Understanding Strategies and Challenges of Conducting Daily Data Analysis (DDA) Among Blind and Low-vision People

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ABSTRACT

Being able to analyze and derive insights from data, which we call Daily Data Analysis (DDA), is an increasingly important skill in everyday life. While the accessibility community has explored ways to make data more accessible to blind and low-vision (BLV) people, little is known about how BLV people perform DDA. Knowing BLV people's strategies and challenges in DDA would allow the community to make DDA more accessible to them. Toward this goal, we conducted a mixed-methods study of interviews and think-aloud sessions with BLV people (N=16). Our study revealed five key approaches for DDA (i.e., overview obtaining, column comparison, key statistics identification, note-taking, and data validation) and the associated challenges. We discussed the implications of our findings and highlighted potential directions to make DDA more accessible for BLV people.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in accessibility**.

KEYWORDS

blind and low vision, BLV, qualitative study, data exploration, daily data analysis, DDA, interview, think-aloud, data accessibility

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1 INTRODUCTION

On a typical workday, Tom opens a spreadsheet of a list of commodities with product information and prices. Instead of glancing at it to get an overview (e.g., number of rows and columns), as a blind person, Tom moves the cursor in the spreadsheet cell by cell while carefully listening to each value being read by the screen reader. Tom has to spend quite some time gaining a general understanding of the data in the spreadsheet before making calculations and comparisons among the commodities. This is a typical scenario of how blind and low-vision people (BLV) perform daily data analysis (DDA). DDA is a series of common tasks people perform in certain situations (e.g., splitting expenses amongst friends, computing stock portfolio changes, and calculating average scores). In particular, the word "daily" emphasizes its common occurrence in our everyday lives.

Access to data is a prerequisite for DDA. Recent studies uncovered BLV people's practices and accessibility challenges with various data sources and platforms, presented recommendations on how to overcome these challenges, and provided guidelines and design considerations on how to make these data access processes more accessible. The areas they explored include web and social media [14, 20, 51, 73], smartphone data [2, 22, 47], and online-shopping [38, 41]. To improve access to data for BLV people, researchers have investigated various assistive technologies, such as printed Braille and refreshable Braille displays [29, 31], screen readers [42, 71, 79], sonification approaches [30, 56, 66, 67], and haptic devices [15, 19, 29].

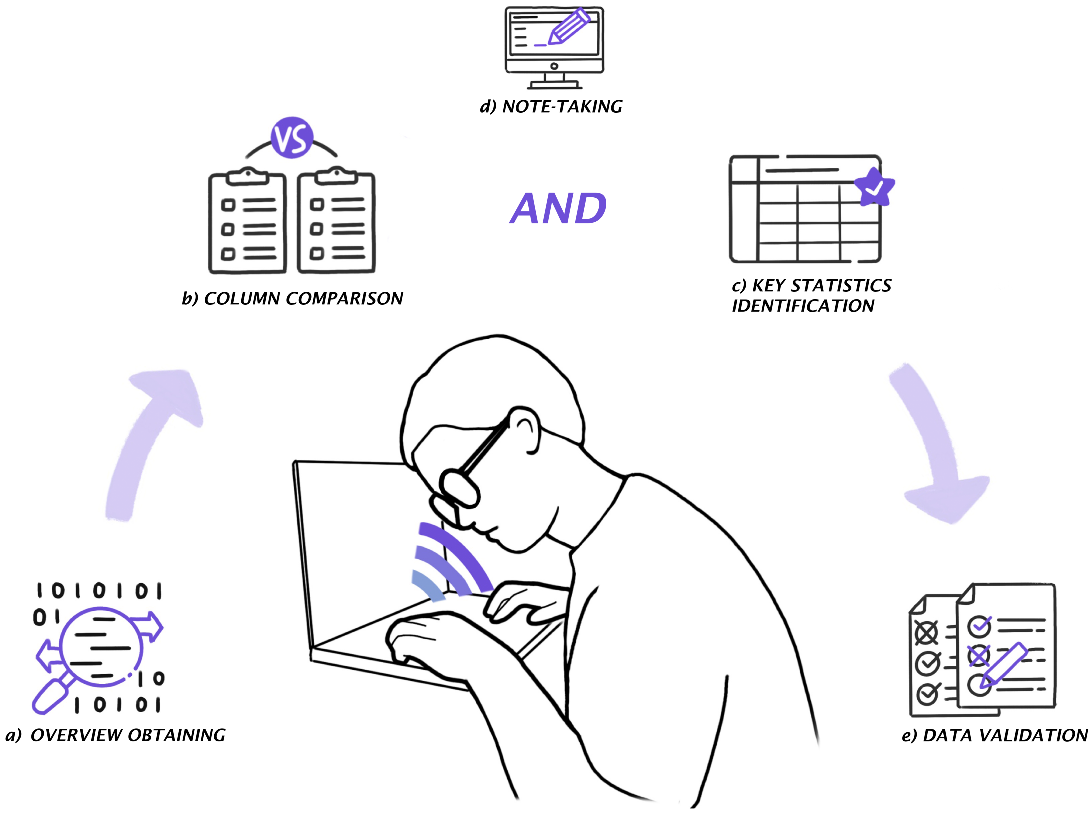


Figure 1: Our research revealed five key approaches to performing DDA among blind and low-vision (BLV) people: a) Overview Obtaining; b) Column Comparison; c) Key Statistics Identification; d) Note-Taking; e) Data Validation;

In addition to uncovering and addressing access to data challenges, researchers have investigated how BLV people use spreadsheets [13, 34, 75, 76]. For example, Doush et al. [13] found that the large amount of information stored in the spreadsheet, the multi-dimensional nature of the contents, and the several features were factors that prevented BLV people from getting the overview of various elements (e.g., charts and tables) in the spreadsheet. Similarly, Stockman found that navigating spreadsheets with most screen readers is time-consuming, and places a large load on users' short-term memory [75]. While informative, prior work primarily focused on how BLV people conduct non-visual navigation of spreadsheets. In contrast, performing DDA is a comprehensive activity that involves not only non-visual navigation but also how to make sense of the data. It remains largely unknown how BLV people perform DDA to make sense of the data and the challenges they encounter in the process. By gaining insight into their strategies and challenges, we can identify opportunities for developing assistive technologies that cater to their needs more effectively. Inspired by this need, we investigate the following research question (RQ): **How do BLV people perform DDA, and what are the associated challenges?**

To answer this RQ, we recruited 16 BLV people to participate in a mixed-methods study, which consisted of semi-structured interviews and think-aloud sessions in which they completed a series of DDA tasks using screen readers while verbalizing their thoughts. By analyzing their interviews and think-aloud data, we identified five key approaches that participants used to conduct DDA: overview obtaining, column comparison, key statistics identification, note-taking, and data validation. We also identified particularly challenging operations such as obtaining the quantity, layout, and relationships between the elements in the spreadsheet, as well as possible ways of improving assistive tools for more efficient DDA.

