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WhaleBot Alerts Telegram Channel and Google Alerts as Information Media for XRP Cryptocurrency Traders

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Abstract

Ripple (XRP) is one of the most significant cryptocurrencies that attracts many traders to invest. Traders often look for information from the media as a reference for their trading management strategy. This research aims to utilize WhaleBot Alerts Telegram channel and Google Alerts as trading information media by looking for the relationship between whale transactions, news sentiment, and price returns. The researcher collected XRP whale transactions from the WhaleBot Alerts Telegram channel and XRP news from Google Alerts within a crypto winter period, from November 2021 to January 2023, and analyzed the data using descriptive statistical analysis. This research also follows several variables and formulas from previous studies. After analyzing 457 XRP whale transaction datasets, the researcher finds a significant relationship between the number of trading days and trading return on investment. The relationship shows that the more days, the greater the chance of profit. The other variables give reference patterns, such as the number of whale transactions, total whale transaction value, the most significant transaction value, and news topic. Finally, this research develops a simple XRP short-term trading model using the WhaleBot Alerts Telegram channel data and Google Alerts. In conclusion, trading initiated by XRP whale's transactions and XRP news could give a 76.53% chance of making a profit. Therefore, XRP traders can use the WhaleBot Alerts Telegram channel and Google Alerts as their trading information media.

Keywords: XRP cryptocurrency, WhaleBot alerts, Telegram Channel, Google, Trading information media.

1. Introduction

Ripple is a technology company that created XRP as a cryptocurrency and uses it to carry transactions in the XRP blockchain ledger (Rodeck & Curry, 2022). The name XRP is the ticker symbol for the cryptocurrency, and it derives from the term "Ripples," and the "X" is a prefix for currencies that do not belong to any country, following the ISO 4217 standard (XRP Ledger, 2023). As a result of Ripple's blockchain ledger development, XRP makes transactions faster and available 24/7 as it does not need to depend on traditional payment systems from financial institutions (Qiu, Zhang, & Gao, 2019). In addition, the XRP cryptocurrency also gained popularity as it became one of the nine significant cryptocurrencies (Abakah, Caporale, & Gil-Alana, 2022).

In general, several factors affect cryptocurrency price movements, and a previous study by Erdogan, Ahmed, and Sarkodie (2022) concludes that whale transactions are among those factors. They state that whales represent investors that hold nearly 40% of the market. Therefore, whales can cause a sudden significant transaction on the market and affect price movement. That shocking volatility can influence retail investors' decisions, leading to investment loss (Erdogan et al., 2022). Despite the sudden price change, investors can monitor whale transactions through several media and platforms (Saggu, 2022). Those platforms can inform the real-time whales' transaction to warn investors about the effect that may caused by the transaction (Saggu, 2022).

Furthermore, Chalkiadakis, Zaremba, Peters, and Chantler (2022) State that there is a causal relationship between news sentiment and cryptocurrency prices. They conclude that a notable event in the news, such as a worldwide crisis, can affect the cryptocurrency market. Banerjee, Akhtaruzzaman, Dionisio, Almeida, and Sensoy (2022) discovered that sensational news in the media can create unrealistic cryptocurrency price demand and cause price bubbles.

This research aims to fill several gaps based on the studies about XRP, whale transactions, and news sentiment. First, this research will find more straightforward methods for XRP traders' trading management strategy rather than using advanced machine learning procedures. Also, this research focuses only on XRP's whale transactions data reported on the WhaleBot Alerts Telegram channel. WhaleBot Alerts is a popular platform that publishes whale transactions on several media, including Telegram (Urbas, 2023). In addition, this research focuses on XRP-related news listed on Google Alerts.

This research's objectives are summarized into these two research questions:

1. What are the characteristics of XRP whale transactions and news sentiment that cause profits?

2. Can WhaleBot Alerts Telegram channel and Google Alerts become information media to provide data for a simple short-term trading model that helps regular traders make investment decisions?

2. Literature Review

2.1. Cryptocurrency Whales

Whales are investors with a large amount of money, buying and accumulating certain cryptocurrency coins (Quamara & Singh, 2022). They also try to persuade traders to buy and sell the coins, causing the price to rise and drop quickly (Quamara & Singh, 2022). Traders recognize this action as a price manipulation commonly called a "pump and dump" scheme (Hamrick, Rouhi, Mukherjee, Feder, et al., 2021).

