. This dissatisfaction lead to the development of the very first “Coding Bootcamps” in the United States, allowing students to save both time and money while still gaining the crucial skills needed for successful
The course instruction did not require prerequisites and allowed individuals from all walks of life to apply for their programs. Initially, all of these programs were delivered through in-person, full-time instruction and targeted skills in the web application development sphere [4].

Students at one of these coding bootcamps could expect to receive education in programming basics such as: variables, loops, conditionals, functions, classes, API’s, RESTful interfaces, and web and client interactions. Coursework focused on projects and team-based activities that facilitated students to learn these software concepts [1].

3.3 What a Bootcamp is Not

In order to understand what a coding bootcamp is, it is helpful to briefly discuss what a bootcamp isn’t. Bootcamp programs were originally not taught through universities, nor could they be used for credits towards a traditional University degree. This has changed in recent years, but only in very particular cases [15].

Coding bootcamps have also historically not been included in the same category of self-teaching materials that are prevalent. While there are some parallels to self-teaching materials, due to the different financial models of these programs, we would not consider them similar in nature.

In the last few years, a concept known as Massive Open Online Courses (MOOC) has emerged as a free way for individuals to train and learn new skills in many different fields, including software engineering [17]. These are typically not considered coding bootcamps, as their nature is similar to the free education methods mentioned above.

Lastly, in the UK, there is a concept known as digital apprenticeships [18]. These are internship-like concepts where participants are expected to finish their education while also working for an institution. While this concept is mentioned as being in the UK, there may also be similar programs in other nations. While coding bootcamps may share similarities in concepts with these programs, they are closer to what we would consider a work-study or an apprenticeship.
3.4 Taxonomy

3.4.1 Delivery Method

A taxonomy of delivery methods has been provided by multiple sources. For our study, CourseraReport.com has a notable taxonomy [19] that we will use as part of our delivery method classification. CourseReport identifies four different delivery methods: Full-time In-person, Full-time Remote, Self-paced Online, and Part-time Career-focused.

Full-Time In-person

When introduced to the concept of coding bootcamps, Full-time In-person is the delivery method that most people encounter. Depending on the bootcamp, students start their learning in a group of 15-30 students called a cohort. Each cohort attends a physical class for 8-10 hours a day for 12-16 weeks. The average student will spend a minimum of 40 hours per week learning introductory programming material [19]. Some of the more aggressive programs have students spending upwards of 80 hours per week between in-class instruction and coursework. The classes are taught in privately-owned commercial buildings that are either owned or rented by the bootcamp administrators. Students are required to come to the physical location so as to participate in instruction and be involved in team-based projects that are accomplished on-site with the other students in the cohort.

Full-Time Remote

Full-time remote programs share many of the same characteristics as Full-time In-person programs. The main difference lies in that students can attend and be involved in team-based projects through remote means such as Zoom or Google Meet. Coursework is managed through remote tools such as Canvas [19].

Self-Paced Online

Students enrolled in self-paced online programs will have access to a centralized portal containing all their educational materials, such as videos, assigned readings, slides, and
projects. Because of the asynchronous nature of their learning, these students may not participate in team-based projects, which are more commonly found in other programs. [19].

**Part-Time Career-Focused**

The Part-time Career-focused delivery method shares many similarities with the Full-time In-person delivery method. Students are still required to come to a physical location and participate in both individual and team-based projects. The difference in this delivery method is the amount of time students will expect to give on a weekly basis. “Classes will be anywhere from 6-15 hours per week, with additional coursework being another 10-15 hours per week.” [19]. While full-time students may finish their coding bootcamp in 12-16 weeks, part-time students will expect to take 6-9 months to finish their certification [19].

These programs are typically taught early in the morning or late in the evening to benefit individuals who are working full-time in a career or participating in other forms of education, such as a university degree or high school diploma.

### 3.4.2 Subject Matter

Initial coding bootcamps targeted the lack of web application developers in the US market. [20] They almost exclusively taught concepts and technologies related to web application development. As coding bootcamps became more popular in the United States, the number of subjects taught expanded. The full list of engineering subjects includes Fontend, Backend, Full Stack, Mobile, DevOps, and Quality Assurance Engineering. Tangential engineering subjects such as data science, cybersecurity, and UX design have emerged [21].

For the purpose of this paper, we will provide high-level details of the subject matter taught for all of the engineering-focused bootcamps.

**Full Stack**

In Web Application Software Engineering, engineers have created separate domains of knowledge referred to as frontend and backend engineering. The combination of these two
domains together refers to Full-Stack Engineering. We will provide a brief breakdown of the technologies used in each domain below [22].

**Backend**

Twenty years ago, backend engineering would have simply been referred to as web engineering. It focused on the server-side operations involved in web applications. However, as web technologies have matured and become more robust, engineers are unable to keep on top of all of the technologies related to web programming. The growing list of technologies currently includes RESTful api interactions, language-specific web libraries, Micro-Service vs Monolithic Architecture, Database administration and interactions, Event queue and asynchronous architecture, and lastly language-specific syntax. Backend Bootcamps focus on these specific skills or a subset of them. The important distinguishing factor between backend bootcamps will be the language and framework it is focused on. Some examples include Express/Node, Rails/Ruby, Django/Python, Spring/Java [22].

**Frontend**

In 2010, a brand new web technology known as AngularJS was released to the market [23]. It provided a single Javascript framework that allowed engineers to easily create single-page applications using Javascript. The user would receive a single Javascript packet from a web server and would run the majority of the website content in their own browser. This technology simultaneously simplified and complicated the writing of web applications. This added complexity justified the extra education being taught specifically for a Frontend Bootcamp. As such, Frontend bootcamps teach the fundamentals of programming while also targeting one of these modern frameworks. Examples of current frameworks being taught are ReactJS, Angular, and VueJS [22].

**Mobile**

June 29th, 2007 marked the release of the Iphone 1. This release created a new era of mobile applications based on touchscreen technology. Since that point, the entire industry
of mobile application development has only expanded. Languages like Swift and Kotlin have come into existence, as well as Toolchains to simplify common interactions [24].

In recent years, brand new technologies such as React Native and Ionic have even made it possible to use Frontend technologies to create mobile native applications [25].

The combination of all of these technologies has created a myriad of coding bootcamps that target one of these technology stacks. It is impossible to truly cover all of the different variations in platforms for mobile development, so coding bootcamps will target a single stack, and empower their students to understand that stack along with programming fundamentals.

Quality Assurance

Historically, quality assurance has been a dedicated manual process performed by large numbers of Quality Assurance Analysts [26]. The ability to scale these endeavors has always been primarily a process of either training your analysts to be more efficient or hiring more of them. This was the case for both desktop-based applications and web-based applications.

With the onset of Selenium Webdriver on April 30, 2022 [27], engineers had the ability to programmatically create test suites to ensure the quality of specific web applications. As coding bootcamps target web application engineering positions, it naturally makes sense that they also target quality assurance processes related to that same field. Students at Quality Assurance Coding bootcamps are taught the fundamentals of quality assurance, basic HTML, CSS, and Javascript [28]. They frequently will pick a quality assurance framework such as Jasmine, Protractor, Cucumber, or Cypress and the corresponding language that the framework supports.

3.4.3 Institution Type

There are four major types of institutions currently involved in the coding bootcamp education space. Originally all of these programs were for-profit institutions, but they have now expanded to also include: non-profit institutions, technical colleges, higher-level universities, and colleges.
For-Profit Institutions

As the original contributor to the coding bootcamps, for-profit institutions make up the majority of the space. These institutions are privately held, do not have government funding, and demonstrate diversity through the curriculum taught or community connections. It is very common for these organizations to make connections with local businesses in order to establish internships for their graduating classes. Some programs will start a new cohort every week, others will only do three to four cohorts a year.

Many of these programs now have an application and interview process for applicants. Some boast a very low acceptance rate, as they will only take the best students available for each cohort. This enhances the prestige of the coding bootcamp and ensures that they have a high graduation rate for each cohort of students. The high graduation rate in turn attracts a greater number of applicants providing the bootcamp with a large pool of potential students from which to select.

Non-Profit Institutions

Many of the non-profit institutions on the market are attempting to target and assist a particular demographic that is unlikely to move into technology. For example, Ada Developers Academy is a non-profit coding bootcamp that are only for women in financial need [29]. The bootcamp is offered for free for participants in the program. Other non-profits will offer tuition at a reduced or economic cost [30]. Some of these programs have nuances in comparison to their for-profit counterparts, but for the most part operate similarly.

Technical Colleges

In the state of Utah many of the technical colleges offer software engineering certificate programs alongside their more traditional programs such as welding, nursing, or automotive technology classroom [31]. The advantage of these programs is that they are backed by public funding, and students can benefit from government grants or federal aid loans to pay for their education. In speaking with advisors in these programs, they do not consider
themselves “coding bootcamps”, but rather a software engineering certificate program. For the purposes of our taxonomy, they share similar attributes that make them viable for our study.