In sum, we make the following two contributions: 1) We identified the process by which BLV people perform DDA and the challenges they encountered; 2) Based on the findings, we present design considerations for improving the accessibility of the DDA process for BLV people.

2 RELATED WORK

Our work draws on prior literature in three areas: data sensemaking, BLV people's practices and challenges in accessing data, and non-visual navigation of spreadsheets.

2.1 Data Sensemaking

Data sensemaking is the process of constructing meaning from information [4] and is an iterative process that involves linking different pieces of information into a single conceptual representation [27, 60]. Weick et al. also defined it as an *ongoing retrospective development of plausible images that rationalize what people are doing* [84]. Prior work has investigated various perspectives of data sensemaking, such as Weick [82, 83], Stefik, Pirolli, and Card [61], and Dervin [12]. Researchers have also developed a model for the cost structure of sensemaking and found that sensemaking is a cyclic process that involves searching for representations and then organizing information in these representations while reducing the cost of task operations [61]. They presented four case studies to show that making sense of complex information always appears to follow a common pattern despite differences in domain [61]. Thus, we were motivated to explore how this process may map to how people make sense of a data set during DDA. They also found that the main cost (i.e., time and effort) associated with sensemaking is data extraction, in which people try to find relevant information and then transform that information into a canonical form [61]. Hence, we will investigate if a similar step in the DDA process causes challenges for BLV people and seek to identify improvements to reduce that cost.

Researchers have also explored the types of common tasks that are involved in DDA with sighted people [1, 5, 37]. Boy et al. found six fundamental data literacy questions, which include determining the maximum (T1), minimum (T2), variation (T3), intersection (T4), average (T5), and comparison (T6) [5]. Amar et al. presented 10 low-levels tasks that help people make sense of data visualizations, which include retrieve value, filter, compute derived value, find extremum, sort, determine range, characterize distribution, find anomalies, cluster, and correlate [1]. Although the tasks that BLV people engage in during DDA are the same as sighted people, the way they approach them may differ. While sighted people may glance at a chart to find extremum, BLV people rely on assistive tools. Thus, we will investigate the various strategies that BLV people employ and the challenges they encounter during this process.

2.2 BLV people's Practices and Challenges in Accessing Data

In order for BLV people to perform DDA, they first need access to such data. The process of accessing data was investigated by previous studies that focused on BLV people's practices and challenges in various data sources and platforms, which resulted in recommendations, guidelines, and design considerations. For instance, previous work has explored web accessibility [14, 35, 64, 73], smartphone data accessibility[2, 33, 48, 59, 73, 77], social media data accessibility [20, 36, 51, 63, 78], and online-shopping data accessibility [38, 41, 80]. In particular, Siu et al. found that many BLV people experienced barriers when trying to access accurate information about COVID-19, which highlighted data access inequalities in the BLV people community during a time of crisis [73]. Lee et al. examined how screen readers narrate different out-of-vocabulary (OOV) words (e.g., abbreviations, wordplays, slang) on Twitter and how the presence of these words influences the interaction behavior and comprehension of blind screen reader users. They found that screen readers rarely narrated the standard form of OOV words (e.g., *bros* as "brothers"), even for popular words such as acronyms. Thus, blind users relied on tedious workarounds to discover the actual meaning, which included repeatedly listening to the tweet, searching on Google, asking friends, and creating custom pronunciation dictionaries for select OOV words [36].

2.2.1 *Assistive Tools for Data Access.*

To improve BLV people's access to data, researchers have developed various assistive tools, such as printed Braille and Braille displays [6, 17, 29, 31, 39, 49], screen readers [25, 42, 50, 52, 65, 71, 74, 79, 88], sonification [16, 30, 56, 57, 66, 67], and haptic devices [15, 19, 23, 29]. BLV people have used Braille for decades, but due to its high cost and inflexibility, printed Braille is not frequently used when accessing data in spreadsheets [6, 49]. Recently, multi-rows refreshable Braille displays and pin array haptic displays have been developed, which enabled BLV people to understand complicated figures and graphs [17, 29, 31, 39]. Screen readers, as a frequently used tool, have been widely researched, with applications including but not limited to reading text, tables, figures, and charts [14, 25, 42, 50, 65, 68, 71, 79, 88, 89]. Some researchers focused on screen readers' user experience and design principles [14, 25, 42, 71, 89], while others developed new functions or plug-ins for screen readers [50, 65, 68, 79, 79, 88]. Sonification is used for BLV people's access to both tabular data and visualized data. The increase or decrease in the value of the data is communicated to users via the change of sonification's pitch, amplitude, and tempo [16, 30, 56, 67]. Among these works, some developed sonification for charts or figures [16, 30, 67], while the others focused on data sets [56]. The use of haptic devices allowed users to feel the data through their fingers or hands [15, 18, 19, 23, 29, 72], harnessing different interactions such as active surfaces [29, 72], vibrations [19, 23], and force [18].

Our review demonstrates that prior work has primarily focused on data access (e.g., how BLV people access data and what challenges they encounter), while our study aims to explore the full DDA process from the point where BLV people open a data set until the end of their analysis. Specifically, we will investigate the strategies that BLV people utilize and the challenges they experience when making sense of data sets.

2.3 Non-visual Navigation of Spreadsheets

Apart from revealing and addressing issues found in accessing data, researchers explored how BLV people interacted with spreadsheets via non-visual navigation with screen readers. Compared to figures, participants preferred to access data with tabular and textual data to acquire detailed information [64].Previous work has explored BLV people's challenges when conducting non-visual navigation of tabular data presented in spreadsheets [13, 34, 75, 76], which includes slow navigation speed, large load on users' short-term memory, difficulty in understanding the spatial structure of the spreadsheet, and lack of hierarchical presentation of the data [13]. Since BLV people must remember the data that was just read, they felt that their memory deteriorates over time due to fatigue [76]. Additionally, Kildal et al. found that it can be challenging for BLV individuals to obtain an overview of complex tabular numerical data sets, which is the first step in their navigation process [34].

Table 1: Participants' demographic information.

