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A Systematic Review of Technical Analysis-Based Forecasting Techniques: Global v/s Indian Perspectives

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ABSTRACT
This paper conducts a systematic review of Technical Analysis (TA) based forecasting research from 2013 to 2022, encompassing global and Indian authors. It addresses the evolving landscape of financial forecasting, including tool choices, variable selection, error measurement, and accuracy. Employing the PRISMA framework, we analyze 176 papers (88 global, 88 Indian) to examine trends in TA research. Key inquiries involve the publication trends, popular forecasting approaches, consideration of Transaction Costs and Data Snooping Bias, research time cycles, outcomes, and performance metrics. The study reveals that Indian researchers favor TA-based machine learning (ML) techniques, while global counterparts rely more on manual forecasting methods. Notably, many studies neglect to incorporate 'transaction costs' and 'data snooping bias' in their models. Most research focuses on forecasting within a 5-10-year timeframe, with TA-based techniques generally viewed as profitable. However, Indian authors tend to prioritize risk mitigation in their models, in contrast to global authors who often measure performance through return and profitability metrics. Additionally, this paper critiques the prevailing forecasting techniques, highlighting gaps in both global and Indian research. Its aim is to aid future researchers in identifying gaps, formulating research questions, and understanding methodological considerations within financial forecasting.

Keywords: *Technical Analysis, Forecasting, Stock Market, Systematic Literature Review, PRISMA, Review Paper etc.*

JEL Codes: G17, C32, G17

1. Introduction

Financial forecasting, as defined by Boyles, refers to the process of predicting a firm's financial future, by examining historical performance data, such as cash flow, sales, stock price levels, dividends etc. [23]. The modern-day financial forecasting offers its practitioners two options to choose from i.e., Technical Analysis (TA) and Fundamental Analysis (FA). On one hand, where FA talks about discovering the intrinsic value and identification of mispriced stocks by analysing their financial statements (Abarbanell & Bushee), TA is more concerned with tracking the stock price action with the help of graphs and charts (Pring) [1, 142]. Both the techniques make use of historical data to generate forecasts and offer an antithesis to the efficient market hypothesis (Kirkpatrich & Dahlquist) [75]. Out of the two techniques, TA has gathered a lot of attention in recent years owing to its wide applicability in most market forms and varying market conditions (Mintarya et al.) [105]. However, the predictive prowess of TA has been questioned time and again, not simply because of operational inefficiencies that exist within the technique, but also due to unforced human errors (Marshall & Cahan) [100]. It was then, that the discipline of financial forecasting witnessed the emergence of machine aided forecasting techniques. With the advent and popularity of machine learning, most of the financial operations are now being dealt by sophisticated machines working on complex set of algorithms and codes. The machine trading systems require very little participation from human, thereby cutting down heavily on involuntary trade errors (Macchiarulo) [91]. Since then, the field of machine/algo trading has come a long way and presently offers a competent substitute to manual trading.

The plethora of content available on the said subject advocate manual as well as automated methods of application of TA for predicting the stock price levels. As discussed earlier, the domain of forecasting has undergone a massive change in the last decade in the form of choice of tools, choice of variables, measurement of error and accuracy and so on. There is a dearth of comprehensive studies that capture how researchers at global level and at India level are adopting and adapting to these financial forecasting techniques over the time. It is through this research effort, the authors aim to serve a significant cause of reviewing the studies that have been conducted since January 1, 2013 up until December 31, 2022, thereby offering a crisp and concise backdrop of variables and aspects addressed in the existing literature. The underlying agenda of this study is to facilitate prospective researchers in identifying research gaps, exploring potential research questions and understanding methodological considerations in the field of financial forecasting.

The authors have conducted a systematic literature review (SLR), using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Refer Appendix Figure-A1) to achieve this purpose. This research study presents both global and Indian perspectives in the domain of TA based forecasting techniques. It offers an abreast comparison between the major patterns and trends in the financial forecasting research, as studied by global researchers and Indian researchers in the last 10 years. Specifically, this paper intends to answer the following research questions:

1. What is the year-on-year publication trend of TA based research papers?
2. What forecasting approaches have been popularly adopted by the researchers?
3. What proportion of papers have used the Transaction Costs and Data Snooping Bias in their forecasting techniques?
4. What is the most commonly adopted research time cycle?
5. What are the major outcomes of the reviewed papers?
6. What is the most popularly adopted performance matrix deployed by the researchers?

1.1 Important Concepts & Terminologies in Financial Forecasting

1.1.1 Technical Analysis Based Forecasting Techniques

As defined by John Murphy in his book “Technical Analysis of Financial Markets”, and backed by the Chartered Market Technician’s Association (CMT Association), USA, TA is a technique of studying market action, primarily through the use of charts and graphs, with an intention to forecast future price trends [111, 35]. Owing to its versatility and ease of deployment, the applicability of this forecasting technique has risen exponentially. What began as a simple methodology for anticipating stock prices, has now evolved into a highly sophisticated concept forming the foundation of a large number of complex mathematical predictive models (Murphy) [111]. Lately, many forecasting algorithms, trend and pattern recognition software are based on the principles of TA. Depending upon the nature of operations, TA based forecasting techniques can broadly be classified into the following categories:

- Manual Forecasting: This methodology incorporates significant degree of human intervention, wherein all aspects of trading, such as trade identification, trade selection, trade execution etc., are performed by the trader.
- Automated Forecasting: This method represents a trading style that has restricted involvement of traders in forecasting and trading process. Here, the pre-fed algorithm acts as the primary decision makers in all aspects of trading (Chan) [28].

This review paper takes into account research papers falling in both the categories to ensure a holistic representation of the researches conducted within this discipline.