Many of the programs in the state of Utah are also designed to be a high school vocational credit for students. These programs will have a wide range of ages starting as young as sixteen [32].

**Universities and Colleges**

Coding bootcamps have been in practice in the US for over a decade now and market factors have currently indicated that they are not leaving the educational space. This is most evidenced by the fact that universities and colleges are now offering coding bootcamp programs alongside their traditional four-year degree programs [19].

More and more universities are offering either coding bootcamp opportunities [19] or condensed Master’s Degree programs that provide a similar education to a standard coding bootcamp [33]. For example, the University of Utah is offering a Masters of Software Development program that requires an undergraduate degree. However, the undergraduate degree can be from any background. It essentially allows students to get an extended crash course in computer science concepts.
CHAPTER 4
META-REVIEW OF CODING BOOTCAMP OUTCOMES

4.1 Introduction

Coding bootcamps are non-traditional in nature. As such, they have required non-traditional metrics to measure their success. Many accreditation bodies in the US focus on measuring education success through the quality of specific curriculum being provided to those students.

For example, ABET accreditation in the US requires that programs to meet objectives using measurable assessment practices. Until recently, the process stipulated that programs offer certain courses in Calculus, Discrete Mathematics, Data Structures, and a series of courses in advanced computing [34]. ABET has now established periodic audits and assessments for accredited programs.

Many code schools choose to provide curriculum that is contrary to that status quo as they perceive it as too bulky and unwieldy for modern software engineers. They contend that students can graduate with a much smaller curriculum set and still be successful engineers.

Thus coding bootcamp success is typically measured with student outcomes. Multiple organizations were formed for the sole purpose of gathering, reviewing and publishing student outcome data for coding bootcamps.

As such, since 2014, there have been a handful of organizations all simultaneously publishing student outcome data. However, there has yet to be a meta-report of this outcome data where all of the results are reviewed simultaneously. The chapter is the results of the completed meta-review that Dr. Edwards and I completed together.
4.2 Institutions that review coding bootcamps

There are three major players in coding bootcamp outcomes reporting. Each of them format their data in different ways. The following is a brief review of those three programs.

4.2.1 Course Report

In 2013, Adam Lovallo and Liz Eggleston founded the online website “CourseReport.com”. The purpose of the website was for students to be able to submit reviews of the coding bootcamp they attended, as well as their current employment circumstances. Course Report has kept this data since their inception and publish reports of coding bootcamp alumni outcomes and demographics. Their latest report was published in 2021 [35].

The report format for CourseReport has been through online publications and PDF distribution. They are yet to publish their 2021 online report, and only have a PDF report of their data. This is likely due to the rise of COVID and it’s impact on the education market. Their online reports from 2017-2020 provided very consistent analysis and data presentation. From 2014-2016 the data provided was not as encompassing as the later years, but some of the data can be gleaned for our study.

In the review of the outcomes institutions, it was shown that Course Report data is accurate. The only caveat to this are the occasions where aggregate reports presented accurate data in misrepresenting manners. For example, there are cases of presenting aggregate data of multiple years on a single year report, or presenting a subset of data in a comparison to a non subset of data.

4.2.2 Switch Up

SwitchUp partners with Burning Glass Technologies (also known as Lightcast) for it’s report. Burning Glass Technologies is a labor market analyst company. As such, it provides data about the labor market to SwitchUp, which they then use to rank the current code schools on the market. In 2017 they partnered with the Council on Integrity in Results Reporting (CIRR) as part of an initiative to create more transparency in the code school market [36].
SwitchUp’s goal is described as follows:

Since 2014, SwitchUp has been helping students reach their career goals by connecting them to highly-rated tech bootcamps with strong outcomes. We believe it’s essential for aspiring students to have unbiased, reliable information to utilize when deciding on the right bootcamp for their future. SwitchUp allows students to easily compare their options for tech bootcamps in coding, data science, web design, and more. [5]

Their rankings have been made public each year, but their outcome data has been kept more private. They published outcome data for the 2015 and 2016, and 2018 student study years.

4.2.3 Council on Integrity in Results Reporting

The Council on Integrity in Results (CIRR) Reporting was established as an initiative to provide a single reporting format that multiple institutions could follow. One of the lead founders of CIRR, Michael Kaiser-Nyman, agreed to interview with our research team. He described the reporting format in this way.

“The CIRR outcomes reporting standard was established to provide a way for students to understand a school’s outcomes and be able to make an ”apples-to-apples” comparison among them. When schools define their own standards, they can manipulate the numbers to make themselves look better, and students can’t make accurate comparisons among them.” [37].

in 2015, CIRR created it’s initial draft of the reporting standard. They describe the reporting format this way:

CIRR provides a standardized system for measuring and reporting student outcomes that all of its schools use. The measurement standards are straightforward
for schools to implement; and the reporting standards are both simple for students to understand, and complete in that they account for 100% of enrolled students. [7]

With this standard in place, they attracted over a dozen different code schools throughout the US to use the standard. Reports were put together by the code school, and provided to CIRR for publishing. Schools were encouraged to have their outcome data audited by a third party institution to confirm its validity. The reports are currently published as a series of PDF reports. Each report represents the outcome data for a single institution for either the first half or second half of the year. In total, CIRR has just over 300 published reports, with 277 of those reports being from US based institutions.

4.3 Data Extraction

The outcome data of the above programs was publicly available. The method of testing was the process of scraping the data from each individual format. Below is a list of the methods used in this process based on each provider.

- CIRR - PDF’s downloaded from organization website. Data scraped from PDF using programmatic means. Data manually reviewed and adjusted after scraping accomplished
- CourseReport - Outcome data is pre-aggregated on a yearly basis. Organization reports opened in a web browser and manually extracted into a CSV
- SwitchUp - 2018 report opened and information manually extracted into a CSV. The 2015 and 2016 reports required using “The Wayback Machine” [38].

The main data points that can be reviewed between all three organizations are as follows.

- Median and Average Salary Data
- Employment rate of graduates
• Percentage of employed graduates who work in software related fields

Analysis comprised of taking these three main pieces of data and comparing the results between the different organizations. We have broken down the results in the section below and will review the data for each of the data pieces independently.

It would be admirable to compare the results of this meta-review to similar outcome data from computer science graduates of traditional universities. However, such data is not immediately available for review. It would be an exceptional next step for future research.

4.4 Results

4.4.1 Salary Data

All three programs reported average and median salary data of the graduates who participated in the data collection process. Between the two, the average salary data (Figure 4.1) presented by each program provided the more enlightening results. Each program had varied amounts of graduates within each year of study, and is not reported for this and following diagrams.

The comparison between the different programs are very interesting. Each program shows variance between the salaries of each year. Independently, it could cause one to hypothesize as to the highs and lows in the dataset. However, when combined, we note that where one dataset was publishing a high point, the other was publishing a low point.

The SwitchUp data only provides data for 2015, 2016 and 2018 in this category. In the context of the other two datasets, we present it as a potential low water mark for the true data in the market. It sits between $2,000 - $5,000 less than the other data datasets for the years in which it has data.

Figure 4.2 shows the linear distribution of averaging the average data between all of the programs. The data is less volatile than the individual graphs, and tends to be the least extreme when we have corresponding data from all three programs.
Fig. 4.1: Average Salary from outcomes programs
Grouped Bar charge displaying the average salary of all three outcomes programs from
2014 to 2021. CIRR, Switchup and CourseReport

We see a dip in salary in 2015, which slowly rises in the later years. The initial spike
in the first year could be explained by only having Course Report as the sole data source.
It could also be that their reporting process became more accurate as they progressed in
later years.

There are some extra insights that can be gained from the CIRR dataset. As it provided
a greater depth of data to be explored on an individual program basis. The CIRR dataset
is broken down into different PDF’s of individual program data. Each program provided
a mean salary of the graduates that participated in their program for that calendar year.
They also provided the location of the coding bootcamp and the graduates. As such, we
can get more enlightening results such as figure 4.3 and figure 4.4

Figure 4.3 provides a box and whisker plot of the reported median salary of each
program during the year it participated in CIRR. We note that top node of each plot shows
a linear trend as the top level salaries of graduates continue to go up while the median
salary stays fairly consistent.

A potential hypothesis for this is that overall top level salaries have increased through
Fig. 4.2: Combined Average from outcomes programs
Bar chart displaying the combined average salary of all three outcomes programs from 2014 to 2021.

the United States for software engineers. Another interpretation may be that since CIRR is self-reported data, that the programs involved in later years were based in geographic regions that had higher salary bands. Further analysis could be conducted to review this trend in greater detail.

