Developing a Security Risk Assessment based Smart Beta Portfolio Model for Robo Advising

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Abstract

Our study develops a unique Security Risk Assessment based Smart Beta (SB) portfolio construction model for Robo Advising investors belonging to different risk categories. This model will cater to the Gen Z tech-savvy retail investors who have become more active and are interested in online investment platforms like Robo Advising. Our study differs from prior studies as it proposes a portfolio construction model for equity investors belonging to different risk categories while traditional approaches map debt portfolios to low risk investors and equity portfolios to high risk investors. Investors are generally risk-averse but prior studies have developed SB portfolios without considering their risk appetite. In this study, we assess the riskiness of stocks and then categorise them into different risk categories by mapping SB factors such as quality, value, alpha, momentum, etc. We further construct SB portfolios that minimise risk for each category of stocks to cater to investors belonging to low, moderate, high, as well as very high risk categories, using Machine Learning (ML) algorithms. Through a wide range of risk and return performance indicators, we provide evidence that our model offers higher returns at lower risk than human-managed portfolios. Our model proves to be more reliable and encourages Robo Advisors to offer SB portfolios catering to retail investors' needs and their risk appetite. The study contributes to the evolving literature on Robo Advising, SB investing and to the debate on whether algorithms can replace human portfolio managers.[4]

JEL: G11, G20, G23
Keywords: Algorithmic Investments, Smart Beta, Portfolio Management, Robo Advising

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1. INTRODUCTION

The Fourth Industrial Revolution is considered to be a series of technological disruptions through Artificial Intelligence (AI) and Machine Learning (ML). The younger generation is driving the big changes in retail investment (Nasdaq, 2022).The emergence of new Gen Z tech-savvy investors with a knowledge of digital technologies has augmented the adoption of Robo Advising, an AI-based automated financial advising framework. As many retail investors do not have adequate financial decision-making experience, they seek professional financial advice (Fecht et al., 2018). However, as the young tech-savvy retail investors have limited financial resources, they are willing to try seeking advice from the low-cost, AI-based Robo Advisors (Belanche et al., 2019). While prior studies have mapped only mutual funds and Exchange Traded Funds (ETFs) to investors, there is a need to develop portfolios for Gen Z retail investors who prefer to invest in direct equity, based on their risk appetite. A Robo Advisory model, which measures the riskiness of individual stocks and maps Smart Beta (SB) factors to different risk categories, may provide optimal portfolios on a more reliable and low-cost platform to such investors. This study develops a Security Risk Assessment based SB portfolio construction model using ML-based algorithm to cater to tech-savvy equity investors with low, moderate, high and very high risk appetite.

By construction, Robo Advising is neutral to the behavioural idiosyncrasies of human portfolio managers and offer low-cost financial advice (D'Acunto et al., 2019). In the financial services industry, Robo Advisors are alternatives for human portfolio managers as they provide easy setup of accounts, effective financial planning, optimal portfolios and customised services to investors at lower costs, especially to those investors who are concerned about potential conflicts that could arise from human investing advice (Brenner & Meyll, 2020). ML methods in portfolio management contribute to enhanced returns and even during crisis periods such as the financial crisis, robo investors have the advantage of quickly cashing out their securities leading to overall superior returns (D'Hondt et al., 2020). The Assets under Management (AUM) of Robo Advisors globally grew from USD 0.19 trillion in 2017 to USD 2.45 trillion in 2022 and is expected to touch USD 4.66 trillion by 2027 at a Compounded Annual Growth Rate (CAGR) of 14% (Statista, 2023b). However, the studies on Robo Advising are still in a growth phase.

Another application where algorithm-based quantitative models are used for stock selection is SB or factor-based investing. The use of factors for stock selection was proposed in literature for better performance over traditional Cap-Weighted (CW) portfolios. Factors such as size (Fama & French, 1992), momentum (Jegadeesh & Titman, 1993), volatility (Ang et al., 2006), beta (Frazzini & Pedersen, 2014) and quality (Asness et al., 2019) were found to outperform traditional portfolios. Firm-based fundamental factors were also tested for their ability to outperform CW portfolios. Revenue, cash flow, book value, gross dividend, total employment and profits were used to construct equity portfolios and were found to earn consistently higher returns than CW portfolios in the US market in the long run (Arnott et al., 2005), European market (Hemminki & Puttonen, 2008) and in the Indian market (Kumar & Tiwari, 2022). Although there were studies that brought out the shortcomings of SB investing in different markets, such as US (Chen et al., 2015) and the Middle East and North Africa (MENA) region (Abadi & Silva, 2019), SB funds have been growing in terms of both number of factors applied and the AUM value globally.

