Assessing the impact of chart design and time intervals on the usability of time series data visualization: A Case Study on Cryptocurrency Data

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Abstract. Based on Google Trends, searches related to cryptocurrency have significantly increased in the last couple of years. One crucial aid for cryptocurrency traders or investors is the graphical visualization, which shows the time series data of the cryptocurrency prices. However, problems may occur in data visualization, such as visual noise and information loss, which cause perceptual and cognitive errors in data reading. Therefore, good visualization is needed to avoid decision-making mistakes, particularly in the cryptocurrency trade and investment activities. This study aims to investigate the effect of chart design and time interval on the usability of data visualization. The experiments are conducted in two scenarios, i.e., with and without time pressure. The participants recruited in this study were non-experienced and experienced people classified based on their familiarity with cryptocurrency investment/trading. Objective usability testing is performed by eye tracking, while subjective assessment employs the System Usability Scale (SUS) questionnaire. There are four quantitative dependent variables: response time, number of errors, number of fixations, and time to first fixation. The results show that time interval and time pressure significantly affect usability for both groups of respondents. Although chart design does not substantially affect the dependent variables, a candle chart is generally better than a line chart. By comparing all the combinations of chart design and time intervals, this study concluded that combining candle charts with 1-hour or 4-hour time intervals gives the best results for both respondent groups.

1 Introduction

Incredible amounts of data were produced or copied in 2020 despite the challenges posed by the COVID-19 pandemic, according to Dave Reinsel, senior vice president of IDC's Global DataSphere [1]. The large amount of data results from various sources such as sensors, devices, and humans, eventually are coined as big data. This data is valuable to determine needs, improve performance, support the decision-making process, create transparency, and

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innovate new services and products[2]. Three characteristics describe big data: volume (indicating a large number of records or ample storage), velocity (frequency of creation or transfer of data), and variety (diversity of data sources). Currently, two additional properties are added to them, i.e., value (how data can be valuable for the decision makers) and veracity (the accuracy of the data)[3], [4]. This "5Vs" model describes the associated challenges in big data, such as data retrieval, storage, search, sharing, transfer, analysis, and visualization [4].

Data visualization represents data in several systematic forms, including attributes and variables for building information units [5]. Data visualization allows users to combine different data to create custom analytical views to be integrated into creating interactive graphs [6]. The visualization approach can be in tables, diagrams, images, and other intuitive displays to represent data. According to [7], as visualization is one of the main challenges in data exploration, proper data visualization techniques are needed. So, choosing a suitable data representation is essential when visualizing data.

Many conventional data visualization methods have been used broadly, including histograms, bar charts, tables, pie charts, line charts, area diagrams, and data flow diagrams [5]. A study conducted by [8] revealed that data visualization evokes a variety of feelings in people who engage with them, which are activated by the visualization's textual content, contextual factors such as the user's previous experience (with the visualization, their subject, or relevant phenomena), or by the user's physical and psychological situation. Thus, the primary goal of visualization is to create interactive visual representations of information that utilize human cognitive perception abilities in solving problems[9].

According to [10], 98% of companies dealing with big data will more effectively analyze data if they visualize them. Therefore, human factors/ergonomics in interaction design is essential here since it makes sure the data visualization easy to use, understand, and interpret [5]. The goals of data visualization designs can be classified into five categories: comparing values between groups, displaying connections or relationships between variables, displaying hierarchical structures, illustrating changes over time, and displaying data patterns on maps or geographically [11]. Of the five data visualization goals, this study evaluates the usability of data visualizations that represent changes over time (i.e., time series data). There are hierarchical steps involved in perceiving the visualization of time series data, including reading data, reading between data, and reading/determining/projecting future data values [12].

Cryptocurrency data is an example of time series data that is frequently monitored and widely accessible. Cryptocurrency has become a popular investment option that has led to significant growth in market cap and the emergence of many alternative coins [13]. It operates in a virtual system that is supported by a well-structured record of the entire network, which fulfills the 5V's features of big data [3]. To ensure its security and privacy, Blockchain technology is used [14]. As of September 25th, 2023, there were over 9,000 types of alternative coins listed on the CoinMarketCap website, where Bitcoin remains the dominant player in the crypto market, according to CoinMarketCap data. Regardless its popularity, nearly 95% of individuals who conduct cryptocurrency investment or trading transactions fail and lose their money due to factors such as the inability to maintain a stable balance and lack of understanding of cryptocurrency trading methods [15]. While, for investing/trading in cryptocurrency, there are two basic strategies available: the fundamental method based on news and the technical method based on graphic movements[16].