1.1.2 Transaction Cost (TC)

Transaction costs/charges (TC), commonly referred to as brokerage, are the expenses incurred by a trader for buying and selling of financial instruments. TC accounts for commission charged by trade broking firms, and taxes imposed by the government (Shynkevich) (Park & Irwin) [163, 127]. Bernoussi & Rockinger presents it as a fee charged by the broking firm for executing buy and sell trades submitted by a trader [45]. The TC generally accounts for a specific percentage, as decided by the broking firm, of the total value of trade executed by the trader. These costs have a negative bearing on the trade entry price, as they push the break-even point to a higher level (Mitra) [108]. Chen, Huang & Lai extensively studies the impact of TC on portfolio returns, and stated that TC can very well be a differentiating factor between a profitable trade and a loss-making trade [33]. Thus, for an effective and practically useful forecasting, the inclusion of TC in the predictive model becomes imperative.

1.1.3 Data Snooping Bias (DSB)

As defined by Hsu, Hsu, & Kuan, data snooping bias arises in time-series data, when the researchers make use of the same dataset to test the significance of different forecasting models (technical trading rules) [60]. The repeated examination of the same data may cause some trading strategies to look profitable. This profitability, however, may exist simply by chance and may hold low to no merit (Jiang, Tong, & Song) [66]. Furthermore, it is popularly believed that data snooping bias is present in almost all empirical time-series data, and often takes a toll on the profitability of TA (Chen, Huang & Lai) [33]. Thus, expulsion of data snooping bias is of utmost importance, if one desires to discover genuine profitability of TA.

In the present SLR study, all the selected papers are reviewed to see whether they include these two important parameters, viz. transaction cost and data snooping bias while carrying out the forecasting.

2. Research Design

This paper undertakes a systematic literature review (SLR) design to unravel the patterns and trends in researches in the area of stock market forecasting techniques based on TA, and ML using TA. An SLR is a research technique used to identify, assess, and summarise prior works that are pertinent to a certain question or area of study. It entails a thorough and methodical examination of the available literature in order to assemble data and make judgements based on the synthesis of prior research findings (Tanveer & Peričić) [173]. Furthermore, to maintain utmost objectivity and transparency in the data identification and selection process, the research makes use of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The PRISMA framework offers an organised method for carrying out systematic reviews, which entails discovering, choosing, and critically evaluating pertinent papers, synthesising the results, and publicly documenting the entire process. It attempts to maintain the objectivity and transparency of the systematic review, as well as make research more easily reproducible (Moher et al.) [109]. The subsequent sections delineate the detailed steps followed for searching, selecting/excluding and analysing the research papers for the current study.

2.1 Keywords and Search String

Following a scooping review of prominent research papers in the field of stock market forecasting, the authors could identify the following key words: “Technical Analysis”, “Technical Indicators”, “Technical Charts", “Stock Market”, “Share Market”, “Equity Market”, “Machine Learning”, “Machine Trading”. The said keywords were then used to design the following search strings:

Global Review: TITLE & ABSTRACT ("Technical Analysis" **OR** "Technical Indicators" OR "Technical Charts") **AND** ("Stock Market" **OR** "Share Market" **OR** "Capital Market" **OR** "Stock Index" **OR** "Stock Indices") ---(1)

Indian Review: ("Technical Analysis" OR "Technical Indicator" OR "Technical Indicators" **OR** "Candlestick Chart" **OR** "Technical Charts") **AND** ("Stock Market" **OR** "Share Market" **OR** "Capital Market" OR "Stock Index" **OR** "Stock Indices") **AND** (Prediction **OR** Predicting **OR** Forecasting **OR** Forecast) ---(2)

The keywords “Machine Trading” and “Machine Learning” were not included in the final search string as conventional studies, since studies on manual deployment and statistical evaluation of TA were getting ignored. The chosen search string ensures a potent mixture of studies from both research areas, so as to offer a holistic view. In context to the global review, the search string was targeted specifically to look for the keywords in the title and abstract of the papers. A generic search that looks for the keywords anywhere in the document was avoided, since it yielded too many results, most of which were irrelevant. However, for identifying papers from the Indian sub-continent, the search string was tasked to look for the keywords anywhere in the document. It is because, the contributions made by Indian researchers is not overwhelming in the said body of knowledge, owing to which, restrictive filtration may lead to expulsion of research papers, which otherwise would have been a part of the sample.

2.2 Databases Searched

The present research makes use of a number of standard databases for ensuring wide and thorough coverage of literature. The study has procured data from five different databases, namely Proquest, Ebsco-Host, J-Stor, Sage, and Google Scholar. In context to Google Scholar, the study makes use of the application called “Publish or

Perish". It is a software program, offered by Harzing (www.harzing.com), that retrieves and analyses academic citations. It uses a variety of data sources to obtain the raw citations, then analyses these and presents a range of citation metrics, including the number of papers, total citations and the h-index.

2.3 Screening Process

2.3.1 Preliminary Screening

The global review of papers begun with deployment of the Search String-1 on the mentioned databases. This led to the discovery of 23,926 research papers (Refer Appendix Figure-A1), which were then passed through a multi-layer funnel of criteria (see Table-1), in order to identify the most relevant and significant papers. The initial screening led to the expulsion of 23,647 papers, thereby leaving the authors with 279 papers to work with. The remaining papers were then reviewed for the relevance of their title and abstract, and the number of citations received by them. Studies that were completely unrelated to the domain of financial forecasting and the ones that had less than 10 citations, were excluded from further review. This led to rejection of 167 papers, thereby bringing down the effective sample size to 112 papers.