ID	Age	Gender	Visual acuity level	Ability to read characters	Color perception	Contrast sensitivity	Congenital condition
1	19	M	Low Vision	yes	yes	yes	yes
2	23	M	Totally Blind	no	no	no	yes
3	19	M	Totally Blind	no	no	no	yes
4	40	M	Totally Blind	no	no	no	no
5	23	F	Totally Blind	no	no	no	yes
6	20	M	Totally Blind	no	no	no	yes
7	19	M	Totally Blind	no	no	no	yes
8	19	M	Low Vision	yes	yes	yes	yes
9	21	F	Totally Blind	no	no	no	yes
10	19	M	Low Vision	yes	yes	yes	no
11	17	F	Low Vision	no	yes	yes	yes
12	24	M	R: Totally Blind; L: Low Vision	no	yes	yes	yes
13	34	M	Low Vision	yes	yes	yes	yes
14	41	F	Totally Blind	no	no	no	no
15	21	F	Totally Blind	no	no	yes	no
16	19	F	Totally Blind	no	no	yes	no

The current body of work on non-visual navigation is insufficient to extrapolate insights about DDA since performing DDA includes not only non-visual navigation but also requires users to make sense of their data. It remains largely unknown how they perform DDA and what challenges they must overcome. Understanding the strategies and challenges is useful when designing and developing assistive tools for BLV people's DDA process. Thus, our work aims to explore the DDA process and provide suggestions to improve assistive tools for more efficient DDA.

3 USER STUDY

We conducted a mixed-methods user study with BLV participants to understand their strategies and challenges in performing DDA. The entire user study process started with a short demographic survey. Then we proceeded with the semi-structured interview to understand their general strategies and challenges. The interview results helped to inform our design of think-aloud tasks in the next phase. After 1-2 weeks, participants were invited back to perform DDA think-aloud tasks to understand their DDA strategies and challenges in practice. Due to COVID-19 travel restrictions, all sessions were conducted online, and the total time required for both sessions was between 90 and 120 minutes. The study sessions were audio recorded, and the recordings were then transcribed for thematic coding. The study was approved by the ethical review board at the authors' institution.

3.1 Participants

We recruited 16 BLV participants who had prior experience in conducting DDA either for work or personal reasons. As shown in Table 1, participants had various levels of visual acuity and were familiar with Microsoft Excel^{TM} since they had used it before with a screen reader.

3.2 Procedure

The study consisted of two separate components: (1) A *semi-structured interview session* to understand their DDA strategies and challenges; (2) A follow-up *think-aloud DDA task session* to observe their DDA process in practice.

3.2.1 The Semi-structured Interview Session. The semi-structured interview session was designed to understand their strategies and challenges during the DDA process. Participants were asked about when and how they performed DDA, the types of data they analyzed, the tools they used, common mistakes they made, and challenges they encountered. The findings from this session guided the design of the following think-aloud session.

3.2.2 The Think-Aloud DDA Task Session. While interviews relied on participants to accurately recall their experiences [11], the think-aloud study allowed us to observe firsthand how BLV participants perform DDA tasks on different data sets in practice. Through the think-aloud protocol, we gained more detailed insights into their thought processes to further complement the findings on DDA approaches and challenges from the interviews.

Data sets. Based on findings from the semi-structured interview, we curated two data sets to cover the types of data that BLV participants often encountered in their DDA process. The first data set was a spreadsheet about automobiles, which consisted of cross-sectional data collected at a specific point in time (shown in Table 3 in the Appendix). This spreadsheet was adapted from the widely used *Data for Motor Trend sample of 32 automobiles* [28]. The second spreadsheet contained time series data about stock prices that described the changes over time, such as the stock price and commodity quantity (shown in Table 4 in the Appendix). This spreadsheet was adapted from real stock prices in Yahoo Finance from 3/7/2017 to 1/7/2022 [86].

Tasks. We chose three types of tasks to represent the common tasks for DDA: cross-sectional tasks (Task 1 - Task 6), time-series

Table 2: Think-aloud Data Analysis Tasks

Task ID	Task Description
T1	Are there any outliers in the whole spreadsheet?
T2	How many types of cylinders are there in the spreadsheet?
T3	Please calculate the average miles per gallon of all cars.
T4	What is the percentage of Mercedes-Benz cars among all the provided brands?
T5	Please identify all the car models whose displacement is between (but not including) 120 and 175, and determine the maximum and minimum displacement in this group of car models.
T6	Based on the provided prices, which car model is the most appropriate if you have a budget of 60.0 and would like to buy the model with maximum horsepower?
T7	Please describe the trend of stock prices from 3/7/2017 to 1/7/2022 of Company A in as much detail as possible.
T8	Which company's stock price had the highest volatility from 3/7/2017 to 1/7/2022?
T9	Which two companies' stock prices have the strongest correlation?
T10	Please explore both datasets freely.

tasks (Task 7 - Task 9), and the free exploration task (Task 10). The details of tasks are shown in Table 2.

Cross-sectional Tasks. We compared the real-world tasks mentioned by participants in the semi-structured interviews to the ten low-level analysis tasks proposed by Amar et al. [1], noting that some tasks overlapped (e.g., participants had to "retrieve a value" to "find anomalies", and participants had to "find an extremum" to "determine the range"). To avoid repetition, we condensed these tasks into six cross-sectional tasks.

Time-series Tasks. We chose these three time-series tasks because of their frequent occurrence in the analysis of time-series data, as revealed in the semi-structured interviews, which included exploring the trend, understanding the fluctuation, and making comparisons of different trends.

Free Exploration Task. The free exploration task simulated a realistic DDA scenario where participants had unlimited time and freedom to determine their own goals. The following prompt was given to the participants:

> "Please explore the data set according to your own preferences and utilize any techniques you find suitable. There are no restrictions on the time frame for this task, and you are free to choose your objectives."

The free exploration task for both data sets was designed to explore possible DDA approaches that were not covered by the prior tasks.

3.3 Data Analysis

All interviews and think-aloud DDA sessions were recorded and transcribed. Two coders performed a thematic analysis of the interviews and think-aloud sessions to identify BLV participants' strategies and challenges when performing DDA. We followed an open coding approach [10], in which we first independently coded the data and then discussed the codes through weekly research meetings. For cases that had different interpretations, we explained our perspectives and discussed them until we reached a consensus. Afterward, we performed affinity diagramming to group the codes into tentative themes and iteratively refined them, which resulted in five themes. We report our findings based on these themes and corresponding key codes in the following section.

4 FINDINGS

We present our findings about BLV participants' strategies and challenges of how they perform DDA. We identified five key approaches that participants took when performing DDA: *overview obtaining*, *column comparison*, *key statistics identification*, *note-taking*, and *data validation*. Figure 2 shows the corresponding themes and codes.