Typically, whales hold many cryptocurrency coins in their wallets (Herremans & Low, 2022). While the transactions between wallets are recorded and visible on the blockchain explorer, the sender's and receiver's identities are kept confidential (Taylor, Kim, Zainol Ariffin, & Sheikh Abdullah, 2022). Meanwhile, previous research suggests that monitoring whale transactions between wallets is crucial to identifying price manipulation and other abnormal trading behaviors (Baker et al., 2022).

2.2. Messaging Platforms for Cryptocurrency Communities

Moreover, several channels on messaging platforms such as Discord and Telegram organize traders to push the price up and sell the coins for profit (Hamrick, Rouhi, Mukherjee, Feder, et al., 2021). A study by Fang et al. (2022) states that Telegram is a media often utilized to manage information, especially for controlling automatic content published by bots. The study also discovers that Telegram's messages and community activities directly relate to cryptocurrency's volume and price movement (Fang et al., 2022).

Furthermore, traders can get factual information about whale transactions on a platform such as Whale Alert (Baker et al., 2022). Another research finds that transactions reported on the Whale Alert could affect Bitcoin prices (Saggu, 2022). For example, an activity such as a USDT minting event published on the Whale Alert could increase Bitcoin prices significantly (Saggu, 2022). In addition, a previous study discovered a forecasting model to predict Bitcoin prices using CryptoQuant data and the Whale Alert tweets (Herremans & Low, 2022).

2.3. News Sentiment and Cryptocurrency Prices

As mentioned, news sentiment affects cryptocurrency prices (Chalkiadakis et al., 2022). A previous study from Aslanidis, Bariviera, and López (2022) states that most traders try to get information before investing in a cryptocurrency. There are many sources of information, such as online news, that cryptocurrency traders can discover through search engines, namely Google (Aslanidis et al., 2022). Furthermore, research from Agosto, Cerchiello, and Pagnottoni (2022) discovered that news sentiment, news volume, and Google queries can predict cryptocurrency price bubbles. As cryptocurrency price is vulnerable to news sentiment, Banerjee et al. (2022) argue that investment management is crucial.

3. Methods

This research uses data from the WhaleBot Alerts channel on Telegram by importing chat history from November 2021 to January 2023. The researcher selected the timeframe because a report says that November 2021 is the beginning of a crypto winter as the cryptocurrency market starts to experience a prolonged period of price declines (Powell & Curry, 2022).

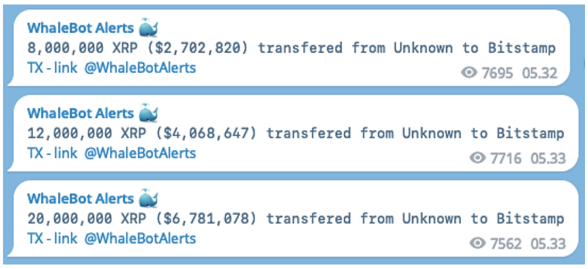

Figure 1. A Screenshot of XRP's Whales' transactions reported on WhaleBot Alerts Telegram channel

Then, following a study on the pump and dump Telegram channels, the researcher determines several variables to make the Telegram chat data more meaningful for further analysis (Hamrick, Rouhi, Mukherjee, Feder, et al., 2021). Another study discovered that after a whale group publishes a signal, it takes up to 7 days to accomplish a pump target (Hamrick, Rouhi, Mukherjee, Vasek, et al., 2021). Therefore, this research will focus on investigating the transactions for short-term trading strategy.

To find relation patterns between XRP whale transactions and XRP prices, the researcher uses a technical trading data collection method from a study on cryptocurrency price categorization (Ortu, Uras, Conversano, Bartolucci, & Destefanis, 2022). First, the researcher collected technical trading data from CoinMarketCap, consisting of several variables, such as opening and closing prices during a trading period (Ortu et al., 2022). Because this research aims to find patterns and relations for short-term trading plans, the researcher uses the daily trading period to collect the technical trading data. Furthermore, following the Return on Investment (ROI) formula from a study on unusual cryptocurrency price movements, the researcher uses this formula from Ozer & Okan Sakar (2022):

Trading return = closing price - opening price

A positive return means the investment gets a profit, but a negative return means the investment loses (Ozer & Okan Sakar, 2022).

