Project Report

Team DAT G

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PUBLISHED
December 9, 2024

ABSTRACT
This report examined four critical questions regarding youth programming in Chicago. The first explored how programs differ by age group, the second investigated program prices by category and potential financial barriers, the third delved into program geographical distribution, and the fourth examined the evolution of online programs in relation to accessibility. Analysis revealed that youth-specific programming dominated, with gaps existing for toddlers and teens. Financial barriers persist, especially in "Sports & Wellness", where more expensive programs lack additional support such as transportation or scholarships. Geographically, central zones tend to host more programs in comparison to outer clusters. Online programs peaked in relation to the COVID-19 pandemic, but have since declined despite their implications for improved accessibility. Recommendations to stakeholders include expanding free and subsidized programs for underserved age groups and geographic clusters, promoting hybrid formats to combat lack of accessibility, and providing additional support and transparency in pricing. Stakeholders should aim to prioritize STEM and career-oriented programs to increase program diversity, particularly in online formats, to address accessibility gaps. While this analysis provides insights for stakeholders, updated data and community feedback are essential for continuing to align initiatives with evolving community needs.

1 Problem Statement

The questions we wish to answer in our course project aim to identify gaps in programming for youth in the city of Chicago. The first unknown we explored is how programs targeting different age ranges differ. How does the availability of family programs differ from that of exclusively youth programs? What does the distribution of programs of different price ranges and categories available for different ages tell us about programming in Chicago? The second question we wish to answer is how the prices of programs, as well as other forms of financial support, vary by category. We aim to look at not only the price but also the availability of scholarships, free food, pay, and transportation to adequately assess where potential barriers to participation might be. The third question we want to answer is, how geographically available are different types of programs? Different programs are sorted into groups under the column title Category Names. To answer this question, we wish to find the geographical distribution of programs based on Category Name. What are the top Category Names? Which geographical clusters have the most and the least programs? What is the geographical distribution of programs based on Category Name? The fourth question we aim to answer addresses how online programs have evolved over time by analyzing trends in their availability, pricing structures, and program types. By examining these factors, we aim to explore the implications of these changes for accessibility and how they may influence participant engagement.

2 Data Source

The dataset we used was 'My_CHI._My_Future._Programs.csv' which provides comprehensive information about various youth programs throughout Chicago. It contains 227,474 entries and 40 columns, each representing attributes such as program details, age ranges, meeting types, locations, and categories. This dataset was obtained as a .csv file from the “My CHI. My Future” initiative, which connects Chicago youth to enriching activities and can be publicly accessed via the City of Chicago Data Portal. While the dataset is updated regularly, the version we are using was last modified on August 5, 2024.

3 Data Quality Check / Cleaning / Preparation

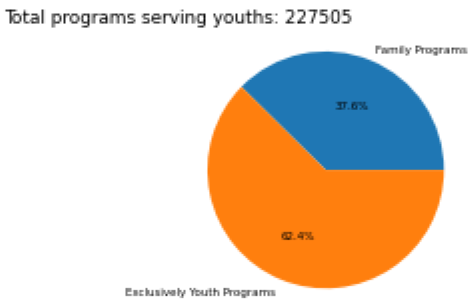
```
                         Missing Vals  Unique Vals  \
Category Name                       1           23
Program Price                       0            4
Geographic Cluster Name         11125           89
Scholarship Available               0            2
Participants Paid                2906            2
Transport Provided               3245            2
Has Free Food                    1748            2
Meeting Type                        0            2

                                                                Top Levels
Category Name            {'Sports + Wellness.': 102011, 'Music & Art.':...
Program Price            {'Free': 125365, '$50 or Less': 72639, 'More T...
Geographic Cluster Name  {'Northwest Equity Zone': 21563, 'West Equity ...
Scholarship Available                        {False: 227151, True: 354}
Participants Paid        {'Not Paid': 223723, nan: 2906, 'Paid, Type Un...
Transport Provided                  {False: 224103, nan: 3245, True: 157}
Has Free Food                      {False: 223304, True: 2453, nan: 1748}
Meeting Type                     {'face_to_face': 217791, 'online': 9714}

              count       mean        std         min        25%        50%  \
Min Age    227505.0   8.641621   6.366059    0.000000   3.000000   6.000000
Max Age    227505.0  44.106934  42.081717    0.000000  11.000000  18.000000
Latitude   219385.0  41.851616   0.099957   38.922466  41.776459  41.863098
Longitude  219385.0 -87.680032   0.118924 -120.961998 -87.717003 -87.680382

                 75%         max  Missing Vals
Min Age    13.000000   25.000000             0
Max Age    99.000000  171.000000             0
Latitude   41.945400   42.147499          8120
Longitude -87.638603  -87.530502          8120
```

4 Exploratory Data Analysis

4.1 Analysis 1

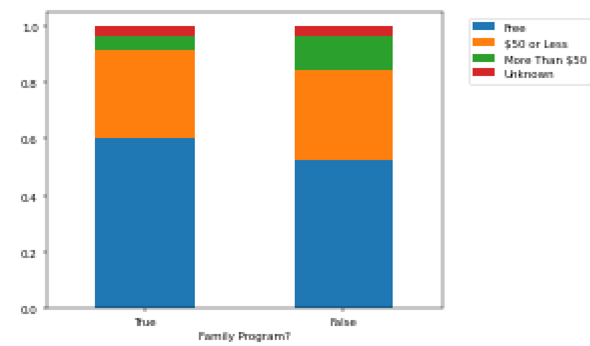
By Giuliana Rodrigues

First, we examined the differences between family programs and exclusively youth programs. Family programs are defined as programs with a maximum age over 25, while exclusively youth programs have a maximum age under or equal to 25. It is important to note that, regardless of classification, both types of programs target youths, as we filtered out any programs with a minimum age over 25. To better understand the data, we visualized the proportion of family programs to that of exclusively youth programs.