It is observed that though Robo Advising has been growing significantly in the past decade, the methodological framework used in these firms has largely been the Modern Portfolio Theory (Markowitz, 1952) and equal weight portfolios, while factor based investing methodology is used by a relatively small proportion of Robo Advisors across 28 countries (Beketov et al., 2018). The proportion is smaller in emerging economies like India where Robo Advising is still in a nascent stage and mutual funds are predominantly recommended to investors.

Among emerging markets, Robo Advising in India has a unique regulatory framework. Indian Robo Advisors are governed by Securities and Exchange Board of India's SEBI(Investment Advisers) Regulations, 2013, which also applies to traditional investment advisors. In 2020, SEBI pointed out that investment advising through automated tools must comply with requirements such as executing physical agreements with investors, maintaining detailed records of clients' risk-profiling, assessing suitability of advice given and interactions with clients. Robo Advisors must also submit quarterly reports to SEBI detailing the AI/ML applications used for automated investment advising and cyber security controls taken to protect investor interest. These requirements result in cumbersome document maintenance costs for Robo Advisors, who aim to provide low-cost investment advice. Unlike in developed markets, there are no exclusive regulations for Robo Advising in India. Despite the above challenges, the regulatory environment may undergo positive changes in the near future as Robo Advising is in a fast-growing phase in India. SEBI may come out with exclusive provisions such as E-agreements, rationalising record maintenance, etc., which may remove the uncertainty, lack of trust and fear in the minds of investors regarding automated investment advising. The AUM of Robo Advisors in India grew from USD 0.03 billion in 2017 to USD 9.55 billion in 2022 and is projected to reach USD 23 billion in 2025 and USD 25.74 billion by 2027. The expected CAGR of AUM from 2024 to 2027 is 9.21%. The number of users of Robo Advising in India is also projected to reach 3.25 million by 2027 (Statista, 2023a). A dedicated regulatory framework would enable tremendous growth of Robo Advisors in India necessitating more research on their portfolios.

This study proposes a novel portfolio construction model that first assesses the risk of individual stocks and then categorises them into very high, high, moderate and low risk categories. The model then maps SB factors such as quality, value, momentum, alpha, low volatility, dividend, beta etc. to each stock risk category and creates 'minimum risk' portfolios. The model is fully automated using ML based algorithms.

This study is unique in several aspects. While prior studies constructing SB portfolios did not consider investors' risk appetite, our model constructs automated SB portfolios for different risk categories. The study uses a unique methodology for risk assessment and stock categorisation and maps SB factors for each risk category for portfolio construction. Another differentiating factor of this study is that while prior studies mapped debt portfolios to low risk investors, we create equity portfolios for investors of all risk categories. Using a wide range of return and risk indicators, we evaluate our portfolios' performance and compare the same with mutual funds offered by human fund managers. The study significantly adds to the literature on Robo Advising and SB portfolio performance. The study also adds to the literature on the debate of whether algorithmic models can replace human portfolio managers.

The study reveals that our portfolios outperform human-managed mutual funds. The results are found to be consistent for different time periods. The findings have important implications for Robo Advisors as they can offer SB portfolios to Gen Z retail investors. In emerging markets where Robo Advisory services are evolving, adopting the proposed framework would help Robo Advisors offer optimal portfolios to investors at lower costs, attracting higher AUM. Investors will benefit as they will earn higher risk-adjusted returns, irrespective of the risk category they belong to. Our risk assessment model gives important insights to capital market regulators such as the

SEBI. SEBI's existing risk assessment framework categorises debt portfolios as low risk and equity portfolios as very high risk. Our model brings out the need for improving SEBI's framework so that investors of all risk categories may choose equity portfolios.