Next, the researcher observes the data based on a previous study on cryptocurrency whale groups on Telegram and Discord (Hamrick, Rouhi, Mukherjee, Vasek, et al., 2021). The study states that after a whale group publishes a signal, it takes up to 7 days to accomplish a pump target. Therefore, the researcher investigates the XRP whale transactions for seven days after every notable transaction occurs. In addition, following a study by Lahmiri, Bekiros, and Bezzina (2022), the researcher also inspects other factors, such as the number of daily whale transactions, the most significant transaction value, and the total value of daily transactions. Additionally, based on the study about the relationship between news sentiment and Bitcoin volatility, the researcher collects and examines news headlines and news content to get the sentiment (Sapkota, 2022).

Moreover, the researcher uses descriptive statistical analysis with JASP to find patterns that show characteristics of profitable whale transactions and XRP news sentiment. Following a study of cryptocurrency price movements, the researcher uses the daily return as the primary comparison data (Katsiampa, Yarovaya, & Zięba, 2022). The researcher analyzes the daily return data compared to other variables. Finally, the researcher develops a simple trading model with Microsoft Excel using functions that are easy for regular traders.

4. Result

4.1. Data and Variables

There are 457 daily whale transaction datasets from November 2021 to January 2023. Next, the researcher determines several variables for a daily dataset, which are:

1. Number of transactions (NT)

NT is the number of XRP whale transactions in one trading day.

2. The most significant transaction value (SV)

SV is the value of the most significant XRP whale transaction in one trading day.

3. Total transaction value (TV)

TV is the total value of all XRP whale transactions in one trading day.

4. Trading return (TR)

The formula for TR is:

TR = closing price - opening price

5. Trading return on investment (TROI)

TROI consists of two types of values, "profit" and "loss." To get the value, the researcher first finds the trading return (TR) value:

TR [day (n)] = closing price [day (n)] - opening price [day (1)]

The researcher checks for TR from the first day of the investment until the day (n). As discussed earlier in the method section, the researcher looks for a positive TR value up until seven days. If one or more days have a positive TR value, the TROI value is "profit." However, if the TR value is all negative until day seven, the researcher looks for a positive TR value for more than seven days. The researcher extends the time because some successful whale pump signals could take up to 12 days to be accomplished (Hamrick, Rouhi, Mukherjee, Vasek, et al., 2021). Because this research aims to find XRP price patterns for a short-term trading plan, the researcher limits the observation to only ten days. Therefore, if the TR value from day one until ten is all negative, then the TR value is "loss."

6. Number of days (ND)

ND is the number of days in which trading gets a maximum profit or minimum loss. As discussed earlier in the method section, after a whale group publishes a signal, it takes up to 7 days to accomplish a pump target (Hamrick, Rouhi, Mukherjee, Vasek, et al., 2021). Therefore, the researcher looks for the day with the highest positive TR value within seven days after trading starts. For example, suppose a trade gets the highest positive TR value on day six; then the value of ND is 6.

However, as discussed earlier, if the TR value is all negative until day seven, the researcher extends the observation to ten days maximum. For example, suppose the first TR positive value is on day eight, then the value of ND is 8. Nevertheless, if the TR value is all negative until day ten, the researcher will look for the smallest negative value within ten days. For instance, suppose the least negative value is on day 5; then the value of ND is 5.

7. Maximum trading profit or minimum trading loss percentage (PL)

After finding the highest positive TR value as the maximum profit, the researcher will count the maximum profit value percentage. Also, the researcher will calculate the percent of the minimum loss.

8. A relationship variable between TV, SV, and NT (TSN)

The researcher also analyzes the relationship between the trading return on investment (TROI) and the other three variables named TSN: total transactions (TV), the most significant value (SV), and the number of transactions (NT). To define the value of TSN, the researcher checks the transactions with several conditions discussed in the following result sections of this paper.

9. News sentiment

Following research on news sentiment by Das, Singh, and Sharma (2021), there are three types of news sentiment values, which are "positive," "neutral," and "negative."

10. News topic

The researcher checks the news topics and categorizes them into several topic categories.