This plot shows that, of the 227,505 youth-serving programs in Chicago, 62.4% are exclusively for youths and 37.6% are family programs.

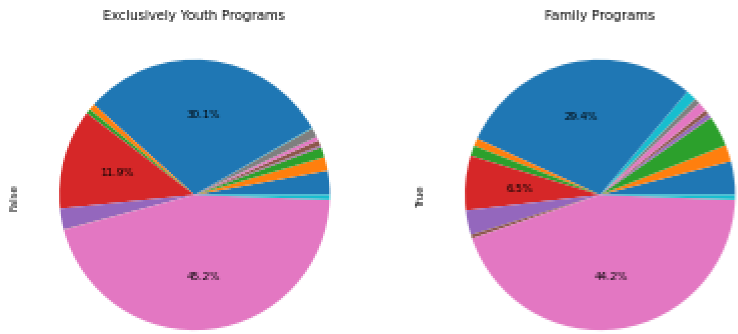
We started by looking into the availability of free family and exclusively youth programs to be able to compare across categories. To do so, we calculated the proportions of programs of different price ranges within each category and visualized them. The “Program Price” column of the data contains no missing values, so this analysis provides a complete picture of the offerings.



	Program Price	Family Program?	Count	Proportion
0	$50 or Less	False	45766	0.322491
1	$50 or Less	True	26873	0.313970
2	Free	False	74002	0.521457
3	Free	True	51363	0.600098
4	More Than $50	False	17623	0.124181
5	More Than $50	True	4539	0.053031
6	Unknown	False	4523	0.031871
7	Unknown	True	2816	0.032901

The graph shows that the largest disparities between family and exclusively youth programs are in the proportion of free and over $50 programs. About 60% of family programs are free and about 5.3% are over $50, while only about 52.1% of exclusively youth programs are free and 12.4% are over $50.

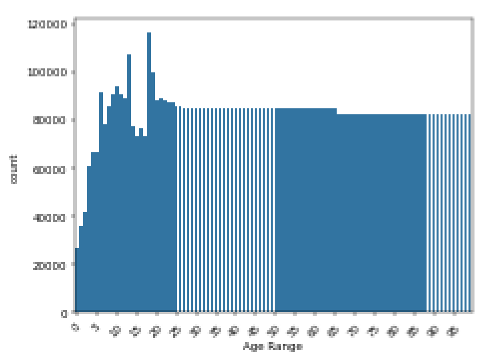
We moved on to looking into the types of programs available per category. We calculated the proportion of every type of program within the family and exclusively youth categories. Like the previous analysis, every program in the database had a “Program Type” tag, so the following figures give a comprehensive look at the data. For both, the top three categories were Sports + Wellness, Music & Art, and Reading & Writing.



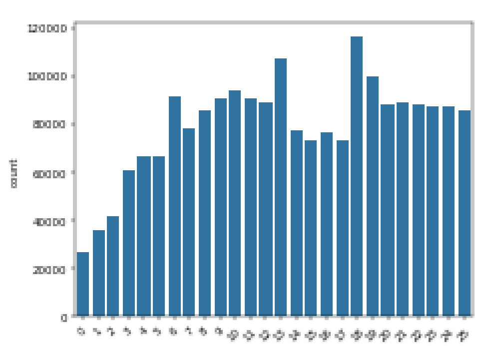
Family Program?	False	True
Category Name		
Sports + Wellness	0.452446	0.441670
Music & Art	0.300917	0.293617
Reading & Writing	0.119489	0.064995

As seen above, the distribution of program type is generally similar across youth-only and family programs, but there is a significantly higher proportion of youth-only reading and writing programs.

To get a better understanding of who Chicago programs are and are not serving, we decided to look into what ages were most and least covered. The graph below shows the number of programs that serve every age between 0 and 99.



After a certain point around 25, around the same number of programs serve each age, probably because the organizers set an arbitrarily high maximum age, like 99. Below, we take a closer look at the graph from ages 0 to 25.



From ages 0-13, as age increases, the number of programs available also increases. Ages 13 and 18 are the best served. We believe this is because 13 is the generally accepted transition point between childhood and teenhood, so 13-year-olds will qualify for many programs serving either one or the other demographic. The same is true of 18, the border age between teenhood and adulthood. There is a noticeable drop-off in the number of programs serving the ages between the two (14-17).