Figure 4.4 is a breakdown of the salary data for each individual program by the US state in which it resides. A single column on the far right demonstrates all of the programs who self-report as being online or remote programs. The majority of the different geographic regions have a similar spread of salary data except for some outliers. Utah and Indiana only report data on the bottom end of the spectrum. California, New York, Illinois and Online programs report significantly higher incomes than the rest of the group. The Utah and Indiana distributions have a very small set of responses, and could be an outlier. The higher salary options within the higher density locations such as New York, California and Illinois tracks with general trends in those locations.
Fig. 4.3: CIRR Median salaries of programs, distributed by year
A box and whisker plot of median salaries of graduates from CIRR related programs. The salaries are distributed by calendar year in which they graduated and the salary reported after 180 days of graduation.

4.4.2 Employment Rate

The second major piece of data within all three datasets is the employment rate of graduates. This is separate from the percentage of individuals employed in software positions, and is a separate distribution that will be discussed below. This is solely focused on the employment rate that graduates reported post-bootcamp, whether in software or not.

Figure 4.5 shows the individual employment rates reported by each program. Course Report has the largest selection of data, with results for each year except 2021. It shows a great degree of volatility. This may be due to the self-selecting nature of the survey distributed by Course Report. CIRR’s reports are more stable from year to year. This may be due to a more comprehensive reporting method. Switch UP only had usable data for the 2018 calendar year for this category. Tt serves as the anchor of the three datasets. All three programs are in very close harmony for the 2018 dataset, with a variance of only 5%
Fig. 4.4: CIRR Median salaries of programs, distributed by state
A box and whisker plot of median salaries of graduates from CIRR related programs. The salaries are distributed by the US state the coding bootcamp resided in.

between the three of them.

Figure 4.6 displays a bar chart of the combined average of all three programs. The years 2014 and 2020 are the outliers for in the averaged data. For the years 2015-2019 and again in 2021, the reported data seems stable. 2014 is the very first reporting year, and may be an outlier due to less accurate data collection. 2020 could reflect the difficulty of COVID on the employment market in general.

The average of these averages is an 82.63% employment rate. This is relatively close to the 79% presented by Course Report when averaging it’s own data in the 2020 outcomes report. [39].

4.4.3 Percentage employed in Software positions

The final category of data that can be reviewed from all three programs is the overall reporting of graduates employed in Software positions. This is not an indication of how many graduates received positions in general. It is only the graduates who received positions specifically within the software or IT fields.

Figure 4.7 is displays a grouped bar chart of the reported average from each program.
Fig. 4.5: Employment Percentage reported by programs
A grouped bar chart demonstrating the employment percentage reported by CIRR, Course Report and SwitchUP. It displays the variance in employment success between each program and calendar year.

They each had different degrees of specificity when reporting this data. We have rounded to the nearest whole integer for consistency among all of the different reporting methods. Course Report is lacking data for the 2021 calendar year, CIRR is lacking data for the 2014 and 2015 calendar years, and SwitchUp only had available data for the 2014, 2015 and 2018 calendar years.

The data presented by CourseReport and SwitchUp is fairly inconsistent, (with a prime example being the 2017 and 2020 calendar years). However, the CIRR dataset maintains a fairly consistent trend.

The variance in answers between the three programs shows the benefit of having a meta-review of all three programs in a single review. Figure 4.8 shows the average software employment rate for graduates of coding bootcamps. The min and max on this graph are 63% and 83%, which is more narrow degree of variance when compared to the min and max 47% and 85% on the grouped bar chart.
The CIRR dataset provides extra insight on the software employment rate for graduates. Graduates had to indicate at which point they received their position. Ranked according to under 90 days or under 180 days of searching. Figure 4.9 plots the percentages from 2016 to 2021 according to those two baselines. There is a 19.46% difference between the amount of graduates who received a software engineering position between the 90 day and 180 day mark of graduation. This shows that many graduates are acquiring their first position within the 3-6 month mark post-graduation. This disparity may potentially be part of the variance in data from CourseReport and SwitchUp. Graduates may have reported their circumstances during any of these periods.

### 4.5 Discussion

This particular article was started as an interest to verify the data being presented by the multiple different outcome organizations. The organizations publishing this data have a
vested interest in the overall benefit of code schools as a whole. The business model of each institution varies, with CIRR being entirely not for profit. However, the programs that are for-profit businesses largely receive their income through ad revenue for coding bootcamps.

On top of this, these institutions are not beholden to the same policies and practices in place for academic researchers when doing research involving human subjects.

As such, as researchers, we have been skeptical that the data presented by these institutions is entirely accurate, or at least has been presented in a way that does not skew the data in favor of the interests of the parties.

For this very reason, it behooved us as researchers to take data from multiple organizations, and compare them together to see if the one verified the other in terms of its accuracy.

In general, we have been pleasantly surprised to find that while the data collected by
Fig. 4.8: Combined Average software employment percentage from outcomes programs
Bar chart displaying the combined software employment percentage of all three outcomes
programs from 2014 to 2021.

these organizations had minor variations, they were mostly in harmony. We can identify
some cases where data has been presented to favor code schools through aggregations and
subsets. However, the full dataset being presented is accurate to the data being collected.
Our esteem for these institutions has increased and not decreased.

Our hope is that by performing this meta-review, it can act as a new benchmark for
continued outcomes research going forward.
Fig. 4.9: CIRR - Percentage of graduates employed in software engineering positions
This line chart shows the percentage of graduates employed in software engineering positions from the CIRR dataset. Two lines demonstrate employment rates at the 90 days after bootcamp and 180 days after bootcamp marks.
CHAPTER 5
WHITE-LABEL BOOTCAMPS - PERSPECTIVES

5.1 Introduction

Since 2011, over 97 \cite{4} coding bootcamps have been formed in the United States. This growth has led to the development of what the industry terms “white-label” bootcamps. A white-label bootcamp is an education provider that develops software engineering bootcamp courses, delivered to students through partner organizations (such as universities). This business model has long term consequences for the white-label provider, its partner organization, and the students involved in its program. White-label providers and partner organizations risk jeopardizing brand loyalty and industry trust; their students risk an education different from what they expected, resulting in compromised career opportunities post-graduation.

We will first review current research on coding bootcamps, describe white-label software and bootcamps, and report our results from a study wherein we reviewed industry perspectives on the educational quality for white-label bootcamps in the United States.

5.2 White-label bootcamps

5.2.1 What is a white-label product

White-label is “a product or service where the provider purchases a fully supported product from another source, then applies its own brand and identity to it” \cite{40}. An example many consumers in the United States interact with is “store brand” products.

In Wal-Mart, customers can purchase “Great Value” brand mustard, mayonnaise, ketchup, salt, pepper, etc. Great Value is a brand exclusive to Wal-Mart. At Target, consumers will find similar products with the “Market Pantry” brand. This also applies to “Kroger”, “Signature Select”, and other store brands. Wal-Mart, Target, Albertson’s,
Smith’s, and other grocery stores are food vendors, not food producers. In this arrangement, Great Value is not sold by other vendors because it is a product branded specifically for Wal-Mart. The store partners with a food producer to provide a generic product, and the product is branded to its specific vendor. It is not uncommon for food producers to partner with multiple vendors, selling an identical product with a figurative “white-label”, to which each store can attach its brand [41].

5.2.2 What is white-label software

While the term “white-label” originates from a physical product, the concept has transferred into software engineering. It refers to third-party software that a company can brand as its own [42]. Large banking institutions, such as Wells Fargo and Chase Bank, can afford a team of software engineers constructing a mobile banking solution. However, this engineering burden exceeds the financial constraints that smaller institutions can expend. Their domain is financial management and lending, not developing mobile applications.

Their solution comes in the form of “white-label” software. Third-party companies compile a general set of features that a financial institution would require. A team of engineers then constructs a generic banking app. The bank applies its unique color scheme, branding, logos, etc. This creates the illusion that the financial institution built the app when, in reality, it did not.

5.2.3 White-label bootcamps

White-label bootcamps apply the white-label software model to the education sphere. A third-party company constructs an online platform, complete with curriculum, grading, tutoring, teachers, financial aid, and post-graduation assistance. They then partner with multiple institutions, who market the platform, provide a branded subdomain to enroll new students, and co-endorse certificates provided to graduates. Since the institution did not create the platform, it becomes a “vendor” of the third-party company’s product.

EdX (formerly Trilogy Education Services) and FullStack Academy are the two main companies that provide white-label coding bootcamps in the United States. They target
higher educational institutions in particular. According to EdX’s website (when they were still marketed as Trilogy Education Services), they offer the following business model:

Trilogy Education partners with universities to offer programs in Web Development, Data Analytics, UX/UI Design, Cybersecurity, FinTech, Digital Marketing, Technology Project Management, and Product Management. Our platform combines a market-driven curriculum, robust career services, and a multinational community of universities, instructors, and employers to prepare adult learners for careers in the digital economy [43].