4.2. Data Filtering

According to research by Nghiem et al. (2021), one of the characteristics of cryptocurrency pump-and-dump activities is the increase in transaction volume. Therefore, the researcher filters the datasets by several criteria that indicate an increase in transaction volume.

Table 1. Daily whale transactions

Descriptive Analysis			
	Number of transactions (NT)	**Total transactions value (TV)**	**Significant transaction value (SV)**
Valid	457	457	457
Mean	9.435	$6.600\times10^{+8}$	$3.271\times10^{+8}$
St. Deviation	6.868	$5.161\times10^{+9}$	$4.674\times10^{+9}$

Criteria 1

The first criterion for selecting a dataset is having a number of transactions (NT) equal to or more than 15 transactions in a trading day. As detailed in Table 1, the mean and the standard deviation for NT are 9.435 and 6.868, respectively. Next, the researcher adds the mean with the standard deviation; the result is 16.303. Therefore, the researcher argues that to be considered to have an immense number of transactions, a dataset should have a minimum NT of 15 times in one trading day.

Criteria 2

However, if a dataset does not meet the first criterion, the researcher will check the dataset based on the second criterion. The second criterion is that a dataset should have a significant transaction value (SV) and an immense total transaction value (TV) in one trading day. As detailed in Table 1, the mean of SV is $3.271\times10^{+8}$, and the mean of TV is $6.600\times10^{+8}$. Furthermore, the researcher decides that minimum values for an increased transaction volume should be above the mean of both variables. Therefore, the researcher defines the minimum values for the second criterion as 100 million XRP for SV and 1 billion XRP for TV in one trading day. Suppose a dataset for a trading day meets both or one of the first and second criteria. In that case, the researcher checks and inputs the value of the return on investment (TROI), the maximum profit or minimum loss percentage (PL), and the number of days (ND) in the filtered datasets.

4.3. Statistical Analysis

After filtering the datasets, the researcher finds 98 daily datasets that meet both or one of the first and second criteria. Regarding the first research question, the researcher conducts statistical analysis using JASP to find relationships between variables. To begin with, as detailed in the contingency table (Table 2), the researcher analyzes the relationship between the number of transactions (NT) and the return on investment (TROI).

The frequency data detailed in Table 2 shows several patterns to give information and reference for XRP traders. The first pattern is that there is a 76.53% chance that trading initiated by a significant number of NT will make a profit. Next, the NT equal to or over 25 indicates a 100% chance of gaining profit. Finally, a particularly significant NT demonstrates at least a 70% chance to make a profit, such as 15, 16, 17, and 22.

Table 2. Contingency Table for Daily Number of Transactions (NT) and Trading Return on Investment (TROI)

NT	**TROI**		**Total**
	Loss	**Profit**	
5	0 (0%)	1 (100%)	1 (100%)
7	0 (0%)	1 (100%)	1 (100%)
8	1 (33.3%)	2 (66.6%)	3 (100%)
9	0 (0%)	1 (100%)	1 (100%)
12	0 (0%)	3 (100%)	3 (100%)
14	0 (0%)	2 (100%)	2 (100%)
15	6 (28.57%)	15 (71.42%)	21 (100%)
16	2 (11.77%)	15 (88.24%)	17 (100%)
17	3 (30%)	7 (70%)	10 (100%)
18	3 (60%)	2 (40%)	5 (100%)
19	3 (75%)	1 (25%)	4 (100%)
20	1 (100%)	0 (0%)	1 (100%)
21	1 (16.67%)	5 (83.33%)	6 (100%)
22	0 (0%)	7 (100%)	7 (100%)
23	2 (40%)	3 (60%)	5 (100%)
24	1 (33.33%)	2 (66.67%)	3 (100%)
25	0 (0%)	1 (100%)	1 (100%)
27	0 (0%)	4 (100%)	4 (100%)
29	0 (0%)	1 (100%)	1 (100%)
48	0 (0%)	1 (100%)	1 (100%)
65	0 (0%)	1 (100%)	1 (100%)
Total	23 (23.47%)	75 (76.53%)	98 (100%)
Chi-Squared Test			
	Value	**df**	**p**
X2	23.022	20	0.288
N	98		

The researcher also analyzes the relationship between the trading return of investment (TROI) and the other three variables (TSN): total transactions (TV), the most significant value (SV), and the number of transactions (NT). For this data, the researcher codes the transactions based on several conditions. The first condition is if the TV is equal to or more than 1 billion XRP and SV is equivalent to or more than 100 million XRP, the researcher codes it as "both." However, if the transactions on that day only meet one of the conditions, the researcher codes it as "one." Finally, suppose the transactions on that day do not meet any of the conditions; in that case, the researcher codes it as "none." Another following state is if the number of transactions (NT) is equal to or more than 15, then the researcher codes it as "more," but if it is less than 15, then the researcher codes it as "less."