2. REVIEW OF LITERATURE

Though Robo Advisory service has been growing significantly across the globe, the literature on Robo Advising is limited and evolving. Robo advising is a disruptor that changes the face of the financial advisory industry and yet there is huge potential untapped (Jung et al., 2019). The prominent advantage of Robo Advising is that it significantly reduces the extent of behavioural biases investors are subject to, is "neutral to the idiosyncrasies of specific human advisors" and also offers diversification benefits (D'Acunto et al., 2019). Through its simplicity, cost-effectiveness, transparency and accessibility, it brings the common masses into the world of investing (Shanmuganathan, 2020). Investors view Robo Advising as a tool that empowers them to become more interested in the performance of their Robo-advised portfolios (Rossi & Utkus, 2021).

The performance of Robo Advisors was studied predominantly in the U.S. market which holds the largest proportion of AUM of Robo Advisors (Statista, 2023b). Investors' share in risky assets increased through Robo Advising and the portfolio performance improved significantly in the near term (Rossi & Utkus, 2020). Robo Advisors exhibited outperformance over equity indices, equity, money market, fixed income, and hybrid funds in the US market (Tao et al., 2021). Robo Advisors do not outperform the market, but they clearly outperform human-managed peer funds due to their superior stock picking ability, lower turnover ratios leading to lower transaction costs and removal of inherent behavioural biases of human fund managers (Miguel & Chen, 2021). Robo Advising ensures better portfolio performance and also has a positive spillover effect on investor behaviour as investors obtain financial education by constantly interacting with Robo Advisors (Hao et al., 2022). The shortcomings of Robo Advising have also been brought out in prior studies, due to which Robo Advisors may not be viable alternatives to human financial advisors. Conflict of interest, incorrect assessment of investor risk tolerance and the lack of personal touch lead to lower risk-adjusted returns of Robo Advisors (Waliszewski & Zięba-Szklarska, 2020). Robo Advisors do not exhibit better market timing ability when compared to human-managed funds (Miguel & Chen, 2021).

With more positive evidence on the performance of Robo Advising, many studies examined the factors influencing investors to adopt Robo Advising over human portfolio managers. A survey of 765 potential Robo Advisory users in North America, Britain and Portugal revealed that the key factors determining the adoption of Robo Advising were consumer attitudes and mass media and interpersonal subjective norms (Belanche et al., 2019). The other main factors were higher financial risk-taking ability (Oehler et al., 2022), financial knowledge, online financial activities (Isaia & Oggero, 2022), trust propensity, performance expectancy and hedonic motivation (Nourallah, 2023). Thus, literature provided essential insights for Robo Advisors as to how they can position their service and who should be the potential target customers.

Though there were studies on the benefits, pitfalls, drivers of adoption and performance of Robo Advising, there is very limited literature proposing portfolio construction models designed for Robo Advising. A modular system was developed using the Black Litterman model (Black & Litterman, 1992) and the Mean Variance Optimisation model (Markowitz, 1952) for portfolio optimisation, taking data for US ETFs, and the portfolio constructed thus, showed better returns than the market (Day et al., 2018). However, the study focused on ETFs following a passive investment style and did not test the model on active equity portfolios. While earlier studies primarily used mean-variance optimisation as the basis for their frameworks, the drawbacks of the mean-variance model namely non-monotonicity and time-inconsistency, were overcome by using a group of utility functions induced by mean-variance, which allowed investors to treat the upside as well as downside deviations from expected returns in different ways (Strub et al., 2018). Though the proposed model was simple and encouraged effective diversification across asset classes, the data on investor preferences was collected through a survey. Hence it may not be accurate for investors with limited or inaccurate knowledge about their own preferences and risk appetite. A reinforcement learning framework was also used for portfolio construction where the Robo Advisor is unaware of the risk profile of investors initially but understands it by observing their investment choices under various market conditions (Alsabah et al., 2021). A Financial Decision Support System based on fundamental factors was also used to create and manage equity portfolios based on AI and ML techniques combined with traditional mathematical models (Patalay & Bandlamudi, 2021). The study found evidence that the use of Financial Decision Support System yielded 15% higher returns than the market in the long term due to the usage of fundamental factors as against prior studies that mainly used technical indicators as parameters for stock selection. Though this study is closest to the current study in terms of using factors, it did not map SB factors for different risk categories to select stocks.