Both EdX and Fullstack Academy have partnered with over thirty United States universities. They increase their list of partners each year.

5.3 Industry perspectives on white-label offerings

Our research questions are:

1. Do industry workers perceive bootcamp offerings at higher-ranked universities as superior to offerings at lower-ranked universities, even when the white-label product is the same?

2. Do industry workers perceive bootcamp offerings at universities as superior to offerings at traditional coding bootcamps?

The terms higher-ranked and lower-ranked refer to rankings issued by Forbes to US universities in 2022 [44].

5.4 Methods

We constructed a 26 question survey to be answered voluntarily by software engineers and software engineering managers.

Our initial questions let participants disclose their personal and employer’s biases toward hiring graduates from coding bootcamps. We also ask participants how the following
items influence their hiring decisions: applicant’s education level, applicant’s education focus, technical assessment interviews, and team fit interviews. This data provides a baseline for later data in the study.

Our next six questions then focus on universities that have partnered with EdX or Fullstack to provide white-label coding bootcamps. We ask participants to consider two hypothetical job applicants. Both applicants have the same professional background; however, the applicants graduated from different universities. Participants provide their opinions on which university offers a superior education.

The survey does not indicate that both universities in question partner with the same white-label company to provide the same coding bootcamp offerings. Here is an example question:

Please choose which of the following institutions provides the best education: Colorado State University Coding Bootcamp VS Columbia University Coding Bootcamp.

1. Institution A
2. Institution B
3. Equal Education Value

In this question, both Colorado State and Columbia offer an EdX coding bootcamp.

After these initial six questions, a second set of six questions ask participants to compare private coding bootcamps to university-partnered coding bootcamps. This question format is identical to the one displayed above, but changes the institution types presented. The first two questions compare white-label bootcamp offerings to bootcamps from their partnered universities—for example, comparing EdX’s bootcamp to the same EdX bootcamp offered through Colorado State University. The remaining four questions compare top-ranked private bootcamps throughout the nation to university-partnered bootcamps in the same region. The survey purposely omits that all named universities partner with EdX or Fullstack to provide white-label bootcamp programs.
After comparing education options, we grant participants two opportunities to provide insights into why they made certain decisions: when comparing universities to other universities, and when comparing universities to private bootcamps.

The remaining questions gather optional demographic data from the participants, such as age, gender, ethnicity, and current employment titles.

In accordance with IRB protocol, we disseminated the questionnaire over multiple social networks: Facebook, LinkedIn, and Reddit. We also provided it in multiple Slack and Discord communities featuring software engineers and software engineering managers. In addition to social media networks, we requested partnerships with a number of companies throughout the state of Utah. Our partners agreed to send the survey link to engineers and engineering managers within their organizations. In total, 65 participants completed the full survey, while an additional 27 participants began, but dropped out midway through the survey.

5.5 Study Results

To interpret the participant preferences, we compiled responses into two simple histograms, by separating university comparison responses from bootcamp comparison responses (figures 5.1 and 5.2). We then created a simple metric ranging from -1 to 1, with each end of the spectrum representing a preference for one institution over another.

Using figure 5.2 as an example: if the participant responded entirely in favor of coding bootcamps, their score would be a -1. If their responses were instead in favor of universities, the computed score would be 1. A score of 0 represents a neutral response. We aggregated all six questions in a comparison set to compute the participant’s final score. Neutrality was factored in two ways: participants either favored neutral answers, or they provided equal responses favoring both camps, aggregating into a neutral score. These diagrams illustrate the overall spread of responses. The following sections dive deeper into insights gained through this method.
Fig. 5.1: University to university comparisons
Computed ranking of participant scores when they were comparing different university bootcamp offerings. With 0 being a neutral answer, positive numbers being in favor of higher-ranked universities and negative numbers being in favor of lower-ranked universities

5.5.1 Lack of strong opinion
The most consistent response from participants in both sets of comparisons was that the educational offerings were equal. For comparisons between universities, 69% of responses were neutral; for bootcamp-to-university comparisons, 64% were neutral.

We gave participants a free-form text field to provide more insight into their education comparisons. Here are some of the free-form responses that best represented the most common responses for neutral answers:

- “All bootcamps are the same to me.”
Fig. 5.2: University to bootcamp comparisons
Computed ranking of participant scores when they were comparing university to bootcamp offerings. With 0 being a neutral answer, positive numbers being in favor of university offerings and negative numbers being in favor of bootcamp offerings

- “I’m unfamiliar with most of the programs and their curriculum/standards so I assessed them as equal.”
- “It comes down to the technical assessment. A great program can’t make up for an unserious student.”
- “Individual contributor output is a measure of quality, not the name of the program.”
- “I think bootcamps are useless and schools are only taking money away from students.”

As a whole, these answers break down into three camps: unfamiliarity with the education options presented, valuing individual skill sets over education choices, and a general
disdain for computer science education. This last item manifested as either a disdain for university education, or a disdain for bootcamp education. In rare cases, as in the above example, it displayed frustration with computer science education as a whole.

Figure 5.3 provides additional insights into education institution neutrality. We asked participants to rank how useful knowing an applicant’s education institution was in the hiring process. Participants gave answers on a scale ranging from Extremely Useless to Extremely Useful. The results are varied, indicating what a very small portion of the sampled population feels is useful for hiring practices. The concentration of responses between Neutral and Extremely Useless may indicate that hiring managers do not value the education institution when hiring. This metric does not indicate how companies and organizations feel; we collected no data on that topic.

Fig. 5.3: Usefulness of education institution to assist hiring
The participant responses regarding the usefulness of knowing the participants education institution when hiring on a scale from: Extremely Useless, Somewhat Useless, Neither Useful or Useless, Somewhat Useful and Extremely Useful.
5.5.2 Higher ranked universities

While neutrality was the most common response, many responses provided opinions. Participants were less opinionated on the university comparisons; only 31% of responses provided an opinion. However, the opinions provided were largely in favor of higher-ranked universities. While figure 5.1 demonstrates the spread of responses on university-to-university comparisons, figure 5.4 focuses on whether a participant was in favor of the higher-ranked universities or lower-ranked universities. 80% of university comparison opinions favored higher-ranked universities. For every participant who favored a lower-ranked university, there were four that favored higher-ranked universities.

![Fig. 5.4: Low-ranked vs high-ranked university comparison](image)

A filtered view of the university comparisons. This focused view only displays the non-neutral response data for the lower-ranked to higher-ranked comparisons.
As mentioned, we gave participants a free-form text field to provide greater insight into their comparisons. Here are some free-form responses that best illustrate why participants weighed one way or the other:

- “Mostly equal except for universities known to have strong tech departments.”
- “University programs equal unless I had a VERY high opinion of school.”
- “Preference to institutions that have a prestige reputation and an assumption to delivery of a high quality program.”

This data suggests that an individual attending a white-label bootcamp at a higher-ranked university has a greater chance for employment than an individual from a lower-ranked university. However, as explained earlier, both students would have received identical instruction from the white-label bootcamp provider.

5.5.3 Universities to bootcamps

The data spread in figure 5.2 demonstrates that there are varied opinions regarding coding bootcamps compared to university offerings. Outside of neutral responses, we gain some interesting insights.

First, participants offered more opinions when comparing universities to coding bootcamps. 36% of our participants provided opinions in this set of questions, compared to 31% providing opinions when comparing two universities. People may be more opinionated on the bootcamp-to-university comparison than when comparing universities.

The answers provided also featured a wider spread of opinions than when comparing universities to universities. However, as figure 5.5 demonstrates, 67% of the responses favored university bootcamps. Many participants indicated they were unfamiliar with the programs presented; they were likely unaware that university programs are white-label programs. We can infer that responses favoring the universities were due to prestige or the general feeling of universities. Clarifying responses offered by participants reinforce this hypothesis.
A filtered view of the university to bootcamp comparisons. This focused view only displays the non-neutral response data for university to bootcamp comparisons.

The comments provided by participants in this section can be broken down into two categories: those that favored universities, and those that favored bootcamps.

Pro-university responses:

- “The university ones sound more reputable I guess? I’ll be honest I don’t filter resumes (HR does) and if the candidate passes the interview rounds I don’t care about the education.”

- “Assumption that university programs would be more rigorous and less profit motivated to graduate low performers.”
• “I generally trust universities’ reputations more than startups. Plenty of bootcamps are flashes in the pan but universities have long-term reputations to uphold.”

• “Devs from non University boot camps can be less prepared.”

These responses reflect a general trust in universities providing higher quality education than their bootcamp equivalents. We can hypothesize that this stems from the maturity of these institutions, and their general prevalence in the United States. The comment noting long-term reputations indicates that the participant believes coding bootcamps have a short-term lifespan.