As detailed in Table 3, the chi-squared test shows a p-value of 0.677, more than the significance level (0.05). Thus, no significant relationship exists between TSN and TROI. These findings contradict a previous study that concludes strong relatedness between volume and trading returns (Yousaf & Yarovaya, 2022). Nonetheless, the findings support a previous study by Tan and Tao (2023), concluding that volume-based prediction is more effective for long-term investment. However, because this research is for a short-term trading plan with short-term trading period data, which aligns with Tan and Tao's study (2023), the volume is not a strong indicator for trading return prediction.

However, there are still patterns in the data that can reference XRP traders. For example, as detailed in Table 4, there are 11 transactions for "both-less 15," and only one gets an investment loss. So, there is a greater chance the trading will profit if the TV is equal to or more than 1 billion XRP and SV is equal to or more than 100 million XRP; also, the number of transactions (NT) is less than 15.

Table 3. Contingency Table between Total Transactions, Significant Value, Number of Transactions (TSN), and Trading Return on Investment (TROI)

TSN	TROI		Total
	Loss	**Profit**	
both-less	1 (9.10%)	10 (90.90%)	11 (100%)
both-more	7 (23.33%)	23 (76.67%)	30 (100%)
none-more	6 (26.09%)	17 (73.91%)	23 (100%)
one-more	9 (26.47%)	25 (73.53%)	34 (100%)
Total	23 (23.47%)	75 (76.53%)	98 (100%)
Chi-Squared Test			
	Value	**df**	**p**
X2	1.525	3	0.677
N	98		

Furthermore, regarding the first research question, the researcher also analyzes the relationship between the number of days (ND) and trading return on investment (TROI). As detailed in Table 4, the chi-squared test shows a p-value of 0.042, less than the significance level (0.05). Thus, there is a significant relationship between ND and TROI. Moreover, the data shows that the maximum profit most likely happened on the seventh day of the investment. The data also shows that from day 8 to day 10, the TROI always gets maximum profit and never a loss. Therefore, if the trading return TR still gets a negative return until the seventh day, the trader can wait until the tenth day for a profit opportunity. Traders should also be aware that there is still a 23.47% chance that the TR will get a negative return until the tenth day.

Table 4. Contingency Table for Number of Days (ND) and Trading Return on Investment (TROI)

ND	TROI		Total
	Loss	**Profit**	
1	13 (50%)	13 (50%)	26 (100%)
2	4 (28.57%)	10 (71.43%)	14 (100%)
3	0 (0%)	9 (100%)	9 (100%)
4	1 (12.50%)	7 (87.50%)	8 (100%)
5	2 (20%)	8 (80%)	10 (100%)
6	1 (14.29%)	6 (85.71%)	7 (100%)
7	2 (11.11%)	16 (88.89%)	18 (100%)
8	0 (0%)	2 (100%)	2 (100%)
9	0 (0%)	3 (100%)	3 (100%)
10	0 (0%)	1 (100%)	1 (100%)
Total	23 (23.47%)	75 (76.53%)	98 (100%)
Chi-Squared Test			
	Value	**df**	**p**
X2	17.454	9	0.042
N	98		

The researcher also analyzes the frequency of the significant transaction value (SV) in one day and analyzes SV that appeared three times or more during the observation period. As detailed in Table 5, five hundred million XRP is the most significant transaction value that frequently appears. Also, when this value appears, there is an 85% chance the investment will get profit.