A preliminary study was carried out to explore the importance of data visualization when doing cryptocurrency investment activities. This preliminary study was carried out by distributing questionnaires to 20 respondents with experience in the investment sector, especially in cryptocurrency. The survey found that 85% of respondents thought data visualization was important when deciding to invest. The data visualization lets the investors locate the support and resistance [17] as a reference for when to sell/buy coins. Furthermore, the historical trend in data visualization is also essential for decision-making.

Indonesia's major platform for trading cryptocurrencies is Indodax, also known as Indonesia Bitcoin and Crypto Exchange. It boasts a membership of more than 5 million users who buy and sell a wide range of digital assets like Bitcoin, Ethereum, and Ripple. Indodax provides a dashboard that presents various data visualizations to support its users in conveniently investing in cryptocurrency, such as selling and buying prices. The users can customize the data visualizations in terms of chart type (candle charts, line charts, and others), time interval, and scale to match their needs.

However, it raised a question of how each factor will affect the usability of the data visualizations, which also means how effective the visualization will help the Indodax users make decisions on their investment. Furthermore, problems may occur in data visualization such as visual noise and information loss, which cause perceptual and cognitive errors in data reading. The usability of data visualizations may also be affected by the available time for users in capturing the presented information. Therefore, this study aims to evaluate the effect of chart type, time interval, and time pressure on the usability of data visualization, particularly in the case of cryptocurrency investment. To collect usability parameters, this study employed eye tracking method.

2 Methods

Among all cryptocurrencies in Indodax, Bitcoin data was selected because this coin is most prevalent in investing or trading and is proven to have the highest market cap both domestically and abroad. In this study, we employed three independent variables, i.e., chart type, time interval, and time pressure. The selected chart types are candle and line charts since both are commonly presented on crypto investment websites/applications. The time intervals used in this study were 15 minutes, 1 hour, and 4 hours. Based on the chart type and time interval combination, we developed six stimuli tested in the experiment, as presented in Figure 1. Image (a) shows a candle chart with a time frame of 15 minutes, while image (b) displays a candle chart with a time frame of 1 hour. Image (c) represents a candle chart with a time frame of 4 hours, whereas image (d) depicts a line chart with a time frame of 15 minutes. Additionally, image (e) shows a line chart with a time frame of 1 hour, and image (f) represents a line chart with a time frame of 4 hours. Two scenarios were employed in relation to time pressure, one with a 10-second time limit and the other without any time limit. The reason for selecting the 10-second time limit is due to the rapid and continuous updates in cryptocurrency data, which necessitates quick decision-making.

The research involved 40 individuals, half with prior experience in cryptocurrency trading or investment and the other half without experience in this field. To test the six stimuli, experimental tasks in the form of questions were assigned to each participant. For each type of visualization, two questions will be asked—the examples are as follows: "Considering the candle chart, if you have Bitcoin saving, will you hold/sell?"; Considering the candle chart, predict the closing value obtained after the last bar."; "Considering the following line chart, predict the closing value obtained after the last point."

Four objective dependent variables (i.e., response time, number of errors, fixation number, and time to first fixation) are collected during this study. Response time refers to the duration between the initial question being asked and the respondent providing their answer[18]. The number of errors [18] is the total number of mistakes made by respondents when answering decision-based questions that require them to analyze the given data visualization. Number of Fixation is the number of times respondents direct their views towards the Area of Interest (AOI) [19]. Time to first fixation is the time needed for respondents to have a first fixation in the AOI on the given data visualization[20]. The number of fixations and time to first fixation is collected by gaze records, an online eye-tracking software that utilizes webcam data.