4.2 Analysis 2

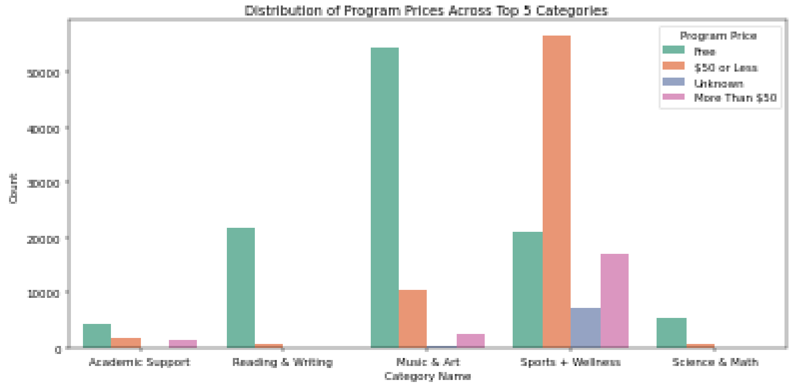
By Taylor Massey

For my analysis, I was primarily interested in exploring the various financial aspects of each program in the "My Chi My Future" dataset. I wanted to explore this because I know that accessibility does not just exist in the form of cost. Thus, I first drafted my research question of, "How do program prices and the availability of financial support vary across different program categories?" Then, I needed to clean the data to make it easier for analysis. This primarily included filtering out observations with a minimum age greater than 25 and removing columns not relevant to my research question or the observation's identity. This left me with the following variables in my dataframe: Program ID, Program Name, Category Name, Min Age, Max Age, Program Price, Scholarship Available, Participants Paid, Transport Provided, Has Free Food, and Meeting Type. Removing NaN or Unknown values was less important in my analysis because they would not have been plotted on my visualizations anyway.

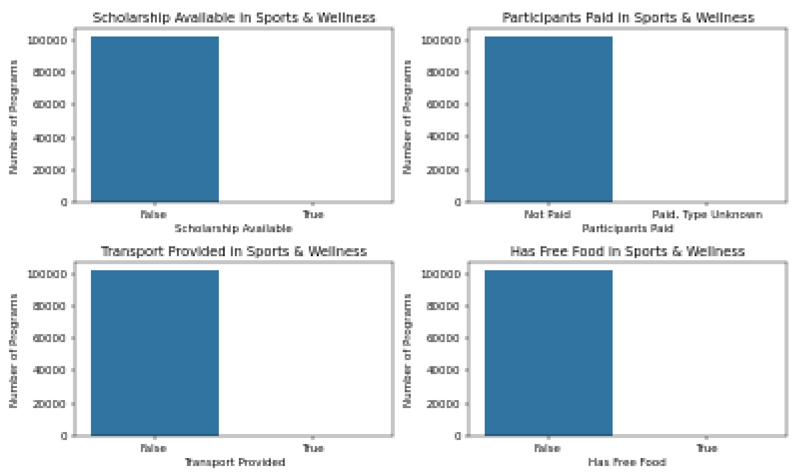
To begin, I wanted to know the distribution of all of the categories; essentially, I wanted to see how many programs were in each category. I noticed upon my first glance at the data that there was a 'Science & Math' category, as well as a 'Science' category and a 'Math' category. I also observed a category called 'Computers.' and another called 'Computers'. I was not planning on this step, but I created and used the function category_merge to combine the individual science and math categories into one, as well as the computers categories into one. This step is shown in our initial data cleaning section. After this, I used the value_counts() function to print the count of programs in each category as a series. I included the top 10 below.

```
Category Name
Sports + Wellness          102011
Music & Art                 67835
Reading & Writing           22520
Academic Support             7510
Science & Math               6054
Computers                    4872
Building & Fixing Things     4013
Helping Your Community       2162
Performance                  1861
Nature                       1858
Name: count, dtype: int64
```

After viewing this, I noticed that the top 5 program categories account for the vast majority of all programs in the dataset (~90% of all programs). So, I decided to narrow this portion of my exploratory data analysis to just the top 5 categories: 'Sports + Wellness', 'Music & Art', 'Reading & Writing', 'Academic Support', and 'Science & Math'. From here, I wanted to visualize program price for each of these 5 categories. I created a barplot looking at the distribution of program prices across the top 5 categories.



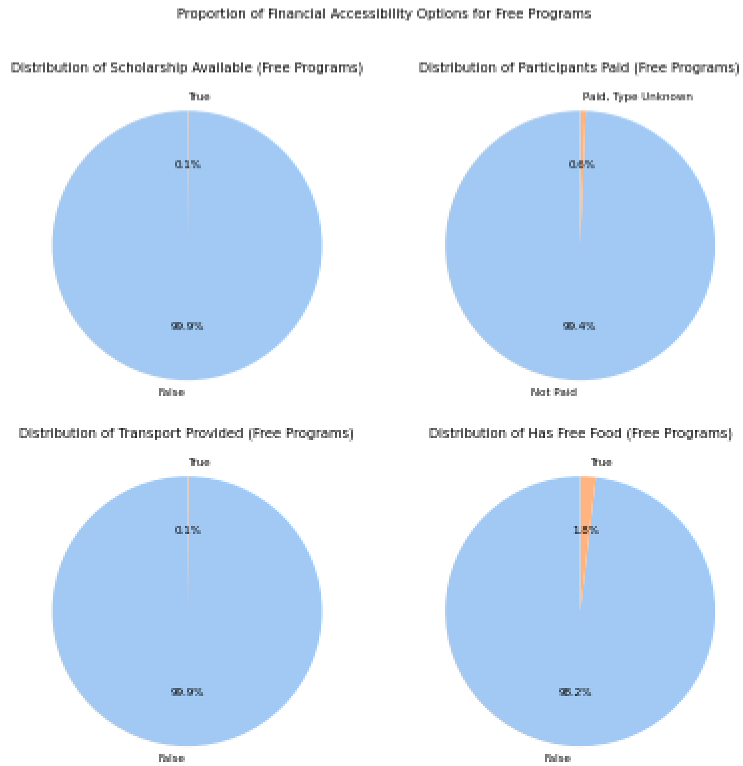
It’s clear to see that ‘Sports + Wellness’ has the largest number of non-free programs, which might indicate some form of financial barrier to youth sports programs. Additionally, the other 4 categories have an incredibly large proportion of free programs. Since ‘Sports + Wellness’ programs tend to be non-free more often than the other 4 categories in this chart, I wanted to take a deeper dive into them in particular to examine whether or not they provided other forms of financial support since they already weren’t free. Note that the variables I examined for this are ‘Scholarship Available’, ‘Participants Paid’, ‘Transport Provided’, and ‘Has Free Food’.