Moreover, the researcher also analyzes the frequency of maximum trading profit or minimum trading loss percentage (PL). As detailed in Table 6, the highest frequency is for 0-5% profit. Thus, to secure the investment, the traders can instantly decide to take profit if it reaches 0-5%. Additionally, the researcher collects the sentiment news from Google Alerts and uses "XRP" as the keyword. Next, the researcher determines the sentiment by checking the news that appeared in the subject of Google Alerts daily emails. Then, following research on news sentiment by Das, Singh, and Sharma (2021), the researcher analyzes the sentiment by qualitatively defining the sentiment of each sentence in the news.

Table 5. Contingency table for most frequently appearing Significant Value (SV) and Trading Return on Investment (TROI)

SV	TROI		Total
	Loss	Profit	
100,000,000	3 (37.50%)	5 (62.50%)	8 (100%)
110,000,000	0 (0%)	3 (100%)	3 (100%)
120,000,000	1 (20%)	4 (80%)	5 (100%)
140,000,000	0 (0%)	3 (100%)	3 (100%)
500,000,000	3 (15%)	17 (85%)	20 (100%)
80,000,000	2 (40%)	3 (60%)	5 (100%)
Total	9 (20.46%)	35 (79.55%)	44 (100%)

Chi-Squared Test

	Value	df	p
X2	0.451	5	0.478
N	44		

Table 6. Frequency table for maximum trading profit or minimum trading Loss Percentage (PL)

PL	Frequency	Percent
5%- 10% loss	5	5.10%
0% - 5% loss	18	18.37%
0% - 5% profit	36	36.74%
5% - 10% profit	19	19.39%
10% - 15% profit	9	9.18%
15% - 20% profit	4	4.10%
> 20% profit	7	7.143%
Total	98	100%

Next, the researcher analyzes the relationship between news sentiment and the trading return on investment (TROI). As detailed in Table 7, the chi-squared shows a p-value of 0.801, more than the significance level (0.05). Thus, there is no significant relationship between the variables. This finding aligns with previous research on Google Trends and cryptocurrency volatility, which states that cryptocurrency volatility most likely affects how traders pay attention to Google Trends and not otherwise (Aslanidis et al., 2022).

In particular, when writing, the popular news topics concerning XRP are the legal battle between the US Securities and Exchange Commission (SEC) and Ripple about XRP security regulation (Tsegu, 2022). Therefore, the researcher categorizes the news into two topics: "SEC & Ripple" and "others." As detailed in Table 8, news topics regarding the SEC and Ripple case indicates a 74% chance of gaining profit.

These findings align with a previous study that found that news sentiment does not directly impact the returns (Banerjee et al., 2022). However, the study also states that specific issues that are popular in news media, such as COVID-19-related news, can significantly affect cryptocurrency volatility (Banerjee et al., 2022). Therefore, traders should also be ready for volatility when the most popular news topic is the legal issue between SEC and XRP.

Table 7. Contingency table for news sentiment and Trading Return on Investment (TROI)

News Sentiment	TROI		Total
	Loss	Profit	
Negative	7 (22.58%)	24 (77.41%)	31 (100%)
Neutral	2 (16.67%)	10 (83.33%)	12 (100%)
Positive	14 (25.46%)	41 (74.55%)	55 (100%)
Total	23 (23.47%)	75 (76.53%)	98 (100%)

Chi-Squared Test

	Value	df	p
X2	0.443	2	0.801
N	98		

Table 8. Contingency table for news topic and Trading Return on Investment (TROI)

The News Topic	TROI		Total
	Loss	Profit	
SEC & Ripple	13 (26%)	37 (74%)	50 (100%)
Others	10 (20.83%)	38 (79.17%)	48 (100%)
Total	23 (23.47%)	75 (76.53%)	98 (100%)

Chi-Squared Test

	Value	df	p
X2	0.364	1	0.546
N	98		

5. Discussion

5.1. Simple Trading Model Based on XRP Whale Transaction

This model includes several steps as follows.

Step 1.

At the opening trading time, at midnight GMT, the traders should check the number of transactions (NT) that happened the day before. For example, if the number of transactions equals or exceeds 15, the traders can consider buying XRP with the opening price.

Step 2.

Suppose the number of transactions is less than 15. In that case, the traders should check whether the transactions on the day before have a minimum of 1 billion XRP for total transactions (TV) and 100 million XRP for the most significant value (SV). Then, they can consider buying XRP with the opening price if the transactions meet both minimum conditions.

Step 3.