4.1 Overview Obtaining

Participants' first step was to get an overview of the spreadsheet. The spreadsheets they received usually included two elements: tables which consisted of several columns of data, and charts based on the tables' data (e.g., bar chart, pie chart, and line chart). They typically traversed the spreadsheet with their screen readers to get an idea of the types of elements (e.g., tables and charts) in it and their quantities. They then traversed the title row of each table before focusing on a specific column. In addition, participants used OCR functions to read charts (e.g., bar charts and pie charts). Participants mentioned that they would form an initial rough estimation of the structure and size of the spreadsheet, and they continued to revise their estimation as they traversed. During this process, participants reported three challenges in *difficulty in getting the layout of the elements and their quantities*, *difficulty in figuring out the relationship between the elements*, and *difficulty in reading line charts*.

4.1.1 *Difficulty in getting the layout of the elements and their quantities in a spreadsheet.*

Participants mentioned that it was hard for them to get a full understanding of the layout and quantities of the elements in a spreadsheet as they might miss some elements. Participants did not know how much they had to traverse when receiving a new spreadsheet and continued until they believed it was the end. Elements varied in layout and quantities as they received spreadsheets from different people. Some put each element close together while others spread these elements out with space in between. In this process, participants might miss elements that were isolated from the rest of them. A lack of standardization of spreadsheet layouts made it hard for participants to discover the full content. One participant mentioned:

> "If the spreadsheet is too complicated, such as having several tables and charts in it, then it is relatively hard for me to comprehend it. In fact, it is even hard to

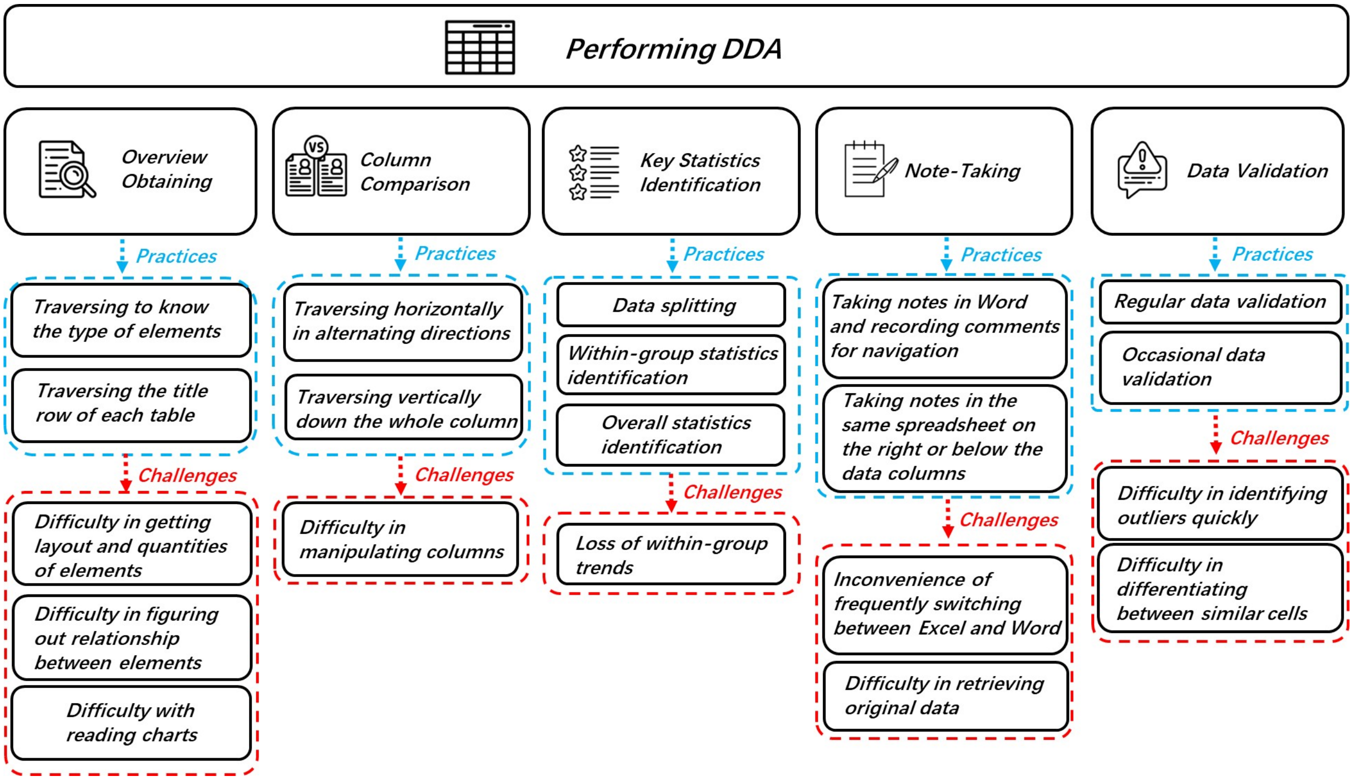


Figure 2: Summary of the five key approaches and associated challenges for performing DDA.

> know the existence of all elements if I don't traverse all possible areas in the spreadsheet, which takes a significant amount of effort. In many cases, if my sighted colleagues are available, I will have to bother them to tell me the layout of these elements." -P13

4.1.2 Difficulty in figuring out the relationship between the elements in a spreadsheet. Participants found it hard to discover the relationship between elements in a spreadsheet as they had to identify and memorize the theme and content of each element. In addition, the same data may be used as key components by different tables.

For example, the table of students' demographic information and the table of their final scores were connected by the "Name" and "Student ID" data columns. Therefore, to figure out the relationship between tables, participants have to read each element and memorize their main content, which was tedious and time-consuming.

4.1.3 Difficulty with reading charts. While in the think-aloud sessions of our study, no participants chose to generate charts from data while performing DDA. They provided two main reasons. First, it was challenging for them to use the functions in spreadsheets to generate charts. This process required them to be able to locate the chart generation functions, select the data to be plotted, and choose the right type of charts to be used. Afterward, they had to be able to locate the generated chart in the spreadsheet. Second, even if they could generate the right chart and locate it in the spreadsheet, their screen readers often did not read out the chart's content in a comprehensible manner.

However, participants mentioned that they might receive data with charts, from their friends or colleagues, in their daily lives. As a result, as part of their DDA, they might also need to read charts. Most (N=15) of the participants found it hard to get meaningful information from line charts, even with the use of OCR. Participants used the OCR function integrated within screen readers to extract text from the chart and pasted them into Notepad. The contents were pasted without formatting, making the data scrambled and hard to read.

The lack of alternative text exacerbated the issue of reading charts. On websites, figures are typically accompanied by alternative text, but charts created in Excel during the DDA process lacked alternative text. While participants felt that it did not significantly affect bar charts and pie charts as these contained fewer data points, they found that reading line charts was virtually impossible. Moreover, participants also mentioned the unavailability of assistive tools to help them read line charts. They were either unaware of the existing assistive tools, such as sonification, or could not afford a refreshable Braille display (e.g., "*It costs as much as my parents' two months salary*" -P10). We found that while assistive tools have been developed in research or commercial settings, the limited availability for everyday usage remains a barrier that negatively impacts participants' ability to obtain information from line charts.