Table-1: Selection Criteria

Step-1: Automated Filtration Criteria

Category	Global Review Criteria	Indian Review Criteria
Peer Reviewed	Yes	Yes
Full Text	Yes	Yes
Date Range	2013 and onwards	2013 and onwards
Language Filter	English	English
Location Filter	No	Yes (India)
Search Source	Scholarly Journals	Scholarly Journals
Document Type	Research Papers & Conference Papers	Research Papers & Conference Papers

Step-2: Manual Filtration Criteria

Category	Criteria
Relevance of the title and abstract of the papers	Yes
Number of citations	≥10
Removing duplicate papers	Yes

In context to the papers representing Indian perspective, the initial string search (Search String-2) resulted in the discovery of 1198 research papers (Refer Appendix Figure-A2). Multiple automated filters (Table-1) were applied on the resulting papers in order to narrow down the search outcomes and develop to a cohort of most relevant and significant papers. Similar filtration criteria were used as in case of global literature to ensure uniformity of selection. This brought down the paper count to 169, from which 15 papers were excluded on account of being duplicates, 20 papers for being completely unrelated to the subject matter, and 28 papers for having less than 10 citations. The remaining 106 papers were then subjected to detailed screening, to further assess their relevance and quality.

2.3.2 Detailed Screening

Post completion of the initial filtration process, for the papers representing global research, the remaining 112 studies were then sought for retrieval, of which, full text of 16 papers could not be obtained. The remaining 96 papers were fed into the final leg of the filtration process that required in-depth review of papers. From this set of papers, 8 studies were excluded on account of being not directly related to the research topic. The final count of research papers under the global outlook, came out to be 88. The detailed scrutiny of the prevailing papers by Indian authors (106 in number), was initiated with elimination of 15 studies that could not be retrieved. Following this, 3 papers were found to be unrelated directly to the research questions under the present study. This operation led to the final selection of 88 papers and were selected for in-depth review.

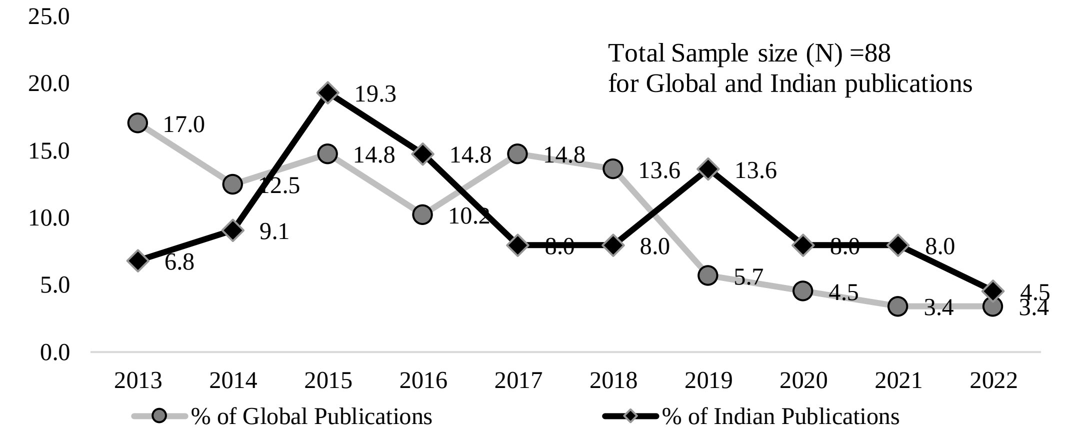
3. Analysis & Results

A detailed review of the selected papers (88 papers from global publications, 88 papers from Indian publications) was conducted by the authors. The review involved going through the data with a fine-tooth comb and interpreting the results with respect to the stated research questions. The following sections present the results of this extensive literature review.

3.1 (RQ-1): What is the year-on-year publication trend of TA based research papers?

The study encompasses all the relevant research papers that have been published during 2013 to 2022. The year of acceptance of the research paper by the respective journal has been considered as the year of publication. Figure-3 depicts the percentage distribution of the research papers over the last ten years.

Figure-3: Year-on-Year Publication Trend



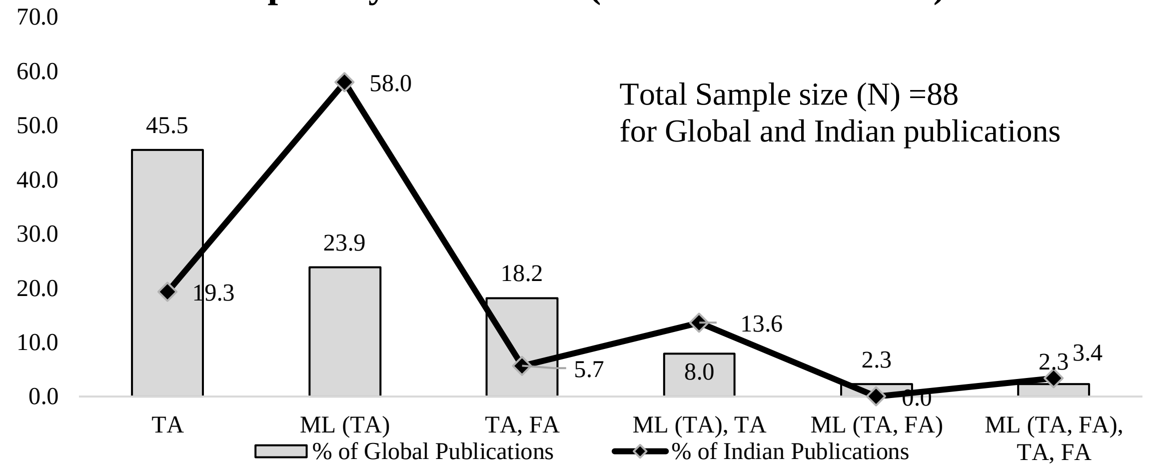
The analysis reveals that over the years the global research community has experienced a shift in research interests. Since 2013, the number of papers published by foreign authors, on the topic of TA based forecasting has declined substantially. Also, the distribution of papers is majorly clustered around the first half of the decade. The fall in publications in the subsequent years is an indication that the said topic may have failed to keep the interests of the global researchers warm. A declining trend may also reflect saturation of the subject area, and a lower possibility of making novel accomplishments in the said body of knowledge. Furthermore, within the realm of possibilities, factors such as publication bias, maturation of the research area and mobility of researchers, may also act as contributing causes.