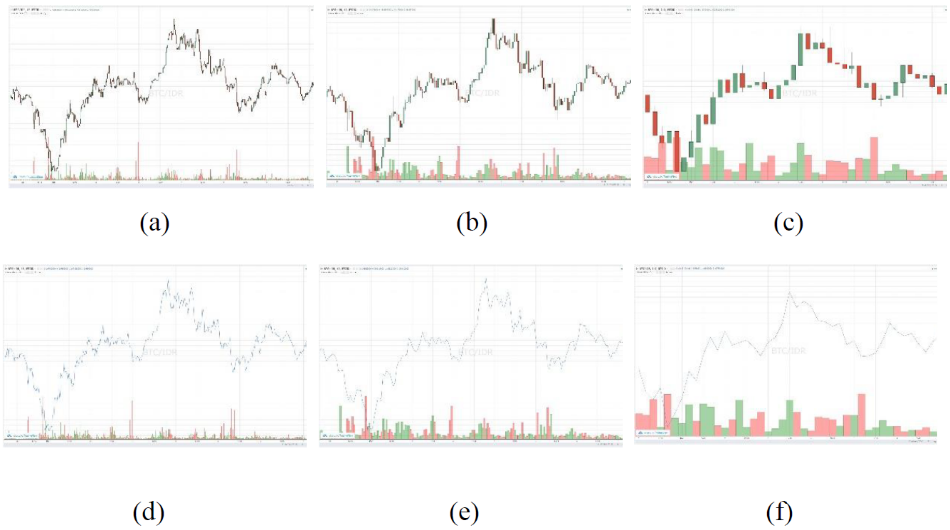


Fig. 1. Six stimuli tested in this study.

To complete analysis, this study also measured subjective usability parameters, employed System Usability Scale (SUS) questionnaire [21]. The questionnaire consists of ten questions that adhere to the structure developed by [21], but with some minor adjustments to fit the visual aspect being assessed in this study. Additionally, respondents are provided with a rating scale ranging from 1 to 5, utilizing the Likert scale method.

3 Results and discussion

3.1 Usability evaluation with objective parameters

Tables 1-4 summarize the descriptive statistics collected during this study. In general, experienced users have shorter average response times, fewer fixations, and shorter time to first fixation for both without and with time pressure scenarios. The result indicates a significant effect of platform familiarity. As a user frequently accesses the cryptocurrency investment website, he/she can locate the critical area on the visualization faster and do decision-making or predictions compared to the novice one. However, no significant difference was shown by either group of participants if we analyzed the number of errors. This data indicates that although the experienced participants may be faster, their evaluation does not necessarily result in correct decision/prediction.

Table 1. Response time (s).

Combination of chart design and time interval	Without time pressure				With time pressure			
	Non-experienced users		Experienced users		Non-experienced users		Experienced users	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Candle Chart, 15 Minutes	14.93	3.16	9.66	2.90	8.13	0.95	8.01	1.03
Candle Chart, 1 Hour	14.63	2.43	7.92	2.16	6.63	1.22	5.99	1.12
Candle Chart, 4 Hours	16.01	2.43	8.33	1.68	7.31	1.19	7.24	1.23
Line Chart, 15 Minutes	15.12	2.11	8.85	2.25	7.93	0.94	8.01	1.11
Line Chart, 1 Hour	15.69	2.28	9.08	2.01	6.53	1.25	6.24	0.94
Line Chart, 4 Hours	15.58	2.67	8.63	2.40	7.20	1.12	7.75	0.97

Table 2. Number of errors.

Combination of chart design and time interval	Without time pressure				With time pressure			
	Non-experienced users		Experienced users		Non-experienced users		Experienced users	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Candle Chart, 15 Minutes	0.65	0.49	0.55	0.51	0.25	0.44	0.30	0.47
Candle Chart, 1 Hour	0.55	0.51	0.30	0.47	0.10	0.31	0.10	0.31
Candle Chart, 4 Hours	0.55	0.51	0.40	0.50	0.30	0.47	0.35	0.49
Line Chart, 15 Minutes	0.45	0.51	0.65	0.49	0.30	0.47	0.35	0.49
Line Chart, 1 Hour	0.55	0.51	0.70	0.47	0.10	0.31	0.30	0.47
Line Chart, 4 Hours	0.45	0.51	0.55	0.51	0.35	0.49	0.30	0.47

Table 3. Number of fixations.