After obtaining an overview, participants utilized two approaches to gain insight into the data. They either conducted *column comparison* to make a coarse but rapid comparison or *key statistics identification* to determine the trends and extremes, which yielded more precise results but took more time. To assist their insight generation, participants often took notes during the intermediate steps, which we describe in the following sections.

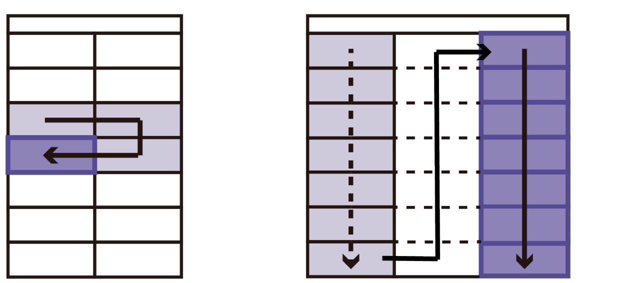
4.2 Column Comparison

Participants conducted comparisons between two columns by (1) traversing horizontally in alternating directions and (2) traversing vertically down the whole column and switching to another column, as shown in Figure 3. For columns that were close to each other, they used the first method, which ensured quick comparisons between data in the same row. The second method was used when the columns under comparison were not adjacent to each other as mentioned by P4. In this case, participants had to quickly traverse down the first column, and then switch to the next.

> "When making a quick comparison between two columns, such as reading the car data form, I compared every two columns one by one such as the cylinder numbers and displacement. While comparing the columns that are not adjacent, I must go through the whole column before moving to the other. Otherwise, I would have lost the location of each column during the process while switching columns." -P4

4.2.1 *Difficulty with manipulating columns.*

We observed that when comparing columns that were far from each other, participants did not utilize strategies to rearrange the data into adjacent columns, which required multiple operations such as hiding the middle column or copying or pasting to empty columns. This suggests that participants had difficulty manipulating the columns or were unaware these operations could make comparisons easier.



(a) Traversing horizontally in alternating directions

(b) Traversing vertically down the whole column and switching to another column

Figure 3: Visualization of the two strategies for conducting column comparisons: a) traversing horizontally in alternating directions, b) traversing vertically down the whole column and switching to another column. (The arrows indicate the order of traversal, the lighter shade indicates cells that are already been traversed, and the darker shade indicates cells that participants are currently traversing.)

4.3 Key Statistics Identification

After gaining an initial overview of the spreadsheet, participants tended to identify the key statistics of each element, such as the maximum, minimum, and trend of the data set. P13 mentioned:

> "In our daily work, the maximum and the minimum are the two key features that I look for, because these are checked by my boss every morning. The trend over time is also important, which is calculated at different frequencies such as one month, half year, or one year." -P13

To get these statistics, participants took a three-step approach: *(1) data splitting*, *(2) within-group statistics identification*, and *(3) overall statistics identification.*

Data Splitting. Participants first split a data column into several groups. For instance, when the data column contained 1000 rows of data, some participants divided them into groups with 100 rows each. The quantity of each group varied between participants, they either chose hundreds or certain time intervals (e.g., 365 days, quarterly) that were commonly used in time-series data.

Within-group Statistics Identification. When participants looked for within-group statistics (extremes or average) in small data sets, participants either traversed through each group, sorted the data to get the extremes, or calculated the average. For large data sets, participants used a similar method, but more participants sorted the data before traversing so that they could easily get the extremes at the beginning and end of the column (N = 8). Some participants also took notes to reduce the strain on their short-term memory, which is discussed in Section 4.4.

Overall Statistics Identification. Lastly, they made comparisons of the within-group statistics to identify the overall statistics of the full data set. For example, participants either directly traversed or sorted first then traversed within-group statistics. This allowed them to build a mental map of the overall trend of the data set, which was helpful in answering key questions about the data.

Based on the prior observations, we identified a challenge with the loss of within-group trends.

4.3.1 *Loss of Within-group Trends.*

The current data-splitting method resulted in the loss of within-group trends since all the values in the group were aggregated into summary statistics (e.g., a group with 100 rows of data would be represented by its average). Therefore, the fluctuations in the values within the group were smoothed out in this process, which led to the loss of meaningful information. For example, the average is heavily influenced by outliers and may not represent the full picture of the data, making the results less precise. P3 said:

> "The data splitting relieves me from memorizing a huge amount of data in a very short time. However, the drawback is that I have to miss small trends within each group, such as small rises and falls because the data in each group is reduced to just one point." -P3

4.4 Note-Taking

We found that participants took notes using different methods during the process of generating insights on the data. Some took notes by creating a new Word file and recording comments to assist with navigation, while others took notes in the same spreadsheet such as in the empty cells on the right or below the data columns.

Participants' choices for where to take notes also depended on the amount of data that they were analyzing. For small data sets, participants tended to create another document (e.g., a Microsoft Word file) to store key information, such as the maximum of each data group. After taking the notes, they went through them and made comparisons to get the maximum or minimum or other features of the whole data set. If many notes were taken, participants created comments in the document to make navigation through the Word document easier. For instance, P11 created a comment on every section title of her notes. When reviewing her notes, she selected one comment and used the direction keys to switch to the next comment, then used "ESC" to return to the main content. In this way, she could rapidly jump through the contents and get information efficiently. However, this strategy was not prevalent since only three participants chose to take notes with small amounts of data. One possible reason was mentioned:

> "If there is too little data, there is no need to take notes as it would be easier to just remember. While for larger data sets, creating notes and always changing between software is troublesome, so I prefer to take notes in the same spreadsheet." -P8

For large amounts of data, participants utilized two methods for taking notes directly in the spreadsheet: (1) they inserted another column on the right side of the data set and took notes on the average of each row, and (2) they added notes about key statistics of each column below the last cell of the data set. They then used these statistics to make further comparisons if needed. Participants reported two challenges when taking notes, which include the inconvenience of frequently switching between Excel and Word, and the difficulty in retrieving original data.

4.4.1 Inconvenience of Frequently Switching Between Excel and Word. We found that some participants used Excel to read the data but took notes in Word. They had to press Win + Tab and direction buttons to switch frequently between the two windows, which led to extra operations and time delays. This even discouraged some participants from taking notes completely and relied on their memory when analyzing small amounts of data.