Through this grid of barplots, it’s pretty easy to tell that programs with the category ‘Sports + Wellness’ are not only non-free but also rarely offer any of the other 4 forms of support for participants. Initially, I was unsure if my code even properly accounted for the observations with a ‘False’ or ‘Paid, Type Unknown’. So, I decided to run a count of the aforementioned 4 variables and see exactly how many ‘Sports + Wellness’ programs offer each of the forms of support, as well as the total number of ‘Sports + Wellness’ programs for a comparison.

```
Total number of Sports + Wellness programs: 102011
Scholarship Available: 56
Participants Paid: 53
Transport Provided: 18
Has Free Food: 281
```

These printed statistics continue to prove that there is a large lack of financial support in the largest program category. However, I wanted to conclude my analysis by looking at the availability of these forms of support for free programs. Often, people might assume a program is financially accessible just because it operates free of charge to its participants. But, just because a program is free does not mean it is fully accessible. For example, what if someone is unable to find transportation for an in-person program? What if someone is making a decision on whether to participate in a program or eat lunch? To further explore this, I created a faceted pie chart for each form of financial support for free programs.

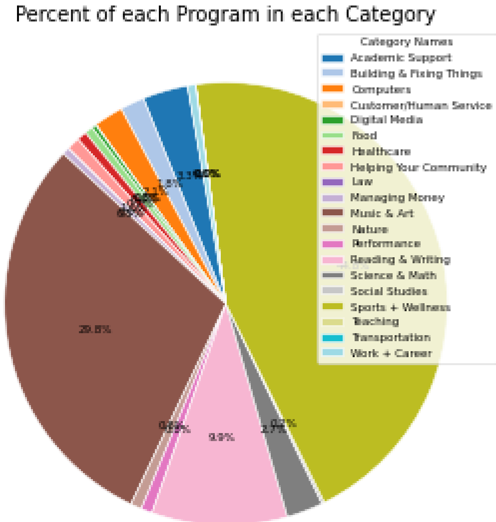


Note that the 'Scholarship Available' variable is less important in this depiction due to the program already being free. While it is unclear exactly what a free program might be giving scholarships for, it might aim to cover any out-of-pocket expenses someone has for attending. In general, though, these pie charts depict an unfortunate reality. The financial variable with the largest proportion of availability is 'Has Free Food', with only 1.8% of free programs having it. All other variables' proportions are less than this. This only proves the idea that most free programs do not offer additional financial support, which could directly hinder one's ability to participate in the program.

4.3 Analysis 3

By Daniela Aves

Using the "My Chi My Future" dataset, I first began by crafting a relevant research question that would guide my understanding of the data and provide a lens through which to view the variables. The question I settled on was, "How does the availability of different types/categories of programs differ across given factors?" Before I could answer this question, I first had to clean the data to only include youth programs. I did this based on the parameter given in class, which was to exclude data where the minimum age was 25 or greater. I then sought to find the percent of each program in each category. My methodology was as follows: group the data by Category Name, then print the number of programs in each Category Name as a 100% circle chart. Using the df.groupby method and plt.figure with plt.pie I was able to achieve the following chart.



I also included a legend that assigned each Category Name a color based on the tab20 color scheme. From this visualization, the stakeholders can easily identify Sports + Wellness as the top category of programs, as well as Music & Art and Reading & Writing as the second and third most common, respectively. For an alternative form of Category Name visualization, I included a table with Category Name and percent of programs that fall beneath that category, seen below.

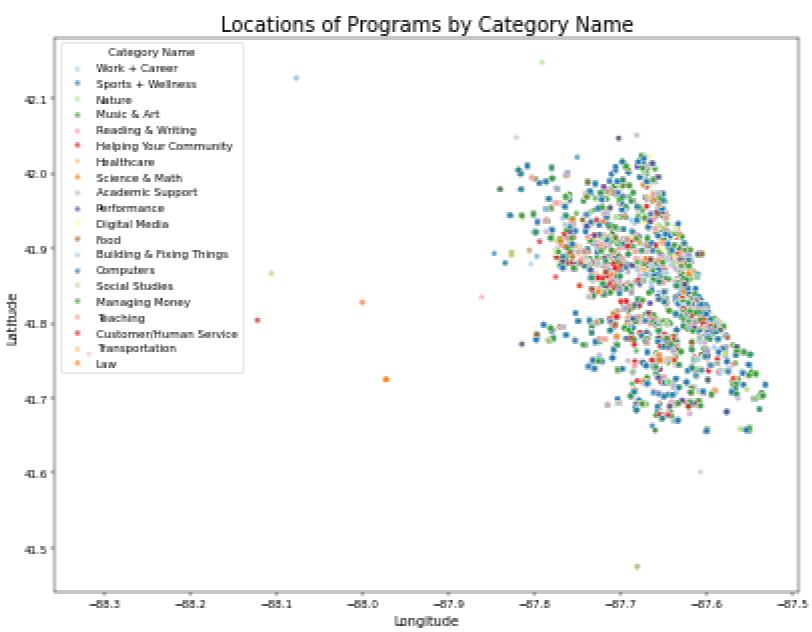
	Category Name	Percentage
8	Law	0.009670
18	Transportation	0.011868
17	Teaching	0.021538
3	Customer/Human Service	0.044395
15	Social Studies	0.196041
4	Digital Media	0.309885
9	Managing Money	0.514277
19	Work + Career	0.569221
5	Food	0.602187
6	Healthcare	0.713394
11	Nature	0.816689
12	Performance	0.818008
7	Helping Your Community	0.950313
1	Building & Fixing Things	1.763925
2	Computers	2.141501
14	Science & Math	2.661052
0	Academic Support	3.301041
13	Reading & Writing	9.898727
10	Music & Art	29.817058
16	Sports + Wellness	44.839212