Sampling of pro-bootcamp responses

• “Coding bootcamps are more modern in their structures.”

• “Because I have more experience with coding bootcamps and have seen high output results from them.”

• “I gave an edge to flatiron because I once poached an instructor from there and he was quite good.”

• “If I had personal experience with a program or boot camp that would play into my decision, whether it be good or bad. If I didn’t have any experience with either program or boot camp they were equal.”

All participants favoring coding bootcamps seem to have personal experience, which either increases their esteem of bootcamps or decreases their esteem of universities. Some responses mention specific exceptional co-workers, or personal experience with quality graduates from a particular program. We can also infer that some responses stem from a negative experience with universities. “Coding bootcamps are more modern” implies that traditional universities are less modern.

Each coding bootcamp selected for this study ranked among the top institutions on CourseReport.com. A follow up study could compare the ranked programs in this study to the overall rankings of programs on that site.
When comparing bootcamps to university programs, most responses appear to favor bootcamp offerings. Some outlier individuals were aware of the white-label nature of university offerings, which we cover in the next section. Other than these, the general trend favoring bootcamps appears to stem from personal experiences moving the individual away from mainstream views of university offerings.

5.5.4 White-label to host university

Our second set of questions asked participants to compare university bootcamp offerings to other bootcamp offerings. Two particular questions paired a university bootcamp offering against its white-label offering. Figure 6 displays the spread of non-neutral answers given by participants.

For EdX, we used the University of New Mexico as the comparison university. There were several institutions we could compare against, but chose the university of New Mexico, as it is one of the lowest-ranked universities on the list of hosts. Even as a low-ranked university, The University of New Mexico received 80% of votes where an opinion was cast.

Votes comparing Fullstack Academy against Utah State University were more split. Fullstack Academy received 54% of non-neutral votes, compared with 46% of votes for Utah State University. Utah State University was likewise selected as a host with a lower university ranking.

Both Fullstack Academy and EdX are white-label bootcamp providers. Both partner with universities across the United States. We assume that if participants knew that a bootcamp offering was provided by a white-label partner, they would rank the two programs as equal. A one proportion z test for EdX yields p = 0.05 (two-tailed), but Fullstack is not significant. Without additional data, we ascribe the difference between Fullstack and EdX to chance.

There are a few comments worth highlighting when comparing white-label offerings to their university hosts. These comments may reveal potential feelings individuals may experience when informed about these white-label bootcamps.
Many university bootcamps are actually provided by a small set of private companies, who license the university’s name. Few of them are uniquely exclusive or particularly well-regarded so it doesn’t really make a difference what the name of the boot camp is.”

“Almost all the university programs are the exact same via Edx and are worse quality.”

“They are all typically ran by contracted out companies to slap the university brand to the price sticker.”

“I know most University programs are run by Edx/2U who have terrible outcomes and “hire” their graduates to teach.”
• “Many university program partner with 2U education, a “white label” bootcamp that allows universities to offer an expensive coding bootcamp taught by somewhat qualified people. It’s all the same contents in a different box.”

Of the total responses, 7% of participant comments provided direct insights regarding white-label relationships. None of the comments about white-label programs were positive; they range from observational to scathing. These responses may indicate that as the public becomes aware of these programs, their overall opinion of them will decrease. However, without clearer data, we cannot draw a definitive conclusion.

5.6 Conclusion

Our results indicate that white-label programs potentially have short-term benefits for all parties involved, with long-term consequences. The data indicates that participants favored university programs over code bootcamp programs. They also favored higher-ranked universities over lower-ranked universities. Given this public perception, there are likely short-term benefits for both students and white-label providers when high-ranked universities partner with these programs.

However, our data indicates that as participants become aware of the white-label model, their overall opinion of organizations involved in these programs could decrease. These programs may become a risk for the white-label provider, affiliated universities, and program graduates.

Universities participating in white-label programs potentially risk compromising their public image. Code bootcamps which develop a white-label program risk developing a public image of subpar education. Lastly, students risk connecting their long-term career outcomes with the brand image of these programs.
CHAPTER 6
LONG TERM GRADUATE OUTCOMES OF CODING BOOTCAMPS

6.1 Introduction

Multiple related organizations measure student success through outcome data. Outcome data varies from organization to organization, but generally focuses on collecting information regarding graduate employment, salary, and the time required to achieve these. This type of outcome data can be found at CourseReport.com, SwitchUp.com, and Cirr.org.

Currently collected outcome data focuses narrowly on the initial success of graduates following graduation. All of these organizations focus on graduate successes in the first 90-180 days post-graduation. They collect data at a maximum of 1 year. While such data is useful, we only see data for the first and possibly second positions held by graduates following program completion.

This study aims to collect long-term (1 year+ post graduation) outcome data from graduates of two different types of programs. First, myself and Dr. Edwards gather data from graduates of full stack web-development coding bootcamps. These programs range from three to six months in length, focusing on essential skills for web application development. Second, we gather data from graduates of Utah software engineering certificate programs. These are accredited programs taught at technical colleges in Utah; they focus on a wider base of software engineering fundamentals.

We curated our survey questions provided to these graduates to help answer the following:

1. What factors most impact graduates’ ability to transition and keep software-engineering positions in the long term?

2. What factors have the largest impact on the long-term salary of coding bootcamp graduates?
6.2 Methods

We collected data by surveying graduates of different code schools. We recruited participants mostly through partnerships with code schools throughout the US, but we recruited seven percent of our participants through IRB-approved social media campaigns.

We invited fifty coding bootcamps throughout the United States to participate in our study. We chose institutions with an in-person coding bootcamp program in the US, or a program focused on full-stack or frontend web development. Out of the fifty coding bootcamps contacted, we established partnerships with two programs. This lack of representation may create biases in our results. We wish more programs were more open to participating in this sort of research in order to collect a more accurate picture for success.

There are eight technical colleges in the state of Utah. Six of these feature a general purpose software engineering program; a seventh has a mobile development program. We contacted all seven of these programs, and established partnerships with four of them. Each program agreed to coordinate contacting their graduates and offering them the opportunity to fill out the survey. The programs contacted students with details regarding the study; students responded via Qualtrics.

Our survey of 26 questions covered demographic information, programs of study, current workforce titles, salaries, and locations. Participants also gave feedback on their frequency of mandatory retraining within employment, and factors that have led to their success/failure in transitioning into software engineering. We collected data for these surveys from December 2022 to March of 2023, in accordance with protocols approved by our IRB.

6.3 Study Results

We received 77 responses for our coding bootcamp survey, and 27 responses for our certificate program survey. We break our results into three categories:

- Comparison of key data to the baseline data set.
• Demographics affecting graduates ability to transition to software engineering posi-
tions

• Demographics impacting current salaries for graduates

We will address both the coding bootcamp and certificate programs in these contexts.

6.3.1 Comparison of data to baseline data

The baseline metric is the computed average of data from annual reports published by CourseReport, SwitchUp, and CIRR. This data was collected in the meta-review described in chapter four.

Our three key datapoints, identified in our meta-review, were graduates’ salaries, per-
centage of employment, and percentage of successful transition to software engineering. We display all three metrics as grouped bar charts with a standard error. The y-axis displays the item of interest, and the x-axis renders the number of years post-graduation that we collected the data. We collected all data within the meta-review from six months to a year post-graduation. As such, we only show meta-review data in the first grouping of each chart.

We did not have a sufficiently large pool of participant responses for each graduation year of our dataset. As such, we only display data for graduation years for which we received more than three responses. Each bar chart provides a standard error line with the overall data, which is an indication of the years that received less responses and the years that received more responses.

Salary

Post-graduate salary averages (figure 6.1) demonstrate good growth on a year-to-year basis for coding bootcamp graduates. The baseline average salary lies roughly $12,000 higher than what is reported by the graduates themselves. However, the baseline data is almost within the standard error of the collected data.
Certificate program data lacks the same level of growth, but it maintains a steady average, similar to the initial baseline value. This data suggests that coding bootcamp graduates achieve higher salaries than certificate program graduates in the long-term.

![Baseline salary](image)

**Fig. 6.1:** Comparison of Long-term salary data to meta-review baseline salary data
A line plot comparing the long term outcome data to the meta-review outcome data. Focused on the reported current salary, plotted by years since graduation from 1-9 years

**Employment**

Figure 6.2 visualizes general employment status of the participants, regardless of whether the position is software-related. The baseline data sits at 83% employment six months post-graduation, with a standard error of 2.

In general, participants’ reported employment rate rests near 100% employment after the first year, post-graduation. Outliers for this trend are from years 2018 to 2020. Participant responses indicate this was due to personal choices, such as deciding whether to attend school or be a stay-at-home parent.
Fig. 6.2: Comparison of Long-term employment data to meta-review baseline employment data
A grouped bar chart comparing the long term outcome data to the meta-review outcome data. Focused on the reported current employment status, plotted by years since graduation from 1-7 years.