4.4.2 Difficulty in Retrieving Original Data. It was hard for participants to retrieve the original data from their notes, especially for large data quantities. For example, participants mentioned that after taking notes of the averages of each group, it was difficult to go back to the specific start point and end point of each group without re-traversing the entire row or column. Therefore, if the participants wanted to check the correctness of their notes, they have to conduct another round of traversal.

After gaining insights into how participants extracted information and took notes on the data, we observed that some participants performed data validation to check whether their findings contained any errors.

4.5 Data Validation

Participants conducted data validation after the DDA process. Some participants (N=8) checked for potential errors regularly because they wanted to ensure the accuracy of their analysis. For example, they checked whether all the necessary data were included during their calculations and whether correct formulas were used (e.g., using STDEV.P instead of STDEV.S). In contrast, some (N=8) only checked errors occasionally because they found the process to be time-consuming and tedious. Unless Excel reported errors (e.g., #REF, #NUM, #NAME, #N/A, #VALUE, #NULL, #DIV/0) or obviously wrong answers (e.g., a negative value for price), they would skip data validation.

Some challenges that led to this reluctance include (1) difficulty in identifying outliers quickly; (2) difficulty in differentiating between similar cells.

4.5.1 Difficulty in Identifying Outliers Quickly. While sighted participants may easily notice outliers on a chart due to their relative location to the other data points, it is more difficult for BLV participants who must rely on each value being read by screenreaders. Thus, they must memorize the existing values to identify values that seemed abnormal, which is both time-consuming and often fruitless. P8 said:

> "Unless I know that there is an outlier, and determined to find it, I will never know its existence in the whole process as it is like searching for a needle in the haystack." -P8

4.5.2 Difficulty in Differentiating Between Similar Cells. Participants often skipped to the next cell without waiting for the full content to be read, which led to them missing subtle differences at the end of similar cells (e.g., STDEV.P instead of STDEV.S) and making incorrect calculations. We found that some participants had to sacrifice validity (conducting DDA thoroughly and correctly) for efficiency (conducting DDA quickly).

5 DISCUSSION

DDA is a common strategy to derive insights from data. Given the era of big data and the benefits of mastering data science, DDA is an essential skill for deriving insights and performing daily activities. Thus, we argue that it is critical to ensure BLV people have equal access to performing DDA so that they could also, as their sighted peers, tap into the benefits provided by data analysis. As a result, in response to recent calls to make data more accessible for BLV people, we conducted a mixed-methods study to understand how BLV people currently perform DDA, including their strategies and challenges. By using a mixed-methods approach, we observed firsthand the struggles that participants experienced and gained insights into nuanced operations that participants made which would not have been identified with only interviews. Specifically, we identified five key approaches and the corresponding challenges. While there is a body of trending research investigating ways to make data visualizations more accessible to BLV people [7, 15, 16, 30, 65–67, 69] and making different forms of data more accessible [21, 56, 80, 85], little is known about how BLV people currently explore raw data in spreadsheets to derive insights through the process of DDA and the associated challenges. Our research contributes to the understanding of this gap.

5.1 Connection between DDA and Data Sense-Making and Information-Seeking Models

We identified some connections between our findings and various models on data sense-making and information-seeking. As discussed in Sec 2.1, data sensemaking involves searching for representations and organizing information in these representations [61]. Our findings show that participants first tried to obtain an high-level overview of the data set, then refined their understanding by conducting comparisons between specific columns and identifying key statistics. They continuously updated their mental model of the data set as new information was discovered. Russell et al. also found that data extraction led to the highest cost, while we observed that participants spent the most time on key statistics identification. Both processes involve finding relevant information amongst the larger body of data and making use of that information.

Furthermore, Marchionini et al. presented a 7-step information-seeking model, which includes *recognizes an information need*, *accepts the challenge*,*problem formulation*,*express the information need*, *examination of results*, *reformulations*, and *use the information* [46]. Although this model is more applicable to the web searching process while our paper focuses on the data analysis approaches, we can still draw parallels between certain steps (e.g., "overview obtaining" aligns with the formulate step, "column comparison," "key statistics identification," and "note-taking" align with the expressing step, and "data validation" corresponds to the examine and reformulate steps). In particular, we observed that the reformulate step was often neglected, as half the participants found error checking to be tedious. Future work should explore methods to facilitate easier reformulation for BLV people.

The information scent model posits that the user's behavior is guided by information scent, which is determined by their perception of the value and cost of the information concerning their final goal [8]. Our findings indicate that participants typically opted for strategies that saved time and were more likely to reveal the desired information. For example, they preferred splitting data into fewer groups to obtain a rough trend rather than a detailed one. Additionally, they rarely focused on error detection as the scent for errors was weaker compared to traversing. Next, we will discuss the implications of our results and highlight possible ways to make performing DDA more accessible to BLV people.

5.2 Challenges in Performing DDA and Potential Solutions

Prior research has mostly focused on making the DDA process visually more accessible. The visual information design mantra, proposed by Shneiderman et al. [70], is "overview first, zoom and filter, then details-on-demand." Zhao et al. later proposed an auditory information-seeking principle, which is "gist, navigate, filter, and details-on-demand", to guide data sonification design [87]. Our empirical research provides insights into how such principles are reflected in BLV people's five key approaches in the DDA process. The principles of "overview first" and "gist" (i.e., quick grasp of overall trends) are partly reflected in our findings about "overview obtaining" and "key statistics identification." The principles of "filter", "zoom" and "detail-on-demand" are grouped in steps of "key statistics identification" and "column comparison" that BLV people took when exploring data in detail and on demand. Our study revealed that as opposed to zooming in on data visualizations like sighted people, BLV people instead traversed raw data, split data into groups, performed interim calculations, and took notes. Moreover, our study also provided novel insights into how BLV people traverse data, such as traversing horizontally in alternating directions and traversing vertically down the whole column.

5.2.1 Overview Obtaining. BLV people conducted a thorough traversal with screen readers to obtain an overview of the spreadsheets, which is different from "overview first" and "gist". "Overview first" refers to the control of a movable field-of-view (FOV) box to get the contents of a data set [70], while "gist" refers to the understanding of an overall trend or pattern [87]. Since BLV people were unable to glance over the overall spreadsheet and quickly get an overview, they had to figure out the layout and relationships between cells using screen readers, which was time-consuming. An earlier study by Stockman et al. found that the spatial nature of spreadsheet contents challenges BLV people's non-visual navigation tasks, especially during spreadsheet overview [75]. Later, Doush et al. also suggested that BLV people can lose structural information in a spreadsheet when conducting non-visual navigation [13]. More than a decade later, our findings revealed similar challenges in DDA for BLV people even when technologies have advanced significantly from these earlier works. Although the HCI and accessibility communities have investigated ways to make data and visualization more accessible by designing various assistive tools such as sonification and haptic devices, our work highlights the challenges that BLV people still encounter when performing DDA. Future work should investigate easier ways for BLV people gain an overview of data so that they could better perform the rest of the DDA steps.