This, however, is not the case with the Indian publications. The papers published by the Indian authors offer a more even distribution as against the global authors. Time and again, the research domain of TA based forecasting has experienced a spike in the researcher's interest. This suggests that the aforementioned area of research has managed to retain some momentum over the years among Indian authors. The fact that the Indian capital market is relatively less efficient than the global markets, there exists a greater degree of possibility for researchers to achieve breakthroughs and make noteworthy contributions to the discipline. Also, Indian journals have demonstrated greater interest in publishing papers on TA based forecasting techniques as evident from more publications on the said topic even in the later years.

3.2 (RQ-2): What forecasting approaches have been popularly adopted by the researchers?

TA based forecasting techniques can broadly be classified into two categories on the basis of deployment method i.e., Manual Application and Automated Application. Figure-4 presents different types of forecasting methods popularly adopted by researchers at global and national level over the last decade. Apparently, the manual application of TA has been the most popular forecasting tool among the foreign authors. On the other hand, the majority (58%) of Indian researchers have adopted automated deployment of TA through machine learning techniques. Evidently, the Indian researchers have been more responsive in adopting modernised (automated) techniques of financial forecasting than its global counterparts. Indian research fraternity turns out to be more sensitive towards eliminating the involuntary human errors that can create bias in forecasting. By minimizing the role of humans in the overall trading process, more efficiency in forecasting can be achieved. However, with more than 45 percent of publications using (manual) TA and a substantial 18 percent publications using TA, FA, the foreign researchers appear to be more focused towards development of newer and better ways of forecasting market action through data sequences and chart patterns than merely automating the forecasting process. Thus, the Indian researchers have taken up a deductive approach towards this body of knowledge, whereas, foreign researchers have assumed a more inductive outlook towards the same.

Figure-4: Percent distribution of forecasting approaches adopted by researchers (Global and National)



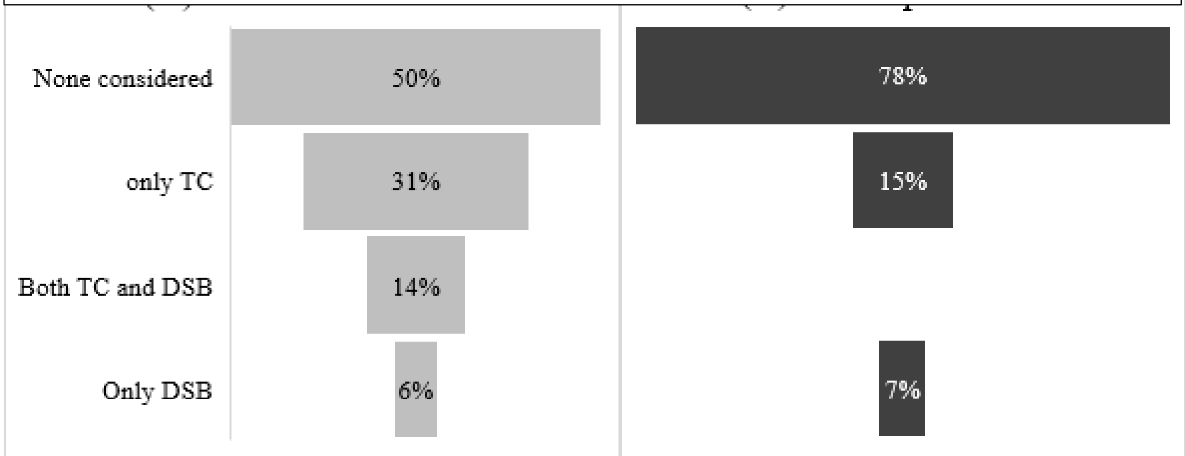
Source: computed from the publications data fetched through PRISMA technique
Note:
TA: Papers on manual application of Technical Analysis
TA, FA: Papers on manual application of Technical Analysis and Fundamental Analysis
ML (TA): Papers on automated application of TA
ML (TA), TA: Papers on automated application of TA and its comparison with manual TA system
ML (TA, FA), TA, FA: Papers on automated application of TA & FA and their comparison with manual TA & FA systems

Apparently, the manual application of TA has been the most popular forecasting tool among the foreign authors. On the other hand, the majority (58%) of Indian researchers have adopted automated deployment of TA through machine learning techniques. Evidently, the Indian researchers have been

3.3 (RQ-3): What proportion of papers have used the Transaction Costs and Data Snooping Bias in their forecasting techniques?

Inclusion of TC and eradication of DSB while determining the forecasting efficiency of a tool or model is of utmost importance. There exists sufficient literature stating that both the aforementioned variables have a significant impact on the gross returns generated by a stock portfolio. Still a large number of financial forecasting papers leave it out of the scope. The data available in following figure (Refer Figure-5), further reinforces that claim.