Combination of chart design and time interval	Without time pressure				With time pressure			
	Non-experienced users		Experienced users		Non-experienced users		Experienced users	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Candle Chart, 15 Minutes	7.10	1.41	4.60	1.31	2.85	0.67	2.85	0.99
Candle Chart, 1 Hour	5.90	1.52	3.25	0.85	2.55	0.76	2.30	0.66
Candle Chart, 4 Hours	7.00	2.15	3.75	0.79	2.65	0.75	2.80	1.01
Line Chart, 15 Minutes	7.70	1.84	4.45	1.15	2.90	0.72	2.95	0.76
Line Chart, 1 Hour	6.80	1.32	4.50	1.15	2.70	0.66	2.75	0.64
Line Chart, 4 Hours	6.70	1.63	4.25	1.80	3.10	0.85	2.95	1.00

Table 4. Time to first fixation (s).

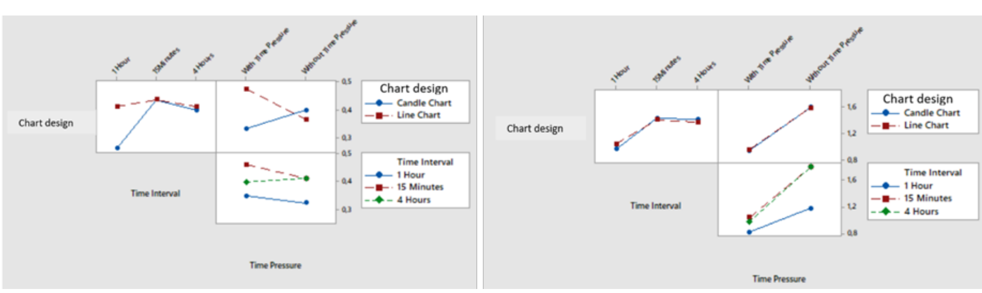
Combination of chart design and time interval	Without time pressure				With time pressure			
	Non-experienced users		Experienced users		Non-experienced users		Experienced users	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Candle Chart, 15 Minutes	2.26	0.61	0.96	0.33	1.34	0.34	1.40	0.70
Candle Chart, 1 Hour	1.46	0.42	0.76	0.28	0.85	0.20	0.80	0.80
Candle Chart, 4 Hours	2.35	0.49	0.91	0.32	1.35	0.34	1.20	0.80
Line Chart, 15 Minutes	2.24	0.58	1.02	0.39	1.36	0.33	1.30	1.10
Line Chart, 1 Hour	1.58	0.62	0.89	0.29	0.84	0.19	0.90	0.80
Line Chart, 4 Hours	2.21	0.71	0.96	0.30	1.30	0.41	0.80	0.70

3.2 Inferential analysis on objective usability parameters

This study performed an Analysis of Variance (ANOVA) to examine further the impact of chart design, time interval, and time pressure on the usability of data visualization. Based on the findings summarized in Table 5, time interval and time pressure significantly influence response time, fixation numbers, and time to first fixation ($p < 0.05$). Post Hoc analysis with the Bonferroni Pairwise Comparison test showed that a 1-hour interval has a significantly faster response time than a 15-minute interval ($p < 0.05$). As expected, response time is significantly faster if time pressure is given to the participants. On the other side, chart design also barely influences fixation numbers. However, candle charts tend to have fewer fixations to indicate that the participants have less difficulty recognizing the information presented in the candle charts. The interaction between chart design and time pressure is almost significant in determining the number of errors. Figure 2 (a) shows the interaction plot for the number of errors. In the time pressure scenario, the candle chart has a substantially lower error rate than the line chart. In contrast, for the without time pressure scenario, the line chart has a slightly smaller error rate than the candle chart. Since fast decision-making may frequently be needed in cryptocurrency investing/trading, candle chat is more suggested in presenting the cryptocurrency data. Finally, the interaction between time interval and time pressure significantly affects the time to first fixation. However, this interaction effect only happens between 15-minute and 4-hour time intervals, while a 1-hour time interval consistently shows a shorter time to first fixation in both scenarios (See Figure 2 (b)).