**IT related employment**

The numeric rate of successful graduate transition compelled us to set up this long-term outcomes study. We wanted to see how successful coding bootcamp graduates are in the long-term, post graduation. Figure 6.3 depicts those results. The meta-review shows a 73% rate of IT-related employment (3% standard error) within six months of graduation.

Ignoring the very first year, coding bootcamp responses show successful transition rates similar to the meta-review average from 2 years onward. This could indicate two things. First, coding bootcamp graduates may have achieved fairly stable transition rates to software engineering positions. Second, once graduates transition to software engineering, they likely remain within software engineering.

Certificate program responses are more varied. However, for all but one year, the baseline result falls within the standard error. Follow-up research could show outcomes much closer to the baseline result.
Fig. 6.3: Comparison of Long-term IT employment data to meta-review baseline IT employment data

A grouped bar chart comparing the long term outcome data to the meta-review outcome data. Focused on the reported it employment status, plotted by years since graduation from 1-6 years

**Baseline review - Summary**

Comparing data from long-term outcomes to the baseline data suggests that the data for coding bootcamps shows lower initial success rates than the comparative baseline data. However, graduates remedied this lower performance rate within their second year of work.

Software engineering certificate programs showed lower performance in all factors, aside from general employment. This could indicate lower performance from these programs, but we hypothesize that this is instead due to two items. First, certificate programs serve high school communities alongside professional communities. For some high school graduates, the goal of the program is to prepare for college, not obtain a job. Second, we received fewer responses from graduates of certificate programs. The data may not reflect the true success rates of these graduates.
6.3.2 Successful transition to software engineering

Our main goal for our study was to determine which factors lead to successful transitions into software engineering, and secure higher salaries post-transition. Due to the low response rate from certificate program graduates, and the differences between coding bootcamps and certificate programs, we focused our individual factor review to our coding bootcamp responses.

We generated a series of visualizations of our results. Following visual analysis, we performed T-Tests and $\chi^2$ on items demonstrating the greatest significance. Age and gender were the most significant factors impacting successful transitions into software engineering. Prior education level and prior education focus could also potentially impact transition success; this hypothesis requires additional data.

**Age**

Figure 6.4 shows a Kernal Density Estimation of participant ages upon graduation. We separated the two distributions by their transitioned status. Ages of individuals who successfully transitioned appear to distribute at a lower level than individuals who did not transition. This hypothesis is reinforced by calculating a t-value and p-value of this data using a two tailed T-test designed for two independent means. We calculated a t-value of -3.86397. and a p-value is .000235. With a significance level of .05, our results appear significant. This indicates that age is significant in determining transition success to software engineering. The lower a participant’s age when graduating from a coding bootcamp, the more likely they are to successfully transition.

**Gender**

Figure 6.5 displays the successful transfer of graduates, broken down by gender. Based on our data, despite a similar number of graduates failing to transition between the two genders, male graduates are almost three times more likely to succeed than female graduates. Among responses we received from female participants, female graduates had a higher failure than success rate in transitioning into software engineering.
Fig. 6.4: KDE distribution of age of when participants graduated segmented by successful transition status
A Kernal Density Estimation distribution displaying the age of graduates, segmented by their transition status. Plotted from 18 years to 62 years

To compare the significance of these results, we calculated a Chi\textsuperscript{2} test comparing male and female responses. We calculated a p-value of .018445, which would be significant at our significance level of .05.

**Prior education level**

Given the spread of education levels and our study’s smaller sample size, we have not run our presented results regarding education level through an empirical testing method. However, figure 6.6 hints at the impact prior education level may have on successful transitions, and has been included.
The most successful category for transition into software engineering are those who previously only received education from a technical college. This category showed complete transition, with no failures. This is followed by individuals with associates degrees, most of whom succeed. Individuals with Bachelor’s degree show both the highest degree of success and the highest degree of failure. Interestingly, individuals with post-bachelor’s degrees are the least successful to transition.

Prior education focus

Prior education focus is the major/emphasis students studied in their previous schooling. Figure 6.7 also lacked sufficient data to justify an empirical test. However, the results are interesting, and could be examined in future studies. Most graduates who fell into the
education focus of “Computing” either did not finish their prior education, or remained at an Associate’s Degree level. We still consider these participants as “transitioning” into computer science. They merely changed their education method to do so.

In breaking down responses, we chose to ignore values in communication, education, and social sciences. While graduates of these programs displayed 100% ratios of successful transition, we also had very few participants from this background. We are unable to determine if this is a random sampling problem, or true information.

However, we received larger responses from Arts and Computing majors. Each provided interesting results. Arts majors reported a 53% rate of successful transition, and computing majors reported a success rate of 80%. Future studies should compare these findings to their collected data to see if these results remain consistent.

**Transition failure information**

Participants provided free response explanations describing why they were not able to transition into software engineering. This data potentially reinforces prior findings [8].

Figure 6.8 shows the count of responses given by graduates. We provided multiple
Fig. 6.7: Successful transition to software engineering by education focus

Multiple bar charts showing the amount of graduates who successfully transitioned to software engineering jobs, broken down by education focus.

choice options of common challenges faced by graduates, as well as the option to fill in their own answer if they wanted to provide more nuance. Their most cited reason for transition failure was an inability to find initial employment in their new field. Once they secure initial employment, graduates tend to remain in their new career path.

The second most common response was the “other” category, where graduates could provide their own freeform answers. These responses range from describing the purpose of their education, to expressing dissatisfaction with the education given. Here is a list of the responses:

- “Coding boot camps are worthless, just get a 2 year at a cc if you want to code.”

- “I started a family and my partner earns more than I would have in a starting software job.”

- “My place of work didn’t offer me a software engineer job and I value the company I work in. I also preferred the design portion of websites more.”
Fig. 6.8: Failed transition to software engineering by reported reason of failure
Multiple bar charts showing the amount of graduates who failed to transition to software engineering. Broken down by the reason indicated for failure

- “Massive anxiety filling out applications and running the job application projects, no call backs on applications.”
- “I took [the] boot camp to help me inform the developers of the software startup I co-founded. The company is still active.”
- “Combination of not learning enough in boot camp and not being able to get a job so I gave up.”
- “I was working full time while doing the boot camp. I can’t afford to quit working to go to school so I haven’t found the time to really focus on learning it. I don’t understand it yet.”
- “Imposter Syndrome + Time.”
6.3.3 Items that impact salary change

Similar to factors impacting successful transition, we generated a series of visualizations reviewing participant responses. We then performed t-tests on how gender and successful transitions impacted salaries. We also created a visualization for how time since graduation impacts salary.

Successful transition to software engineering positions

One of our most striking pieces of data collected was the range in salaries between graduates who transitioned and those who did not. Figure 6.9 shows participant salary ranges, distributed by their transitioned status into a software engineering position. Our visualization cuts off on the left side as salaries decrease below zero. The distribution for transitioned graduates begins, peaks, and ends at higher salaries than non-transitioned graduates.

Reviewing these values in a two-tailed t-test, we compute that the t-value is 3.97875 with a p-value is .000158. Overall, this indicates that a successful transition into software engineering is significant for improving salary growth in a long-term career.

Gender

While female graduates achieve successful careers with decent salaries, Figure 6.10 shows that the salaries reported by female graduates has a much lower cap than salaries reported by males. While male graduates enjoyed a salary ceiling higher than $250,000, female graduates capped at $135,000.

This discrepancy may be due to having less female participants than male participants. This may also be due to the lower transition rate of female graduates.

To provide further analysis, we compared the salary results against the Bureau of Labor Statistics (BLS). The BLS published two articles in 2020 and 2021. Its 2020 article focuses on the highlights of female earnings [45], discussing differences in salary and occupational numbers in various sectors. These differences include ages, career types, ethnicities, and education levels. BLS focuses on its initial graph of female earnings as a percentage of
male earnings. It illustrates that female earnings have increased since 1979, but as of 2020, women earned 82% of the total earnings of men. The second article [46] details the median earnings between men and women, and breaks them down by race. It likewise focused only on full time employees in its dataset. Its overall findings maintained the percentage difference at 83%.

The responses our study received did not reflect the earnings ratio as reported by the Bureau of Labor Statistics. Women in our study who transitioned into software engineering earned a median salary of 72.63% of the median salary of men. Women who failed to transition earned a median salary of 77.48% of the median salary of men. In aggregate,
women earned a median salary of 65.97% of men in our study. The women in our study consistently earned less than the men in our study. This may be attributable to a lack of data points, rather than a true difference. We performed a one-tailed t-test with the results of our participants, which resulted in a t-value of 2.61069 and a p-value of .005466.