The next subquestion to be answered was which geographical cluster whose boundaries are determined by the city of Chicago have the greatest and the least number of programs. By using the value_counts function I was able to return the top three and bottom three geographical clusters based on the number of youth programs. The results are as follows.

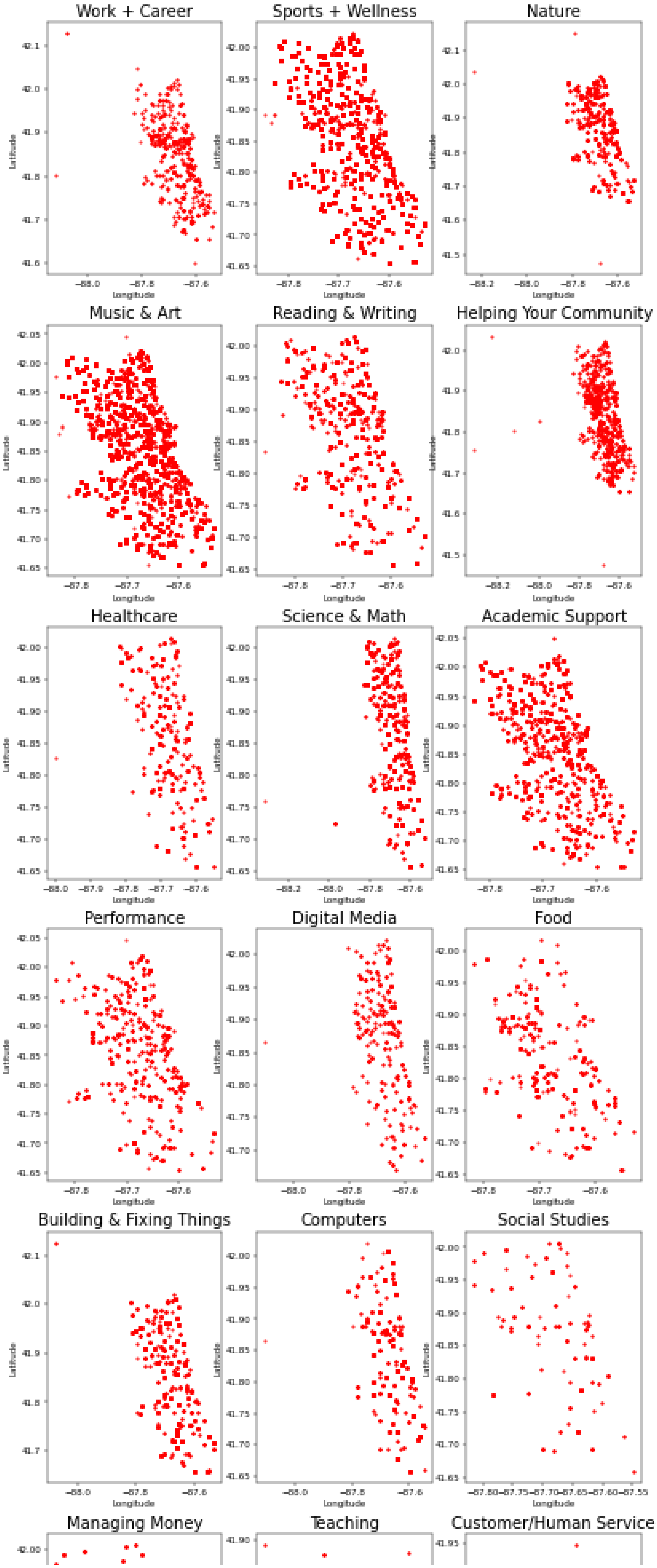
```
Geographic Cluster Name
Northwest Equity Zone        21563
West Equity Zone             16041
North/Central Equity Zone    15634
Name: count, dtype: int64

Geographic Cluster Name
NEW CITY    142
OHARE         6
BURNSIDE      6
Name: count, dtype: int64
```