There is evidence in literature on the outperformance of SB portfolios. Factor-based investing was found to outperform traditional CW indices in different markets. Factors such as size (Fama & French, 1992), momentum (Jegadeesh & Titman, 1993), volatility (Ang et al., 2006), beta (Frazzini & Pedersen, 2014), quality (Asness et al., 2019), minimum variance (Chan et al., 1999; Clarke et al., 2006), maximum diversification (Choueifaty & Coignard, 2008), equally weighted-risk (Maillard et al., 2010), risk factor benchmarks (Jeng et al., 2013), total income, revenue, cash flows, profits (Kumar & Tiwari, 2022). were used to construct factor-based portfolios and contrarian indices (Eggins & Hill, 2010) and were found to outperform traditional portfolios in developed markets. In the emerging Chinese markets, multiple factor-based portfolios (Jeng et al., 2013), minimum-variance, equal-weighting and risk parity (Cai et al., 2018) and Quantitative funds (Manru & Yucan, 2018) were found to outperform traditional portfolios. Though there were studies that brought out the shortcomings of SB portfolios, such as the trade-off between low volatility and liquidity (Cazalet et al., 2014), lack of robustness (Amenc et al., 2015) and lack of consistent performance across different market conditions (Jacobs & Levy, 2015), SB funds have been gaining popularity in both developed as well as emerging markets.

The review of literature thus reveals that though Robo Advising and SB investing have largely outperformed human-managed portfolios, there is very scant literature that designs portfolio construction framework specifically for Robo Advising. No study attempted to create a model to offer SB portfolios through Robo Advisors. This could bring together two objective styles of investing that remove human biases in stock selection. There is hardly any literature that tries to identify SB factors for different risk categories of investors. This is imperative as the choice of factors would differ based on the risk appetite of each investor and a customised risk assessment based SB portfolio needs to be created for each risk category. While prior studies followed the traditional approach of creating debt portfolios for low risk and equity portfolios for high risk appetite investors, our study develops an automated model catering to tech-savvy equity investors belonging to different risk categories.

3. DATA AND METHODOLOGY

3.1 Data specification

Our study attempts to first assess the risk of individual stocks and then construct equity portfolios for different risk categories of investors by mapping SB factors for each category. For this purpose, Indian stocks are chosen as both SB and Robo Advising are in a fast-growing phase here and the existing Robo Advisors mostly recommend only mutual funds to investors based on their risk profiles. The data of all equity stocks listed on Nifty 500 index of the National Stock Exchange (NSE), which is the leading stock exchange in India, is taken. Nifty 500 consists of the top 500 stocks based on market capitalisation and constitutes large cap, mid cap, as well as small cap stocks. As reported by NSE, Nifty 500 represents around 96.1% of the free float market capitalization of all NSE listed stocks as of March 29, 2019. The traded value of all stocks on Nifty 500 for the six-month period ending in March 2019 is approximately 96.5% of the traded value of all NSE listed stocks. Nifty 500 is thus considered the ideal universe of stocks on which our risk assessment based SB portfolio construction model can be applied. The closing prices and other market-related data of all 500 stocks were taken from the NSE website for a sample period of three years, beginning April 1, 2020, and ending March 31, 2023. The period captures the price movements before, during and in the diminishing phase of the Covid pandemic as well as during geo-political tensions. This sample period consists of 746 trading days. Along with market closing prices, the firm level data was also taken for the study and was sourced from the CMIE Prowess database. The firm-level data, which was not available on Prowess, was taken from the Quarterly reports of the respective companies. There were 82 stocks for which some values were missing for the complete period and hence the final sample size was 418 stocks.

The study compares the performance of Robo Advising SB portfolios with human-managed Large cap, Midcap, and Small cap regular mutual funds with growth option. The daily Net Asset Value (NAV) of these funds were taken for the sample period from the website of the Association of Mutual Funds of India (AMFI). For this purpose, the top ten funds from the Large Cap and Midcap category and top twenty from the Small Cap category were chosen based on their AUM as of March 31, 2023. The list of such funds taken for performance comparison is given in Table 1. India's 91-days Treasury Bill rate is taken as the daily risk-free rate from the Reserve Bank of India (RBI) website.