One possible approach for BLV people to gain an overview of data is by creating dynamic hierarchical overviews, which were initially designed to support sighted people's data analysis process. To enhance their exploration of spreadsheets, previous research investigated interactive and detailed interfaces, such as an overall structure of the data alongside the spreadsheet [24] and an overview with detailed interface [9]. However, one limitation of such approaches is that they only provide static summaries in a separate area and do not provide correspondence between the raw data and the summary. This limitation motivated the design of more interconnected overview structures, such as dynamic hierarchical overviews. A dynamic hierarchical overview interface consists of seven main parts: the overview, the aggregate column, the spreadsheet, the history, the breadcrumb, the user's current focus, and the cells corresponding to navigation and aggregation attribute [58]. This design provides a customizable summary of the spreadsheet, allowing users to connect the summary to the raw data. It is highly suitable for BLV people to obtain an overview that allows them to quickly figure out the quantity, layout, and relationships between the elements in one spreadsheet. However, such interfaces were developed for sighted people, and future work should investigate ways to design dynamic hierarchical overviews for BLV people, for example, by supporting screen readers, easy-to-remember shortcut keys, and possible combinations with haptic assistive tools and sonification approaches.

5.2.2 Key Statistics Identification. Key statistics identification is a crucial step for BLV people to obtain important characteristics of a data set. Similar to obtaining an overview, traversing a data set was commonly used to identify key statistics but this process was tedious and time-consuming. When extracting trends from the data set, BLV people adopted an approach, which we called "data splitting", to split data into smaller groups and compute interim statistics for each group before making a comparison. This process of splitting data into smaller groups reduced their short-term memory load. However, the accuracy of the overview depended on the size of each group. While splitting larger amounts of data into one group may lead to the loss of within-group trends, splitting smaller amounts may lead to a plethora of groups and interim statistics to manage. Previous work proposed the use of sonifications to extract trends from both data sets and graphs. However, as Stockman et al. pointed out, sonification is less effective in creating fine-grained presentations [76]. Thus, how to help BLV people efficiently identify key statistics and trends remains to be a key challenge.

There are two possible directions to address this problem: by designing assistive tools to help BLV people read charts generated from data or by assisting BLV people in exploring data directly without visualization. Previous research primarily focused on the former approach, such as designing haptic devices and sonification techniques [29, 30, 67, 72]. However, our findings suggested that BLV people rarely created charts or figures during their DDA processes to gain insights. Toward this end, we suggest that the community focus on exploring data splitting and extremum extraction techniques that are tailored to BLV people's DDA processes, for example, designing tools that allow BLV people to explore data at different granularity on demand [62, 64].

While pivot tables in Excel are available to split data and calculate averages, these tools can be inconvenient for BLV people when dealing with large amounts of data as they have to make adjustments and remember the averages of each group. Previous work has developed data extraction tools and plug-ins to address data accessibility issues, and many are web-based and can be easily used by BLV people [44, 67, 69]. The combination of such tools with sonification and haptic devices might allow BLV people to gain a deeper understanding of data set's key characteristics.

5.2.3 Data Validation. Currently, participants felt that data validation was time-consuming and tedious, or skipped it altogether, which resulted in errors being missed. The development of an automatic error detection system will improve the validity of their results. Previous work has presented various automated approaches for spreadsheet quality assurance (QA), which include visualization-based approaches, static code analysis and reports, testing approaches, automated fault localization and repair, model-driven development approaches, and design and maintenance support [32]. Among these tools, Nixon et al. developed *Spreadsheet Detective*, a static analysis techniques-based spreadsheet auditing tool that checks errors in spreadsheets and presents them as graphical annotations [53]. For example, the system can automatically analyze the entire spreadsheet to identify whether the same formula is repeated throughout a particular row or column. It also provides a complete list of all distinct formulas and named ranges, which no longer requires BLV people to spend time traversing the whole spreadsheet to discover the formulas used. In addition, Barowy et al. presented a static analysis tool specifically designed to find spreadsheet formula errors by exploiting the intrinsically rectangular layout of spreadsheets [3]. Cells and formulas considered potentially incorrect by the system will be automatically shown in a different color. However, these currently available error detection tools are heavily reliant on visual indicators (e.g., displaying notifications as lines and color differences). Thus, accessibility improvements, such as integration with screen readers, sonification, and haptic devices, are required to make such tools more accessible to BLV people.

5.2.4 Considerations for High-Level Strategies. Although our study uncovered low-level strategies that BLV participants employ and the challenges they encountered, high-level approaches should also be considered when developing future assistive tools. Our findings about low-level strategies provide empirical evidence and a foundation to guide the design of high-level assistive technologies. For example, AI technology could automate low-level tasks by responding to natural language queries for calculating averages and identifying trends. These approaches may avoid the necessity of using low-level strategies when BLV people conduct DDA and have potential to reduce the required time and effort. Prior work has discussed how large language models (LLMs), such as ChatGPT, can be used for data science. The applications include data visualization [40, 43, 45, 54] and information extraction [26, 55, 81]. Noever et al. found that ChatGPT can simulate human behavior to conduct data analysis on structured and organized datasets, then present the results by generating graphs using Python code [54]. Maddigan et al. developed a system to provide a reliable approach to rendering visualizations from natural language queries, even when queries are underspecified [45]. Wei et al. proposed a ChatGPT-based multi-round question-and-answer framework for information extraction, which can decompose complex information extraction tasks and generate a final structured result [81]. Although these tools were designed for sighted people, they could become more accessible when integrated with screen readers. However, it is unknown whether BLV people would prefer such approaches as they may lower their control and understanding of the raw data set by directly providing analysis results. Therefore, future research is needed to explore how BLV people will interact with such high-level approaches.

5.3 Limitations and Future Work

We took the first step to understanding how BLV people perform DDA through a mixed-method approach of a think-aloud task session and an interview. Our work provides initial insights into BLV people's strategies and challenges in DDA. More efforts are needed to make DDA more accessible for BLV people so that they could tap into the power of data analysis along with their sighted peers. We highlight a few limitations of our current work and future research directions. First, all participants in our study performed DDA using screen readers. However, people who commonly use magnifiers or refreshable Braille displays may have different DDA strategies and challenges, which prompts future work on understanding the DDA process with other assistive devices.