Figure-5: Percent distribution of global and Indian publications with/without considering the Transaction Cost (TC) and/or Data Snooping Bias (DSB), 2013-2022



Source: computed from the publications data fetched through PRISMA technique

Figure-5 clearly establishes that both TC and DSB have been greatly ignored in forecasting models by both global (50 percent) and Indian (78 percent) researchers. A greater percentage of researchers have opted for inculcation of TC (31% globally and 15% locally), thereby eliminating any address made to DSB. On the flip side, the proportion of papers addressing only DSB, and not TC, has been fairly low (6% for global publications and 7% for Indian publications). While 14% of global papers encapsulated both TC and DSB in their forecasting techniques, none of the Indian literature incorporated both the parameters (Refer Figure-5(A) & 5(B) for data).
The observations suggest that on a comparative scale, TC has been addressed to a greater degree. On the other hand, DSB, an anomaly plaguing time series data with potential risk to make the outcomes inaccurate, still remains relatively expunged from mainstream research. Since TC and DSB have been documented to have unfavourable reverberations on the gainfulness of the forecasting methodology (Mitra) [107], it can thus be concluded, that the degree to which TA based forecasting techniques appear to be rewarding, may be far from genuine.

3.4 (RQ-4): What is the most commonly adopted research time cycle?

Adoption of an appropriate time cycle is central to the effort directed towards discovery of profit yielding capabilities of a forecasting model/tool, especially when dealing with time-series data. It is important for researchers to choose a time frame that successfully encompasses all legs of market cycles i.e., both uptrend/bull run and downtrend/bear run. Time cycles, as defined by Martin Pring in his book "*Technical Analysis Explained*", refer to a recognizable price pattern or movement that occur with some degree of regularity in a specific time period. It has also been defined as prices moving in a periodic fluctuation. Cycles may operate for diverse periods i.e., range from several days to many decades. At any given point of time, multiple cycles are operational and the combined effect of those cycles is what produces fluctuations in the price levels.

Table-2(A): Research Time Cycle (0-5 years)

Research Time Cycle	Global Publications		Indian Publications	
	No. of Papers	% of Papers	No. of Papers	% of Papers
0-1 year	4	15%	4	13%
1-2 years	5	19%	2	6%

2-3 years	6	23%	9	29%
3-4 years	8	31%	13	42%
4-5 years	3	12%	3	10%
Total	26	100%	31	100%
Source: computed from the publications data fetched through PRISMA technique				

Table-2(B): Research Time Cycle (5-10 years)

Research Time Cycle	Global Publications		Indian Publications	
	No. of Papers	% of Papers	No. of Papers	% of Papers
5-6 years	16	53%	23	66%
6-7 years	7	24%	3	9%
7-8 years	1	3%	0	0%
8-9 years	4	13%	7	20%
9-10 years	2	7%	2	5%
Total	30	100%	35	100%
Source: computed from the publications data fetched through PRISMA technique				

Pring points out three important time cycles, namely, the 4-year cycle, the 9.2-year cycle and the 18.33-year cycle. These time cycles have been known to have an edge over other time frames in capturing the market dynamics [140].

In the present analysis, Table-2 depicts that maximum number of research papers undertook 0-5 years and 5-10 years as the time frame for their model building. Table-2(A) and Table-2(B), further provide the data in the form of one-year intervals for the said time frames. Table-2(A) shows that even though 26 globally published papers fall under the time range of 0-5 years, only 3 (12%) research papers have aligned their analysis with the prescribed time cycle of 4 years. Similarly, out of 31 papers authored by Indian researchers, only 3 (10%) have followed the recommended time cycle. For longer duration analysis, Pring (2014) recommends the time cycle of 9-10 years. However, Table-2(B) reveals that just 2 (7%) papers in Global literature and 2 (5%) papers in Indian literature follow the prescribed time cycle. This suggests that the majority of the papers, that are not calibrated as per the stated time intervals, may have possibly failed to ensure complete coverage of all market phases under the study. This further calls into question, the authenticity of results posted by these research papers.

3.5 (RQ-5): What are the major outcomes of the reviewed papers?

A majority of the papers with TA based forecasting techniques have tested the predictive prowess of their proposed model/technique on real market data. The research outcomes of the papers reviewed by the authors are depicted in Table-3.

Table-3: Research Outcomes

Research Outcomes	Global Publications		Indian Publications	
	No. of Papers	%	No. of Papers	%
Positive*	58	66%	62	70%
Negative**	9	10%	3	3%
Mixed***	21	24%	23	26%
Total	88	100%	88	100%

Source: computed from the publications data fetched through PRISMA technique
*Positive: Studies deeming TA to be a profitable forecasting technique.
**Negative: Studies deeming TA to be a non-profitable forecasting technique.
***Mixed: Studies deeming TA to be profitable in selected conditions, and non-profitable in others.

Source: computed from the publications data fetched through PRISMA technique

Table-3 presents the percent distribution of research papers that deemed TA to be a profitable forecasting technique (positive), a non-profitable forecasting technique (negative) and TA to be profitable in selected conditions, and non-profitable in others (mixed). The results obtained by the researchers at both global and national levels are not too far apart. The majority of the research papers rule in favour of TA (66% for global publications and 70% for Indian publications). The papers declaring conditional profitability of TA, are closely placed at 24% and 26% respectively for global and Indian publications. A noticeable difference can be witnessed among papers ruling against TA. While global authors reported 10% of the papers to have negative outcomes, the same for Indian authors came out to be a mere 3%. Thus, Indian authors have communicated greater degree of success with TA based forecasting techniques. One of the plausible reasons for this could be the early adoption of machine aided trading mechanism by the Indian researchers. This would have helped them in overcoming human errors in forecasting. A deeper scrutiny of papers advocating mixed profitability of TA reveals the following insights:

- A majority of the papers have stated that TA’s profitability is significantly dependent upon the ongoing market trend. The studies have demonstrated that TA has proven to be a lucrative forecasting technique, especially during bullish market conditions. The same however, could not be said when the market experiences negative and sideways market action.
- Many academic investigators stated the inclusion of TC as the most prominent reason for the unsatisfactory performance of TA. According to their observations, TA appears to be profitable as long as TC are not taken into account. Once the TCs are brought into play, the model fails to offer encouraging results.