After buying XRP with the opening price, the traders should monitor the price movement for seven to ten days. Also, before making a profit or minimizing risk, traders should consider several conditions based on this research's findings, such as the number of transactions (NT) that happened the day before. For example, as detailed in Table 2, if the NT is 22 or more, there is a more significant chance of gaining profit in the next seven to ten days.

5.2. Study Case Example

As detailed in Table 9, a trader could make a simple table to monitor XRP whale transactions. For instance, on May 12, 2022, there were 22 whale transactions reported on the WhaleBot Alerts Telegram channel. After inputting each transaction value, the trader could automatically calculate other variables using Microsoft Excel functions. For example, the trader can use the sum function to calculate the number of transactions (NT) and the total transaction value (TV).

Table 9. Study case of easy calculation model in Microsoft Excel

Date: May 12, 2022	
Whale Transactions	**Transaction Value (XRP)**
1st	6,000,000
2nd	50,000,000
3rd	50,000,000
4th	15,000,000
5th	50,000,000
6th	52,500,000
7th	12,237,828
8th	60,000,000
9th	55,359,444
10th	10,000,000
11th	30,000,000
12th	40,000,000
13th	300,000,000
14th	49,812,452
15th	55,281,990
16th	120,000,000
17th	300,00,000
18th	33,370,580
19th	16,000,000
20th	33,574,436
21st	12,237,828
22nd	12,237,828
NT	22
TV	1,093,612,386
SV	300,000,000
TSN	both - more
The News Topic	SEC & Ripple

The trader could check the conditions quickly using the data as the reference and directly decide whether it is the right time to trade in XRP. After deciding to trade, the trader could also input the opening and closing price from day one until day(n) and calculate the TR from day one to day (n). As detailed in Table 10, the trading return (TR) is positive from day (1) until day (7). However, the highest TR is on the day (3), directly declining until the day (7). Therefore, it is necessary to calculate the TR every day and directly take profit when the value is already reaching specific ranges, such as the 10-15% range, because, as shown in Table 6, that profit range's frequency is considered low. These findings also align with a previous study that discovered stronger cross-correlation during XRP bull markets, which means the volatility is high during the upward price trend (Kakinaka & Umeno, 2021). Thus, the trader should be aware of extreme XRP price movement during bull markets and consider instantly selling after gaining enough profit.

Table 10. An example of a straightforward calculation model in Microsoft Excel - Trading Return day (n)

Date /day (n)	**Opening price (USD) day one**	**Closing price (USD) day (n)**	**TR day (n)**
May 13 / day (1)	0.3852	0.4234	9.92%
May 14 / day (2)	0.3852	0.4278	11.06%
May 15 / day (3)	0.3852	0.4474	16.15%
May 16 / day (4)	0.3852	0.4225	9.68%
May 17 / day (5)	0.3852	0.4376	13.6%
May 18 / day (6)	0.3852	0.4062	5.45%
May 19 / day (7)	0.3852	0.4200	9.03%

6. Conclusions

This study explores the characteristics of XRP whale transactions and XRP-related news to find relationships and patterns that can reference traders for their short-term trading plans. Regarding the first research question, the researcher reveals a significant relationship between the number of days (ND) and trading return on investment (TROI). Furthermore, the researcher discovers that the seventh day is the right time to make a profit as that day has a greater chance to make a maximum profit than the other days. At the same time, several variables have no significant relationship with TROI. However, based on those variables, the researcher finds several whale transaction patterns that can reference traders to make trading decisions. These findings indicate that traders should monitor these notable transactions, such as unusual trading behaviors and abnormal prices, for trading management strategies.

Concerning the news characteristics, the researcher also discovers that regardless of the sentiment, the news topic about the legal battle between SEC and XRP indicates a greater chance for profit-making in the next few trading days. Thus, monitoring news data as part of a trading management strategy is crucial. Furthermore, regarding the second research question, this research results in a simple trading model for regular traders. Nevertheless, this research shows a 23.47% chance of trading loss. Therefore, it is essential to consider all the variables and manage the risk by immediately making a profit, especially during an uptrend when the volatility is higher than other market conditions. Finally, this study concludes that XRP traders can utilize information from WhaleBot Alerts Telegram channels and Google Alerts as information media to help manage risk for their trading strategy.

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