Table 1: Mutual funds analysed for comparison

Large Cap funds	**Mid Cap funds**
ICICI Pru Blue Chip	HDFC Mid-Cap Opportunities
SBI Blue Chip	Kotak Emerging Equity Scheme
Mirae Asset Large Cap	Axis Mid-Cap
Axis BlueChip	Nippon India Growth Fund
HDFC Top 100 Fund	DSP Mid-Cap
ABSL Frontline Equity	SBI Magnum Mid-Cap
Nippon India Large Cap Fund	Mirae Asset Mid-Cap
UTI Master Share	PGIM India Mid-Cap Opportunities
Canara Robeco Blue chip Equity	Franklin India Prima Fund
Franklin India Blue Chip	UTI Mid-Cap
Small cap funds	

Nippon India Small Cap	Quant Small Cap
HDFC Small Cap	Tata Small Cap
SBI Small Cap	ABSL Small Cap
Axis Small Cap	UTI Small Cap
DSP Small Cap	Sundaram Small Cap
Kotak -Small Cap	PGIM India Small Cap Fund
HSBC Small Cap Fund	Edelweiss Small Cap
Franklin India Smaller Companies	Invesco India Small Cap
Canara Robeco Small Cap	Bandhan Emerging Businesses Fund
ICICI Pru Small Cap	ITI Small Cap

Note: Source: Compiled by authors

Table 1 lists the regular mutual funds identified for comparison of performance

3.2 Methodology

3.2.1 Portfolio Construction

In this study, a novel two-step process is being followed to screen the stocks for portfolio construction. The first step assesses the risk of each stock and categorises them into four risk types. The second step maps SB factors to each risk category, calculates the value of the SB factors and selects stocks for the portfolio for each risk category. The flow chart in Figure 1 shows the steps followed in the study to develop a Security Risk Assessment based automated SB portfolio for Robo Advising.

As seen in Figure 1, Nifty 500 stocks form the universe for our portfolio construction model. Firstly, three parameters, namely market capitalisation, impact cost as a measure of liquidity and daily volatility are obtained for the final sample of stocks from the NSE website for all trading days. These are the parameters prescribed by the Indian capital market regulator, SEBI, in its circular on how the risk of different securities can be identified (SEBI, 2020). Our study considers the same measures to categorise the final sample of stocks based on their risk levels. We follow SEBI's rationale that the larger the market capitalisation, the lower the risk of the stock and the lower the impact cost and daily volatility, the lower the risk of the stock. On this basis, we have divided stocks into four categories of risk, namely very high, high, moderate and low. We improve upon SEBI's prescribed methodology as SEBI categorises all equity shares as very high risk securities, while we postulate that equity shares could also cater to investors with low, moderate, and high risk appetite. SEBI may consider our risk assessment for identifying equity stocks with different risk levels.

Fig. 1: Methodology for developing the model

Securities listed in the Nifty 500 index selected to develop a Risk Assessment based SB portfolio for RA

Applying a two-step risk-assessment-based security selection strategy for our model

Assessing the risk of each security, using parameters of 'Market Cap', 'Daily Volatility' & 'Impact Cost' (as indicated by SEBI's circular (SEBI/HO/IMD/DF3/CIR/P/2020/197))

Excluding securities with data not available for the entire study period from the final list of securities considered for the portfolio construction model

1st level stock screening process – Dividing each stock into four different risk categories – low risk, moderate risk, high risk and very high risk based on the above three parameters – Higher the market cap, lower the risk and lower the volatility and impact cost, lower the risk

2nd level screening process – Mapping of different SB factors to each of the four risk categories based on economic reasoning

Assigning a risk score for each stock based on the measure of SB factors, applying a benchmark score for each of the risk categories and accordingly selecting the securities for these portfolios

Adopting "Minimising Portfolio Risk" strategy in order to assign weightage to each of the stocks

Automating the entire process of risk assessment, SB factor mapping to risk categories, stock selection and semi-annual portfolio rebalancing using ML-based algorithms in "Python"