Second, the think-aloud DDA sessions in our study consisted of specific tasks. We believe that additional insights may be obtained if participants performed DDA on their own in an in-the-field study, such as shadowing BLV people at their workplace. Furthermore, if we did not include certain tasks, we may have missed key challenges that BLV participants experienced (e.g., the task of identifying outliers led to the challenge described in Section 4.5.1). Although our list was curated from tasks reported by participants, we recognize that it is not exhaustive and may have missed other operations that BLV people may encounter in daily life. Thus, future work is warranted to develop a comprehensive taxonomy of tasks for investigating DDA.

Third, different tasks (e.g., cross-sectional tasks, time-series tasks, and free exploration tasks) may influence the selection of DDA approaches. For instance, when BLV people conduct free exploration tasks during leisure time and for personal purposes, they have the freedom to decide on their own approaches and tools. They may be willing to learn and try new approaches, such as learning to program (e.g., Python, R). When BLV people conduct cross-sectional tasks and time-series tasks issued for school or work, they may feel more restricted to the same software (e.g., Excel) and use more tedious but conservative approaches to avoid mistakes such as the three steps we identified in *key statistics identification*. Thus, future work can further investigate how different tasks and settings can impact the choice of DDA approaches.

Lastly, participants were asked to use their computers for the study as they reported using these for DDA. As smartphones become an increasingly important tool in people's daily lives, future work is warranted to investigate why BLV people might not prefer to use smartphones and how future designers and researchers can better support DDA on smartphones.

6 CONCLUSION

We presented the findings of a mixed-method study with interviews and think-aloud sessions to understand how BLV people perform DDA. Specifically, we identified five main strategies (e.g., overview obtaining, key statistics identification) that they adopted in performing DDA and the challenges they encountered (e.g., loss of within-group trends) when performing DDA in practice. We further highlighted how our findings are novel from previous work, and possible ways to improve current DDA processes. Moreover, as an initial work that aims to make the data analysis process more accessible to BLV people, we also highlighted the limitations of our current study and potential future research directions. Overall, our study provides guidance for the future development of assistive tools to facilitate BLV people's entire DDA process.

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A APPENDIX

Table 3: Spreadsheet of Automobile

ID	Brands	Models	Miles per gallon	Number of cylinders	Displacement	Horse Power	Weight	Price
1	Mazda	RX-4	21.0	6	160.0	110.0	2.62	18.0
2	Mazda	RX-4W	21.0	6	160.0	110.0	2.88	39.0
3	Mercedes	240D	24.4	4	146.7	62.0	3.19	41.0
4	Mercedes	230	22.8	4	140.8	95.0	3.15	35.0
5	Mercedes	280	19.2	6	167.6	123.0	3.44	50.0
6	Mercedes	280C	17.8	6	167.6	123.0	3.44	53.0
7	Mercedes	450SE	16.4	8	275.8	180.0	4.07	88.0
8	Mercedes	450SL	17.3	8	275.8	180.0	3.73	118.0
9	Mercedes	450SLC	15.2	8	275.8	180.0	3.78	125.0
10	Lincoln	Continental	10.4	8	472.0	205.0	0.00	61.0
11	Chrysler	Imperial	14.7	0	440.0	230.0	5.35	98.0
12	Fiat	128	32.4	4	78.7	66.0	2.20	10.0
13	Toyota	Corolla	33.9	4	71.7	65.0	1.84	17.0
14	Toyota	Corona	21.5	4	120.1	97.0	2.47	23.0
15	Honda	Civic	30.4	4	75.7	52.0	1.62	13.0
16	Dodge	Challenger	15.5	8	318.0	150.0	3.52	45.0
17	Ferrari	Dino	19.7	6	145.0	175.0	27.70	210.0
18	Maserati	Bora	15.0	8	301.0	335.0	3.57	100.0
19	Volvo	142E	21.4	4	121.0	109.0	2.78	57.0
20	Camaro	Z-28	13.3	99	350.0	245.0	3.84	48.0
21	Pontiac	Firebird	19.2	8	400.0	175.0	3.85	66.0
22	Porsche	914	26.0	4	120.3	91.0	2.14	125.0
23	Lotus	Europa	30.4	4	95.1	113.0	1.51	40.0
24	Ford	Pantera	15.8	8	351.0	264.0	3.17	15.0
25	Buick	EW	16.9	8	350.0	155.0	4.36	78.0
26	Ford	Country	15.5	8	351.0	142.0	4.05	49.0
27	Chevy	Malibu	19.2	8	267.0	125.0	3.61	21.0
28	Chevette	Original	30.0	4	98.0	68.0	2.16	12.0
29	Audi	5000	20.3	5	131.0	103.0	2.83	37.0
30	VW	Rabbit	31.9	4	89.0	71.0	1.93	8.0

Table 4: Spreadsheet of Stock Price

Date	Company A	Company B	Company C	Company D	Company E	Company F
2017/7/3	898.7	34.0	180.0	187.1	67.7	106.0
2017/7/5	911.7	34.1	183.8	190.2	67.7	108.5
2017/7/6	906.7	33.8	181.8	189.9	68.4	107.4
2017/7/7	918.6	34.1	181.4	190.7	68.6	108.5
2017/7/10	928.8	34.3	182.9	192.2	68.6	108.2
2017/7/11	930.1	34.4	184.4	194.4	68.9	108.2
2017/7/12	943.8	34.5	186.8	194.5	68.9	109.9
2017/7/13	947.2	35.0	186.9	194.3	69.1	109.8
2017/7/14	956.0	35.3	188.6	196.5	69.4	110.2
2017/7/17	953.4	35.4	188.2	196.9	69.0	110.3
2017/7/18	965.4	35.5	189.5	196.2	68.2	110.0
2017/7/19	970.9	35.7	190.9	198.7	67.1	109.7
2017/7/20	968.2	35.6	191.3	198.1	68.2	109.8
2017/7/21	972.9	35.6	193.2	199.9	67.0	109.3
2017/7/24	980.3	36.0	198.6	199.9	66.1	109.4
…	…	…	…	…	…	…
2022/6/16	2132.7	130.1	137.4	133.4	108.3	154.5
2022/6/17	2157.3	131.6	139.8	136.8	107.9	153.9
2022/6/21	2240.3	135.9	145.6	136.8	106.4	159.1
2022/6/22	2240.7	135.4	142.7	137.2	106.9	159.1
2022/6/23	2253.7	138.3	146.1	134.0	107.2	157.5
2022/6/24	2370.8	141.7	151.3	141.5	102.7	159.1
2022/6/27	2332.4	141.7	155.2	138.7	104.8	156.5
2022/6/28	2251.4	137.4	153.8	138.7	109.1	157.1
2022/6/29	2245.1	139.2	151.3	138.4	111.9	155.7
2022/6/30	2187.4	136.7	148.7	136.7	112.5	154.2
2022/7/1	2181.6	138.9	151.5	139.8	108.8	155.2