**Time since graduation**

Figure 6.11 demonstrates a linear trend for salary change in all graduates. The linear trend has an almost identical slope for 2018 to 2021. 2016 appears an outlier in this slope, and may be due to having only two responses among the dataset. 2017 responses may indicate that there was a steep upward shift in salary, as developers often gain new titles
later in their career. Further studies would need to confirm this hypothesis. We omitted 2022 data, as only one participant reported a successful transition in that year.

![Salary change: Transitioned graduates](image)

**Fig. 6.11:** Post-bootcamp salary change for transitioned graduates based on year graduated

A plot demonstrating the salary change of graduates after their bootcamp. The plot only displays transitioned graduate data, and is segmented by year of graduation, ranging from 2016 to 2021

**Previous education level**

A category plot shown in figure 6.12 with a breakdown of the current salary of graduates distributed by their education level prior to the coding bootcamp. Individuals with the highest salary had a Bachelor’s Degree. However, the average salary for individuals with a Bachelor’s Degree is lower than some of the other categories. This may be due to graduates of Bachelor’s degrees had the highest degree of failure to transition to software engineering.

Technical college and Associate’s Degree were the categories with the best ratio in terms of successful transfer, but maintain lower total salary options than other categories.
Master’s and PhD students still have high salary options despite not successfully transferring to software engineering. This is likely due to having other career options due to their previous education.

Fig. 6.12: Post-bootcamp salary change for transitioned graduates based on education level. A category plot demonstrating the current salary of graduates after their bootcamp. The plot ranges from High school to PhD in education levels. It also shows salaries up to $250,000.

6.4 Student satisfaction

Figures 6.13 and 6.14 display graduates’ satisfaction ratings for their program of study. Figure 6.13 displays responses from bootcamp graduates, and figure 6.14 displays responses from certificate program graduates.

Both bootcamp and certificate program graduates indicated high overall satisfaction with their program of study. Both sets of graduates also demonstrated less agreement that they would recommend their program to their friends, or that their program prepared them for employment.

6.5 Discussion

When we began our long-term study, we hoped to achieve two immediate goals. First, we hoped to contribute data to help establish a new baseline metric for long-term outcomes of coding bootcamp graduates. Second, we hoped to gather data that would provide insights into factors leading to increased career success for coding bootcamp graduates. Ideally, these
Fig. 6.13: Post-bootcamp satisfaction ratings by graduates
A grouped bar chart showing the satisfaction ratings given by graduates of coding bootcamps

insights could empower code schools or potential students in their software engineering transition.

Through our comparison of our data to the current meta-review baseline, we believe we have established a new baseline for long-term outcomes. After comparing our data to the previous baseline, we believe our results have a moderate standard error. This is due to our smaller participant sampling size. Future studies can improve this data through increased participation from both graduates and code schools.

Our analysis identified common factors among successful graduates. However, most identified factors appear outside the control of both students and institutions. These items include age, gender, and time since graduation. Prior education level, education focus, and successful transition are more within the control of either the code school or the graduate. We expect follow up studies to flesh out these results, but we encourage both code schools and graduates to adjust accordingly.
Fig. 6.14: Post Certificate program satisfaction ratings by graduates
A grouped bar chart showing the satisfaction ratings given by graduates of certificate programs
A main goal of this research was to create a transparent resource that would enable prospective students to understand the risks and pros/cons of coding bootcamps as an education path. The coding bootcamp paradigm has enabled many individuals to lead productive and successful lives. It has also caused others to suffer at the brink of despair.

The results of these studies suggest that some level of regulation or accreditation needs to be put in place within the code school sphere. There are multiple problems in place because such a body does not exist:

- A lack of clear outcome data except through self-reporting.
- The ability to present malicious or purposefully incorrect outcome data to prospective students.
- The ability to white-label programs that obscure which institution is actually providing the education that students are paying for.
- The collected outcome data likely suggesting that these programs best serve demographics that least need the assistance these programs provide: such as young adult males.

These circumstances are symptoms that are likely due to not having a clear organization which provides oversight in this industry. While there are many possible solutions to solve this problem, some of which have been attempted. However, in completing this research, there are two organizations in particular that are on the best path to solving this problem. These two organizations are the Council on Integrity in Results Reporting and the Workforce Training Education Alliance.

CIRR is a gold-standard reporting process, and has been since 2015, and it is the current gold standard for coding bootcamp outcomes reporting. Understandably, this level
of ethical reporting is a high bar and an extra cost for these sorts of programs. In many cases, it may actually decrease their overall profitability to make this data transparent to the public.

However, without a consistent format for outcomes reporting, potential students for code schools nationwide will make poor education decisions. Also, organizations who favor short-term gains over long-term ethics will be walking a path that eventually destroys their business model in the long term.

Due to the problems mentioned above, WTEA will likely be a viable long-term solution for many codeschools. CIRR is an ethical moral standard to follow, whereas WTEA is in the process to become an accreditation body whereby codeschools may gain federal financial aid eligibility. This provides a financial incentive for codeschools to start taking ethical paths of reporting data. This is overall a win because it provides a path which empowers student decisions.

In short, if there is one change to come from the results of this study, it would be to provide awareness and support for CIRR as a reporting standard and WTEA as an accreditation body. These programs can provide long term solution to help bring order to our coding bootcamps. They can only succeed with community support, and require as much support as possible in order for code schools to grow beyond their current impediments.
REFERENCES


APPENDIX A
Questionnaires for study

A.1 Questionnaire to be sent to coding bootcamp graduates

1. Current Age

2. What is your gender?
   (a) male
   (b) female
   (c) trans-gender
   (d) non-binary
   (e) agender
   (f) prefer not to answer

3. Which ethnicities do you identify as? Choose all that apply.
   (a) Asian
   (b) Black or African American
   (c) Native Hawaiian or Pacific Islander
   (d) Hispanic or Latinx
   (e) Middle Eastern
   (f) Native American
   (g) White or Caucasian
   (h) Other
   (i) Prefer not to answer
4. Bootcamp Graduation Date

5. Bootcamp Company Name
   (a) List of Partner Bootcamps
   (b) Other

6. Bootcamp Subject Matter
   (a) Frontend Development
   (b) Backend Development
   (c) Full-Stack Development
   (d) DevOps Engineering
   (e) QA Engineering

7. Bootcamp Delivery Method
   (a) Full-Time In-person
   (b) Part-Time In-person
   (c) Full-Time Remote
   (d) Part-Time Remote
   (e) Self-Paced Online

8. Current Job Title

9. Current Salary

10. Current Location

11. Previous education level prior to bootcamp
    (a) High School
    (b) Technical or Vocational College/Training
(c) Some College Education

(d) Associate's Degree

(e) Bachelor's Degree

(f) Some Post-Graduate Schooling

(g) Master's Degree

(h) PhD

12. If you attended higher education, what was your intended/completed major(s)?

13. Years of professional work experience in any field(s) prior to or during bootcamp?

14. Estimated salary prior to attending coding bootcamp?

15. In what field(s) were you professionally working in prior to or during your bootcamp?
   (example: marketing, business management, retail, ... etc)

16. Do you use the technical skills gained in your bootcamp in your current title?

17. Are you employed in a software engineering position? (Including positions related to the subject matter you studied)

18. If you are not in a software engineering/subject matter position, what was the major factor for not being in that position?
   (a) Unable to find employment in software engineering or subject matter

   (b) Did not enjoy the type of work being done in the software engineering/subject matter

   (c) Better salary in different position

   (d) Better work-life environment in different position

   (e) Unable to perform the duties assigned to me in software engineering/subject matter

   (f) Education prejudice within software engineering/subject matter
(g) Other - please fill in

(h) I am in a position connected to software engineering/subject matter I studied

19. If you are employed in a software engineering/subject matter position, how frequently have you needed any further education outside of on-the-job training to keep your employment?

(a) Every month
(b) Every six months
(c) Every year
(d) Every 2 years
(e) Every 5 years
(f) > Every 5 years
(g) Never

(h) I am not in a position connected to the subject matter I studied

20. If you are employed in a software engineering/subject matter position, at what interval have you needed on-the-job training to keep your employment?

(a) Every month
(b) Every six months
(c) Every year
(d) Every 2 years
(e) Every 5 years
(f) > Every 5 years
(g) Never

(h) I am not in a position connected to the subject matter I studied

21. How satisfied are you with the education you received from your coding bootcamp?
(a) Very Dissatisfied
(b) Dissatisfied
(c) Neither Satisfied nor Dissatisfied
(d) Satisfied
(e) Very Satisfied

22. How much do you agree with the following statement? "I would recommend my friends to attend the coding bootcamp I attended."

(a) Strongly Disagree
(b) Disagree
(c) Neither Agree nor Disagree
(d) Agree
(e) Strongly Agree

23. How much do you agree with the following statement? "My coding bootcamp prepared me for full-time employment in the subject matter taught."