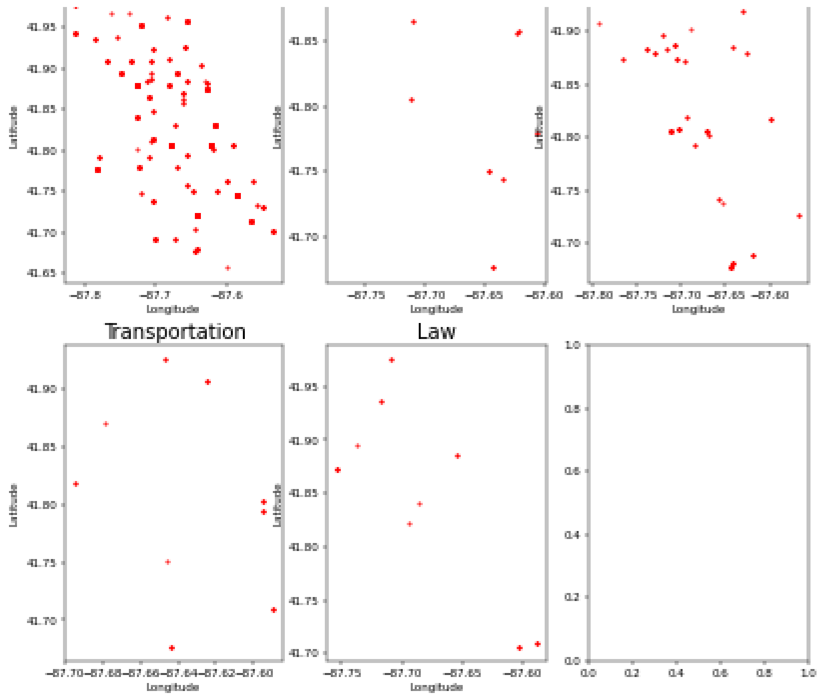
As you can see, Northwest Equity Zone, West Equity Zone, and North/Central Equity Zone have the most number of programs with a program count average of 17,741. The geographic clusters with the least number of programs are New City, O'Hare, and Burnside. By using a map of these geographical clusters, I was able to reason that O'Hare and Burnside are further from the city center, so it is likely they have less programming due to a less dense population. However, New City is relatively close to the center of Chicago and only has 142 programs. This is a possible area of inequity, so it is worth noting. In our presentation, I was also able to include an image of the geographical clusters of Chicago (see presentation).

The next subquestion to be asked was where is each youth program in the geographic area of Chicago and what Category Name are they? I first subset the Latitude and Longitude given for the programs, ignoring the virtual programs that could likely be attended by youth in all parts of the city. From there I removed geographical outliers that were not within the city boundaries, and then used a scatter plot to plot every program based on its location with its associated Category Name color.



I then split each Category Name into separate graphs with red dots indicating the positions of the programs.


Work + Career
Sports + Wellness
Nature
Music & Art
Reading & Writing
Helping Your Community
Healthcare
Science & Math
Academic Support
Performance
Digital Media
Food
Building & Fixing Things
Computers
Social Studies
Managing Money
Teaching
Customer/Human Service
Latitude
Longitude



The first graph, Work + Career, has a fairly even distribution across the city with programs getting slightly more sparse going West where population is less dense. The same is true for Sports + Wellness, this spread being one of the top most fair as we see programs all throughout Chicago. Nature is a less common Category Name and as a result there are fewer dots that tend to group closer to the shore of Lake Michigan. Music & Art, being the second most common Category of program, has a fair spread of programs similar to Sports + Wellness. Reading & Writing is more sparse, and Helping Your Community is bunched almost exclusively toward the East side of the city. This is worth noting and could be explained by a greater need for helping one's community in more populated areas of the city. Healthcare contains fewer programs that are evenly spread, while Science & Math are more concentrated toward the East side. Teaching and Law, while common topics in schools, have very few programs across the city.

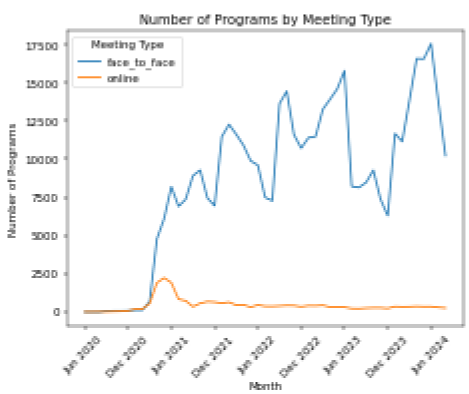
4.4 Analysis 4

By Athena Wenger

I began by examining the dataset and filtering out programs with a minimum age requirement above 25, as these were categorized as family programs rather than youth programs. To focus on the differences between online and face-to-face programs, I concentrated my initial exploration on the 'Meeting Type,' 'Start Date,' and 'End Date' columns. After review, I confirmed that there were no missing values in these key columns, ensuring the data was complete and reliable for further analysis. After parsing and cleaning the data, my first objective was to analyze the trends between online and in-person programs over time. Recognizing the recent influence of events such as the COVID-19 pandemic, I aimed to examine how the availability of programs in these two meeting formats evolved. To achieve this, I converted the start and end dates into numeric values and identified the earliest entry for both online and face-to-face programs to determine the initial time point for analysis.