3.6 (RQ-6): What is the most popularly adopted performance matrix deployed by the researchers?

Performance matrices or evaluation measures play a crucial role in assessing the quality and effectiveness of a model, algorithm, or prediction. The extant literature under the study have made use of a diverse range of evaluation measures as mentioned in Appendix Table-A1. Table-5 highlights the top four performance matrices as used by the researchers in the relation to TA based forecasting.

Table-5: Top Four Performance Matrices used by Global and Indian Literature, 2013-2022

Sr. No.	Global Literature		Indian Literature	
	Name of the Performance Matrix	Measurement of	Name of the Performance Matrix	Measurement of
1	% of accurate predictions of profit/loss Making trades	Accuracy or Precision of the model	Mean Absolute Percentage Error (MAPE)	Error or Risk
2	Average Annual Returns (AAN) after applying model	Profitability of the model	Root Mean Square Error (RMSE)	Error or Risk
3	Root Mean Square Error (RMSE)	Error or Risk in the model	% of Profit/Loss Making Trades	Accuracy or Precision
4	Return on Investment (ROI)	Profitability of the model	Mean Squared Error (MSE)	Error or Risk

Source: computed from the publications data fetched through PRISMA technique
NOTE: Definitions and formulae of the above-mentioned matrices can be referred to in Appendix Table-A2.

Table-5 reveals that the foreign researchers are more inclined towards identifying the returns/rewards generated by the respective model/strategy/algorithm. The most preferred performance matrix, i.e., prediction of % of profit/loss making trades has been used in 14 research papers. Matrices estimating the performance of models and in terms of potential rewards include AAN and ROI. From the given list, it is only RMSE that tries to quantify potential error or risk in the prediction.

Converse to this, Indian authors seem to be more interested in identifying the risk and error associated with the forecasting techniques. Three out of the top four matrices gauge risk/error in prediction. This unfolds the risk averse inclination or defensive approach of Indian researchers as against their global counterparts. So, the researchers at the global level are trying to maximize the amount of returns per unit of risk taken. On the other hand, Indian researchers are striving for minimization of risk per unit of return.

4. Conclusion

The current study presents a systematic and comparative analysis of the literature on Technical Analysis (TA) based forecasting approaches published by foreign and Indian researchers between 2013 and 2022. The findings show that the said area of research is more popular in India with an early adoption of machine learning techniques in financial forecasting. Indian studies focus more on automated deployment of TA, while global studies emphasize manual application. While global researchers prioritize profit maximization of a forecasting model, the Indian researchers prioritize risk mitigation of a model. The extensive literature review under study rules in favour of TA-based forecasting technique as being a highly profitable predictive technique for financial forecasting. However, these results are far from being flawless as the majority of the papers, in global and Indian context, have discounted the impact of TC and DSB on the predictive prowess of TA. Furthermore, very few studies have taken into account, a research time cycle that syncs well with the overall stock market cycle. These deficiencies in the existing literature offer immense research opportunities to fellow researchers in making significant contributions in the said body of knowledge. Additionally, the future researchers may carry out an SLR to explore this domain of research by taking a longer time-span for research, multiple intervening variables, and other biases besides data snooping bias.

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6. Declaration

None of the authors have any conflict of interest, either financial or non-financial.