Table 5. Analysis of Variance (ANOVA) results.

Source	DF	Response Time		Number of Errors		Fixation Numbers		Time to First Fixation	
		F-Value	p-Value	F-Value	p-Value	F-Value	p-Value	F-Value	p-Value
Chart Design	1	0.23	0.64	1.48	0.23	3.81	0.05	0.00	1.00
Time Interval	2	3.37	0.04	1.76	0.17	3.59	0.03	36.65	0.00
Time Pressure	1	109.67	0.00	0.22	0.64	60.64	0.00	209.12	0.00
Chart Design * Time Interval	2	0.54	0.58	1.16	0.31	0.94	0.39	0.69	0.50
Chart Design * Time Pressure	1	0.07	0.80	3.86	0.05	0.04	0.83	0.08	0.78
Time Interval * Time Pressure	2	0.47	0.63	0.17	0.85	0.07	0.94	10.37	0.00
Chart Design * Time Interval * Time Pressure	2	0.24	0.79	0.55	0.58	0.36	0.70	0.26	0.77



(a) (b)

Fig. 2. Interaction plot for number of errors (a) and time to first fixation (b).

3.3 Subjective Usability Evaluation

The usability of various data visualizations was assessed, with the findings presented in Table 6. These scores were determined using the classification system outlined by [21], illustrated in Figure 3. Among the visualizations tested, those featuring candle charts with either one- or four-hour time intervals demonstrated superior usability compared to others, across both participant groups. Nevertheless, the attained scores for both visualization types fell within the moderate range, around 50 out of 100. This suggests a necessity for enhanced data visualization techniques to aid cryptocurrency investors in their decision-making processes.

Table 6. System Usability Scores.

Participant Group	Chart and time interval	SUS Score	Grade Scale	Adjective Rating	Acceptability Range
Non-experienced	Candle Chart, 15 Minutes	43.13	F	OK	NOT ACCEPTABLE
	Candle Chart, 1 Hour	53.50	F	GOOD	MARGINAL LOW
	Candle Chart, 4 Hours	54.13	F	GOOD	MARGINAL LOW
	Line Chart, 15 Minutes	43.86	F	OK	NOT ACCEPTABLE
	Line Chart, 1 Hour	47.25	F	OK	NOT ACCEPTABLE
	Line Chart, 4 Hours	44.50	F	OK	NOT ACCEPTABLE
Experienced	Candle Chart, 15 Minutes	44.75	F	OK	NOT ACCEPTABLE
	Candle Chart, 1 Hour	53.30	F	GOOD	MARGINAL LOW
	Candle Chart, 4 Hours	52.63	F	GOOD	MARGINAL LOW
	Line Chart, 15 Minutes	46.88	F	OK	NOT ACCEPTABLE
	Line Chart, 1 Hour	50.25	F	OK	MARGINAL LOW
	Line Chart, 4 Hours	49.00	F	OK	NOT ACCEPTABLE

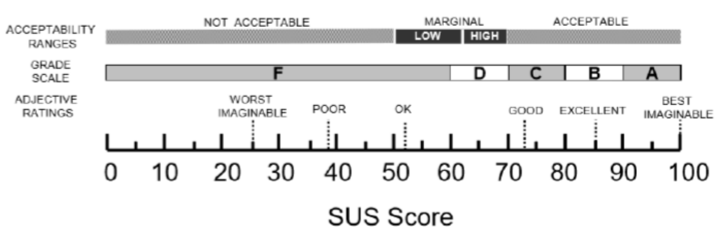


Fig. 3. Classification of SUS scores [21].

4 Conclusion

In conclusion, this study contributes to our understanding of the factors influencing the usability of time series data visualizations. While chart type may not significantly impact usability, choosing candle charts over line charts could provide a slight advantage. On the other hand, time interval and time pressure have been shown to have substantial effects on response time, fixation numbers, and time to first fixation. Although this study was conducted in the case of the cryptocurrency investment field, the findings can inform the design and implementation of time series data visualizations to enhance decision-making processes in various application domains. Researchers and practitioners should consider these insights when developing data visualization tools and conducting usability evaluations.

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