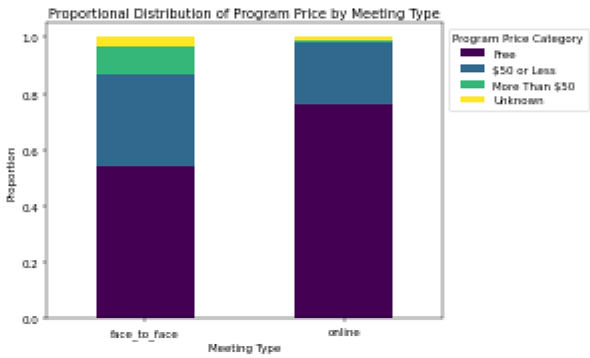
```
Earliest In-person Start Date: 2020-06-01 00:00:00
Earliest Online Start Date: 2020-01-22 00:00:00
Latest In-person End Date: 2050-01-01 00:00:00
Latest Online End Date: 2046-12-31 00:00:00
```

Based on the results, I determined that the graph should begin on 06/01/2020, as this date marked the earliest instance where both online and face-to-face program data would be available. Starting at this point ensured that the trends being analyzed comprehensively represented both meeting types. The latest end dates for programs extended well into the future, but I decided to visualize data only up to the most recent, reliable timeframe. Initially, I had used the interquartile range (IQR) to determine how far the timeline should extend, but I later revised this approach to reflect data up to the present accurately. The cutoff date was set to 08/05/2024, as this was the last modification date of the "My_CHI._My_Future._Programs.csv" file in OneDrive, making it the most accurate and relevant endpoint for the analysis. Stakeholders should note, however, that the data is limited to the version published on this date, and any data added afterwards is not included. To create the line graph, I first ensured that programs were appropriately represented for all months they were active by generating a range of active months for each program, rather than relying solely on start and end dates. This allowed programs spanning multiple months to be accurately included in the analysis. I then grouped the data by month and meeting type to calculate the number of active programs for each combination, ensuring a clear comparison between online and face-to-face programs. I filtered the aggregated data to include only the months within the valid time frame, from 06/01/2020 to 08/05/2024. This ensured that the graph focused only on the relevant period while preserving the integrity of the original dataset. I then formatted the data chronologically to make the graph intuitive, added custom labels for the x-axis to improve readability after some trial-and-error, and grouped the data by meeting type to differentiate trends in online and face-to-face programs.



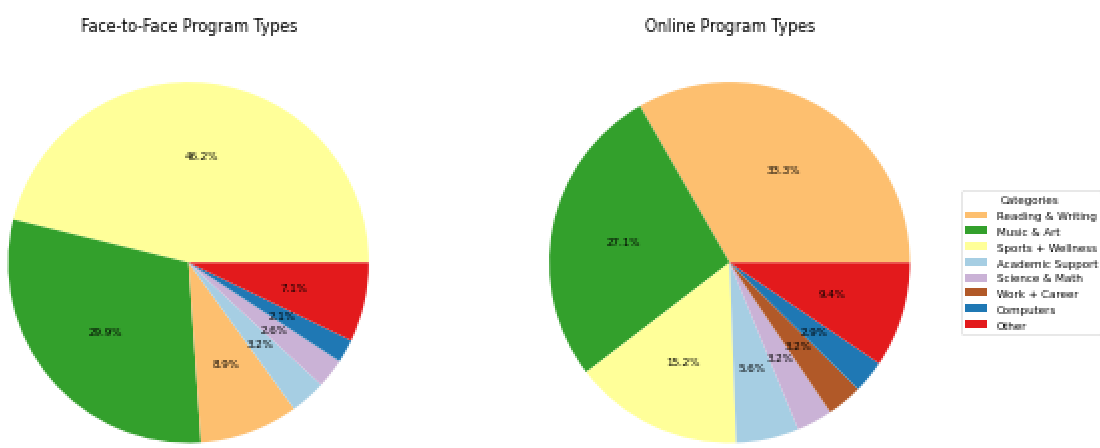
The first takeaway from the graph is that there are significantly more in-person programs than online ones overall. However, at the beginning of the timeline, there are very few of either. COVID-19 began to significantly affect the United States in early 2020, and it is likely that many programs, regardless of meeting type, initially shut down completely as organizations adapted to the unprecedented circumstances. The spike in both in-person and online programs in early 2021 could reflect the gradual resumption of activities under new health mandates, which coincided with adaptations like social distancing measures and the adoption of online platforms. The peak of online programs in mid-2021 likely reflects their increased adoption as a flexible and safer alternative. However, online programs subsequently declined and plateaued at relatively low levels.

For the second analysis, I wanted to further explore the Program Price column to determine how pricing differed between online and face-to-face programs, and how this might impact accessibility. Upon examining the data, I identified that Program Price was a categorical variable with four distinct categories: Free, $50 or Less, More Than $50, and Unknown. I also confirmed the lack of missing values from this column. Given the significantly smaller number of online programs compared to face-to-face programs, I opted to use a proportional stacked bar graph. This visualization allowed for a fair comparison of pricing distributions between the two meeting types. By normalizing the counts into proportions, I ensured that the differences in price structures were clearly visible without being overshadowed by the disparity in overall program counts. I then clarified the categorical order and adjusted the axis and title labels of the graph for improved visualisation.



This graph highlights the proportional distributions of pricing between online and face-to-face programs, revealing implications for accessibility. Both meeting types have a significant proportion of free programs, with the proportion of free online programs slightly higher. In-person programs, however, have a larger proportion of programs in the “$50 or Less” and “More than $50” categories, suggesting that financial barriers could be more common in face-to-face settings. For the final graph, I explored how program availability differed categorically between online and face-to-face formats. I determined that a pie chart would be the most effective way to illustrate the percentage breakdown of program categories for each meeting type. This approach emphasized the relative distribution of categories, especially given the significantly larger number of face-to-face programs.