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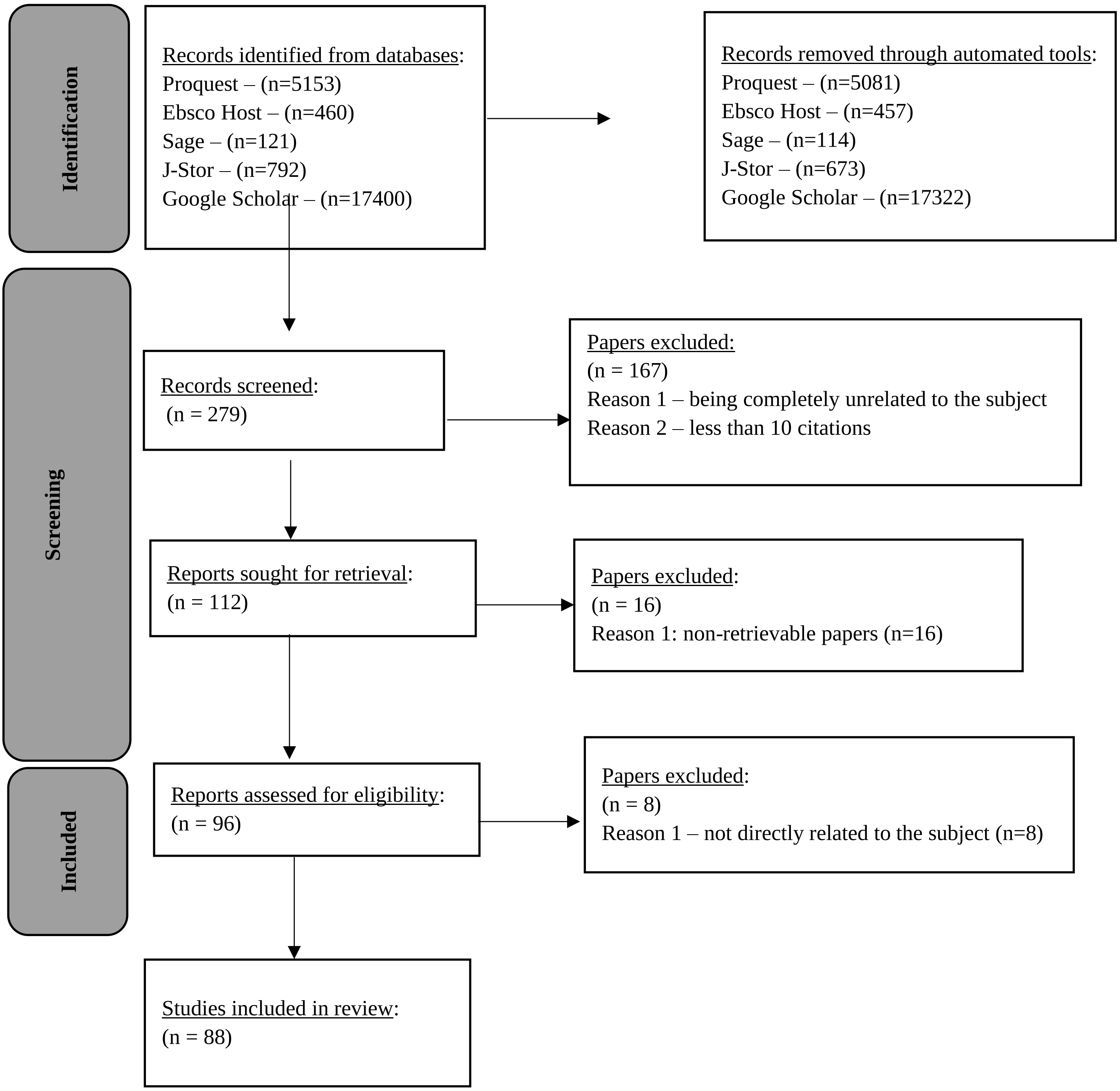
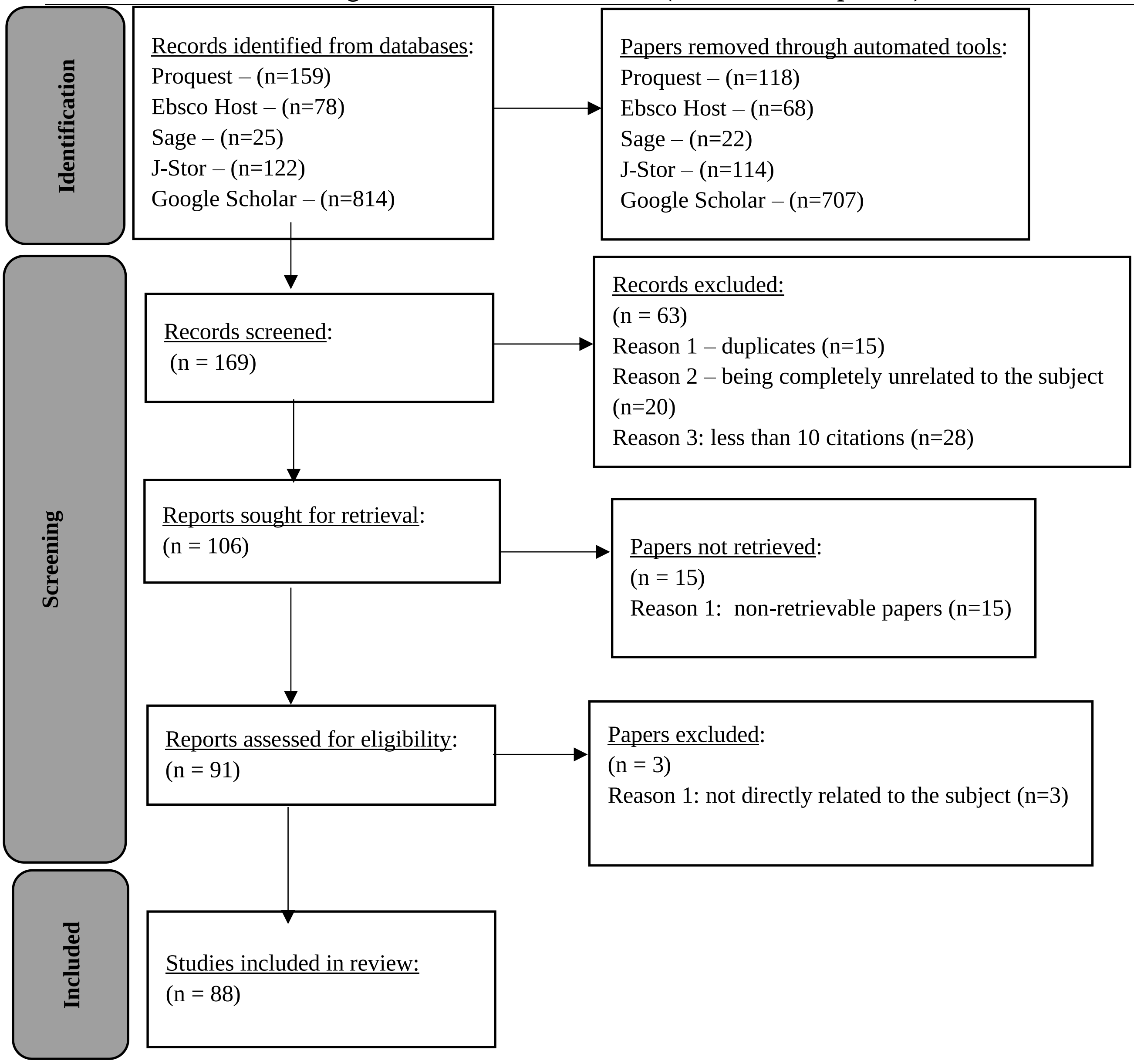
Appendix