(a) Strongly Disagree
(b) Disagree
(c) Neither Agree nor Disagree
(d) Agree
(e) Strongly Agree

A.2 Questionnaire to be sent to software engineering certificate program graduates

1. Current Age

2. What is your gender?
(a) male
(b) female
(c) trans-gender
(d) non-binary
(e) agender
(f) prefer not to answer

3. Which ethnicities do you identify as? Choose all that apply.

(a) Asian
(b) Black or African American
(c) Native Hawaiian or Pacific Islander
(d) Hispanic or Latinx
(e) Middle Eastern
(f) Native American
(g) White or Caucasian
(h) Other
(i) Prefer not to answer

4. Software Engineering Certificate Program Graduation Date

5. Software Engineering Certificate Program Institution Name

(a) List of Partner Institutions
(b) Other


(a) Frontend Development
(b) Backend Development
(c) Full-Stack Development
(d) DevOps Engineering
(e) Mobile Development
(f) Computer Science - General Program
(g) QA Engineering

7. Software Engineering Certificate Program Delivery Method

(a) Full-Time In-person
(b) Part-Time In-person
(c) Full-Time Remote
(d) Part-Time Remote
(e) Self-Paced Online

8. Duration of Program (In credit hours, or months)

9. Cost of Program (Estimated if not able to recall)

10. Current Job Title

11. Current Salary

12. Current Location

13. Previous education level prior to bootcamp

(a) High School
(b) Technical or Vocational College/Training
(c) Some College Education
(d) Associate’s Degree
(e) Bachelor’s Degree
(f) Some Post-Graduate Schooling
(g) Master’s Degree
(h) PhD

14. If you attended higher education, what was your intended/completed major(s)?

15. Years of professional work experience in any field(s) prior to or during bootcamp?

16. Estimated salary prior to attending coding bootcamp?

17. In what field(s) were you professionally working in prior to or during your bootcamp?
   (example: marketing, business management, retail, ... etc)

18. How frequently do you use the technical skills gained in your certificate program in your current title?
   (a) Daily
   (b) Weekly
   (c) Monthly
   (d) Quarterly
   (e) Annually
   (f) Never

19. Are you employed in a software engineering position? (Including positions related to the subject matter you studied)

20. If you are not in a software engineering/subject matter position, what was the major factor for not being in that position?
   (a) Unable to find employment in software engineering or subject matter
   (b) Did not enjoy the type of work being done in the software engineering/subject matter
   (c) Better salary in different position
   (d) Better work-life environment in different position
(e) Unable to perform the duties assigned to me in software engineering/subject matter

(f) Education prejudice within software engineering/subject matter

(g) Other - please fill in

(h) I am in a position connected to software engineering/subject matter I studied

21. If you are employed in a software engineering/subject matter position, how frequently have you needed any further education outside of on-the-job training to keep your employment?

   (a) Every month

   (b) Every six months

   (c) Every year

   (d) Every 2 years

   (e) Every 5 years

   (f) > Every 5 years

   (g) Never

   (h) I am not in a position connected to the subject matter I studied

22. If you are employed in a software engineering/subject matter position, at what interval have you needed on-the-job training to keep your employment?

   (a) Every month

   (b) Every six months

   (c) Every year

   (d) Every 2 years

   (e) Every 5 years

   (f) > Every 5 years
(g) Never

(h) I am not in a position connected to the subject matter I studied

23. How satisfied are you with the education you received from your coding bootcamp?

(a) Very Dissatisfied

(b) Dissatisfied

(c) Neither Satisfied nor Dissatisfied

(d) Satisfied

(e) Very Satisfied

24. How much do you agree with the following statement? "I would recommend my friends to attend the coding bootcamp I attended."

(a) Strongly Disagree

(b) Disagree

(c) Neither Agree nor Disagree

(d) Agree

(e) Strongly Agree

25. How much do you agree with the following statement? "My coding bootcamp prepared me for full-time employment in the subject matter taught."

(a) Strongly Disagree

(b) Disagree

(c) Neither Agree nor Disagree

(d) Agree

(e) Strongly Agree
A.3 White-label bootcamp questionnaire

1. Does your organization hire graduates from coding bootcamps?
   (a) Yes
   (b) No
   (c) I am not familiar with these types of programs

2. Does your organization hire graduates from software engineering certificate programs?
   (a) Yes
   (b) No
   (c) I am not familiar with these types of programs

3. How comfortable do you personally feel hiring graduates from coding bootcamps?
   (a) Extremely Comfortable
   (b) Somewhat Comfortable
   (c) Neither Comfortable or Uncomfortable
   (d) Somewhat Uncomfortable
   (e) Extremely Uncomfortable

4. How comfortable do you personally feel hiring graduates from software engineering certificate programs?
   (a) Extremely Comfortable
   (b) Somewhat Comfortable
   (c) Neither Comfortable or Uncomfortable
   (d) Somewhat Uncomfortable
   (e) Extremely Uncomfortable

5. Please rate how useful the following data metric is in your hiring process - Technical Assessment in Interview
6. Please rate how useful the following data metric is in your hiring process - Applicant’s Education Level

(a) Extremely Useful
(b) Somewhat Useful
(c) Neither Useful or Useless
(d) Somewhat Useless
(e) Extremely Useless

7. Please rate how useful the following data metric is in your hiring process - Applicant’s Education Institution

(a) Extremely Useful
(b) Somewhat Useful
(c) Neither Useful or Useless
(d) Somewhat Useless
(e) Extremely Useless

8. Please rate how useful the following data metric is in your hiring process - Team fit/Culture fit assessment

(a) Extremely Useful
(b) Somewhat Useful
(c) Neither Useful or Useless
9. Regardless of your personal/organization hiring preferences, please choose which of the following institutions provides the best education for the following 6 questions - Colorado State University Coding Bootcamp VS Columbia University Coding Bootcamp

(a) Colorado State University Coding Bootcamp
(b) Columbia University Coding Bootcamp
(c) Equal Education Value

10. Emory University Coding Bootcamp VS University of New Mexico Coding Bootcamp

(a) Emory Coding Bootcamp
(b) University of New Mexico Coding Bootcamp
(c) Equal Education Value

11. Utah State University Coding Bootcamp VS CalTech Coding Bootcamp

(a) Utah State University Coding Bootcamp
(b) CalTech Coding Bootcamp
(c) Equal Education Value

12. University of Denver Coding Bootcamp VS UC Berkley Coding Bootcamp

(a) University of Denver Coding Bootcamp
(b) UC Berkley Coding Bootcamp
(c) Equal Education Value

13. Georgia Tech Coding Bootcamp VS University of San Diego Coding Bootcamp

(a) Georgia Tech Coding Bootcamp
(b) University of San Diego Coding Bootcamp
(c) Equal Education Value

14. University of Texas at Austin Coding Bootcamp VS UC Davis Coding Bootcamp

(a) University of Texas at Austin Coding Bootcamp
(b) UC Davis Coding Bootcamp
(c) Equal Education Value

15. Regardless of your personal/organization hiring preferences, please choose which of the following institutions provides the best education for the following 6 questions - Utah State University Coding Bootcamp vs FullStack Academy Coding Bootcamp

(a) Utah State University Coding Bootcamp
(b) FullStack Academy Coding Bootcamp
(c) Equal Education Value

16. University of New Mexico Coding Bootcamp vs EdX Coding Bootcamp

(a) University of New Mexico Coding Bootcamp
(b) EdX Coding Bootcamp
(c) Equal Education Value

17. University of Texas at Austin Coding Bootcamp VS DevMountain Coding Bootcamp

(a) University of Texas at Austin Coding Bootcamp
(b) DevMountain Coding Bootcamp
(c) Equal Education Value

18. Colombia University Coding Bootcamp VS General Assembly Coding Bootcamp

(a) Colombia University Coding Bootcamp
19. Colorado State University Coding Bootcamp VS Flatiron School Coding Bootcamp
   (a) Colorado State University Coding Bootcamp
   (b) Flatiron School Coding Bootcamp
   (c) Equal Education Value

20. UC Berkley Bootcamp VS App Academy Coding Bootcamp
   (a) UC Berkley Coding Bootcamp
   (b) App Academy Coding Bootcamp
   (c) Equal Education Value

21. For the questions that compared university programs to other university programs, why did you select the answers you did?

22. For the questions that compared university programs to coding bootcamps, why did you select the choices you did?

23. Your current employment title

24. Your current Age?

25. What is your gender?
   (a) male
   (b) female
   (c) trans-gender
   (d) non-binary
   (e) agender
   (f) prefer not to answer
26. Which ethnicities do you identify as? Choose all that apply.

(a) Asian
(b) Black or African American
(c) Native Hawaiian or Pacific Islander
(d) Hispanic or Latinx
(e) Middle Eastern
(f) Native American
(g) White or Caucasian
(h) Other
(i) Prefer not to answer