The initial version of the graph was overly cluttered, with an overwhelming number of sections that made it difficult to read. Additionally, inconsistent color palettes between categories across graphs added to the confusion. To improve visual clarity, I created a function to consolidate all categories that contributed less than 2% to the total into a single “Other” category. This simplification reduced visual clutter and focused attention on the largest and most impactful categories, providing a cleaner and more informative representation of the data. I created the pie chart for each Meeting Type and after several attempts was able to ensure that the color palette was consistent between the two graphs to enable easier comparison. I adjusted the titles and legend for cleanliness.



5 Conclusions

All of the individual analyses connect with each other in that they all focused on finding where there might be gaps in programming for youth across the Chicagoland area. While all 4 analyses covered a different area of youth programming, they all can be examined together in identifying specific disparities in the programs outlined in the dataset. For example, Analysis 1 found that Chicago is prioritizing age-specific programming for youths as opposed to more general programs for both youths and adults. It also found that ages 13 and 18 are the best served because they might be generally accepted “transition” points (child to teenager and teenager to adult). Finally, the drop-off between 13 and 18 might suggest a gap in programming for teenagers. The graph also shows that babies and toddlers are the least-served group. In Analysis 2, it was found that while just over half of programs are free, there might be additional financial accessibility barriers limiting youth participation in programs. Very few free programs have transportation, free food, scholarships, or offer pay for participation. The most popular category of “Sports + Wellness”, which has the highest proportion of non-free programs out of the top 5 program categories, also does not offer additional financial support, even further hindering participation. Analysis 3 proved that there is a need to be met for more math, computers, and social studies programs, as well as more specific programs like managing money, teaching, and law. It also found that “Sports + Wellness” is a popular early childhood program and is likely a good idea for one seeking to employ a well-liked program in their community. Analysis 4 lastly deduced that face-to-face programs far outnumber online programs, creating potential barriers. Online programs show relatively stable numbers but remain significantly fewer than face-to-face options. While both modes of programming have free programs, face-to-face programs have a slightly higher proportion of more expensive options. Face-to-face programs are heavily focused on physical activities whereas online programs emphasize academic and career-focused categories. Overall, while all of the analyses focused on different aspects of programming, they all provide a common insight into what programs might be more or less accessible to youth, which allows us to make recommendations on where to improve accessibility.

6 Recommendations to Stakeholder(s)

In our first analysis, it was proven that expanding free, youth-exclusive programs, particularly for very young children and teenagers aged 14-17, could address a significant gap in services for these age group. These efforts would help ensure that children have greater access to programming tailored to their needs during critical developmental stages. Additionally, increasing family-oriented educational programming in reading and writing would address a discrepancy between family and youth-exclusive programs. By focusing on these areas, organizations can create more balanced and accessible programming for Chicago’s youth. It is important to note, however, that while our analysis highlights potential gaps and opportunities, we do not have data on program outcomes or direct insights into the wants and needs of Chicago residents. To build on our findings, organizers should consider conducting surveys and focus groups to better understand community priorities and assess whether investments in specific types of programs align with residents’ needs.

In our second analysis, it was proven that organizers should aim to expand the number of available youth programs to include more with these various forms of financial support. Having transportation available or free food during the program could make a large number of economically-disadvantaged youth able to particpate in a program when they might not have been able to previously. Additionally, expanding the amount of free programs could also be a solution to making programs more accessible. This might include making more programs online instead of in-person (where there might be more barriers to participation like the aforementioned). However, it is important to note some potential limitations. When merging ‘Science’ and ‘Math’ into ‘Science & Math’, there might have been a slight loss of detailed data when looking at program category. However, my analysis didn’t focus too deeply on the program’s category itself, but rather briefly looked at it before looking at additional variables. Additionally, my analysis could have lost some other valuable information in the other categories I did not focus on (considering I focused on the top 5 because they included over 90% of the data).

In our third analysis, we were able to answer the question of where Chicago youth programs can become more equitable. With the above information, the stakeholder is able to find specific locations in which certain kinds of programs are needed. This will allow the stakeholder to make sound decisions opening new youth programs to help further the livelihoods of Chicago youth. We also mapped the programs so that stakeholders can see in which geographical regions and neighborhoods programs tend to bunch. We believe that stakeholders should find specific areas that need more of a specific kind of childhood program; for example, math programs in South Chicago. While this analysis helped us learn more about the geographical and categorical distribution of Chicago youth programs, some limitations must be acknowledged. Location was determined using the geographical zones provided by the dataset when there might have been a more specific and detailed way to accomplish this. Also, there might be other factors influencing location when considering how location impacts what program categories are available; essentially, thinking about the financial barriers presented earlier.

The face-to-face programs excel in physical and creative engagement, while online programs offer a more diverse range of educational and professional opportunities that are easier to deliver in an online format. Investing in expanding STEM and career development programs in both formats, but especially online, could enhance participants' skill sets and future prospects. Supporting hybrid programs that integrate the strengths of both meeting types could increase access to categories like Sports & Wellness, addressing barriers. Potential limitations of the comparison between face-to-face and online programs is that it may not fully account for participant access to technology or physical spaces, which could impact the effectiveness of these formats. Without considering why/how youth participate in in-person or online programs, it is difficult to measure their effectiveness. Additionally, the location one is in might hinder their ability to participate in an in-person or a youth program.

References

[1] Thometz, Kristen. "Study: Chicago Youth Development Program May Interrupt Cycle of Intergenerational Poverty." WTTW, 13 July 2022, https://news.wttw.com/2022/07/13/study-chicago-youth-development-program-may-interrupt-cycle-intergenerational-poverty.