Fig.-A1: PRISMA Framework (for Global Perspective)



Source: computed from the publications data fetched through PRISMA technique

Fig.-A2: PRISMA Framework (for Indian Perspective)



Source: computed from the publications data fetched through PRISMA technique

Table-A3: List of Performance Matrices Used by Researchers

Sr. No.	Performance Matrix	No. of Papers	
		Global Review	Indian Review
1	Change in Price Levels	5	-
2	Increase in Return	1	-
3	Profit/Loss Making Trades (Accuracy)	14	17
4	Accuracy of TA Indicators on a 5-Point Rating Scale	-	1
5	Adjusted R-Squared	1	1
6	Annualized Number of Transactions	1	-
7	Annualized Return	1	2
8	Autocorrelation	-	1
9	Average 10-Day Return	1	-
10	Average Daily Return	5	1
11	Average Abnormal Returns	1	-
12	Average Annual Returns	7	1
13	Average Annualized Daily Return	-	1
14	Average Directional Accuracy	2	2
15	Average Monthly Return	2	-

16	Average Profit	1	-
17	Average Profit/Loss Per Trade	2	3
18	Average Raw Returns	1	-
19	Average Total Return	1	-
20	Average Transaction Length	1	1
21	Average Utility	1	-
22	Area Under Curve	-	1
23	Basis Points (Absolute Value Value)	2	-
24	Bollerslev-Wooldridge Standard Errors	-	1
25	Brier Score	-	1
26	Comparison Between Actual and Forecasted Trend	-	1
27	Cumulative Return	1	-
28	DAR	1	-
29	Dickey-Fuller Test	-	1
30	DVAR	1	-
31	End-of-Trade Drawdown	1	-
32	Error Rate (With Expected Closing Price)	-	2
33	Extent of Justification of Risk Premium	1	-
34	Final Wealth/Total Return/Accumulated Return	3	-

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35	F-Score	-	2
36	Hurst Exponent	-	1
37	Idle Ratio	1	-
38	JPE (Joint Prediction Error)	-	1
39	MAE	5	11
40	MAFE	-	1
41	Manual Verification of Price Movement	1	-
42	MAPE	3	22
43	MARE	1	-
44	MASE	1	-
45	Maximum Favourable/Adverse Excursion	1	-
46	Maximum Profit/Loss Per Transaction	-	-
47	Maximum/Minimum Capital	1	-
48	MDE	-	1
49	Mean Excess Return	1	-
50	Mean RMSE	-	1
51	MMRE	-	1
52	Model Fitting	-	1
53	MPE	1	-

54	MSE	4	12
55	MSFE	-	1
56	MSPE	1	-
57	MSRE	-	1
58	Net Profit	4	1
59	Number of Points Earned	2	1
60	Out Of Bag (OOB) Error	-	1
61	Portfolio Risk & Return	1	-
62	Predicted Closing Price	-	1
63	Probability Distribution (Representing Accuracy of ML Trading Systems)	-	1
64	Returns in Comparison to B&H	1	-
65	Recall	-	2
66	RMSE	7	20
67	RMSFE	-	1
68	RMSPE	1	-
69	RMSRE	1	-
70	ROI	7	1
71	rRMSE	-	2

72	R-Squared	1	1
73	SDMAE	-	1
74	SDMAPE	-	1
75	Semi-Variance	1	-
76	Sensitivity & Specificity	1	2
77	Sharpe Ratio	3	-
78	SMAPE	-	1
79	Standard Error	-	1
80	Sum Squared Residual	1	-
81	Terminal Value	1	
82	Unit Root Tests (ADF, PP, Run Test)		2

Source: computed from the publications data fetched through PRISMA technique

Table-A4: Description of Most Frequently Used Performance Matrices

Sr. No.	Name	Definition	Formula
1	MSE	It is an error evaluation tool, commonly used to measure the average squared distance between predicted and actual values.	$MSE = (1/n)\ \Sigma_{i=1}(Y_i - Y^{\wedge}_i)^2$ n = no. of observations Y_i = actual values $Y^{\wedge}_i$= forecasted values
2	RMSE	It is an error evaluation tool, commonly used to measure difference between predicted and actual values.	$RMSE = \sqrt{(MSE)}$
3	MAPE	It is an error evaluation tool commonly used in forecasting and time series analysis to measure the accuracy of a model's predictions in terms of percentage errors. It quantifies the	$M = 1/n\ (\Sigma_{t=1}(A_t - F_t)/F_t)$ n = no. of observations A_t= actual values F_t= forecasted values

		average percentage difference between predicted and actual values.	
4	ROI	It is a financial metric used to evaluate the profitability and efficiency of an investment. It measures the return or profit generated relative to the cost of the investment	ROI = (Net Profit / Total Investment) x 100
5	% of Profit/Loss making trades	It is a measure of how close an estimated value is to the true or target value. It is commonly used to assess the performance or correctness of a predictive or classification model. Its value ranges between 0 and 1.	A_P = (No. of Profitable Trades / Total no. of Trades) x 100 A_L = (No. of Unprofitable Trades / Total no. of Trades) x 100 A_P = % of profitable trades A_L = % of unprofitable trades
6	AAN	It refers to the mean or average rate of return on an investment over a one-year period. It is a measure used to assess the performance or profitability of an investment or asset class over time.	ANN = [(Ending Value + Cash Flows) / Beginning Value]^(1 / Number of Years) - 1

Source: Merrin, J. (2017). Introduction to error analysis: The science of measurements, uncertainties, and data analysis. CreateSpace Independent Publishing Platform.