Note: Source: Compiled by authors

The market capitalisation value of each stock as of March 31, 2023, is taken and the stocks are sorted in descending order of the value. The stocks are then divided into Large Cap, Midcap, and Small Cap by identifying the top 100 stocks as Large Cap, 101^{st} to 250^{th} stocks as Midcap and from 251^{st} onwards as Small cap stocks as per the norms practised at NSE. Small Cap stocks are further divided into two groups based on the percentile value of market capitalisation. Large cap stocks are considered to belong to the Low-risk category, Midcap stocks to the Moderate Risk category, the first group of the Small Cap stocks with the higher market capitalisation to the High-Risk category and the other Small Cap stocks to the Very High Risk category. The daily average values of both impact cost and volatility of all stocks are taken and based on these, the stocks are divided into quartiles. The stocks belonging to the lowest value quartile are categorised as the Low Risk stocks. A score is assigned to each stock for each parameter and each parameter is given a weight. The weighted average risk score is then obtained for each stock and based on this score, the stocks are classified into one of the risk categories. After this first level of screening, we get 66 stocks in the Low Risk category, 146 in the Moderate Risk category, 147 in the High Risk category and 59 in the Very High Risk category, totalling to 418 stocks in the sample period. Table 2 shows the first step of the screening process and the number of stocks obtained in each risk category at this stage.

Table. 2: Risk assessment of individual stocks

Low Risk	Moderate Risk	High Risk	Very High Risk
• Large Cap • Q1 –Impact Cost • Q1 –Volatility	• Mid Cap • Q2 –Impact Cost • Q2 –Volatility	• Small Cap • Q3 –Impact Cost • Q3 –Volatility	• Small Cap • Q4 –Impact Cost • Q4 –Volatility
66 stocks	146 stocks	147 stocks	59 stocks

Note: Source: Compiled by authors

Table 2 shows the number of stocks in each risk category after first level risk assessment

The second step of screening in our framework is unique as we identify and map a set of SB factors to each risk category. This has not been attempted in prior studies and we are the first to propose the SB factor mapping for screening stocks for each risk category. The factors chosen are based on those used in the different equity SB indices of NSE. For each of the SB factors chosen, we identify the measures as used in SB indices as well as based on our own rationale. Table 3 shows the mapping of SB factors with each risk category and the measures used for these factors.

Table 3: SB factor mapping to investor risk categories

Risk Category	SB Factors mapped	Measures of SB factors
Low Risk	Low Volatility	Standard Deviation, Downside Deviation
	Dividend	Dividend Yield
Moderate Risk	Alpha	Stock Returns in excess of Nifty 500 returns
	Quality	Return on Equity, Debt-Equity ratio, EPS growth volatility
	Value	Earnings to Price ratio, Book Value to Price, Dividend Yield
High Risk	Alpha	Stock Returns in excess of Nifty 500 returns
	Growth	Price to Earnings and Price to Book Value higher than those of Nifty 500
Very High Risk	Alpha	Stock Returns in excess of Nifty 500 returns
	Beta	Beta greater than 1 in relation to Nifty 500
	Momentum	Risk adjusted return

Note: Source: Compiled by authors

Table 3 lists the SB factors mapped to each risk category and the measures of the factors

Using the above mapping, we calculate the value of the SB factor measures based on the daily values for the three year period. We then assign a weight for each measure of each SB factor and obtain a weighted average risk score for each stock. A benchmark risk score for each category is determined and based on the final risk scores in relation to the benchmark score, we select stocks for each risk category portfolio. For assigning weights to each stock in the portfolio, we use the condition of minimum portfolio risk as investors are generally perceived to be risk averse. After the second step of screening, the number of stocks obtained in each risk category is shown in Table 4.

Table 4: Risk assessment and SB mapping results

Risk category	**Number of stocks after risk assessment**	**Final number of stocks after SB mapping based screening**
Low Risk	66	34
Moderate Risk	146	40
High Risk	147	33
Very High Risk	59	31

Note: Source: Compiled by authors

Table 4 shows the number of stocks in each risk category after first and second level of screening Once the stocks were screened and portfolios constructed for each risk category, we automate the risk assessment, SB mapping process and stock selection process using ML-based algorithms developed in Python. The complete process will be automatically repeated every six months to rebalance the portfolio on a semi-annual basis. This automated process will extract data for the Nifty 500 stocks from the NSE website and the CMIE Prowess database at the end of every six months and construct portfolios for the four risk categories. The Robo Advising platform can use the algorithm to offer SB portfolios to retail investors.

3.2.2. Portfolio Performance Analysis

4. After the portfolio was constructed, the performance of each portfolio was assessed using a wide range of performance indicators categorised as return indicators and risk indicators. The return indicators used are Annualised return, Sharpe ratio (Sharpe, 1966), Sortino ratio (Sortino & Price, 1994) and Treynor ratio (Treynor, 1965), while the risk indicators used are Standard Deviation, Downside Deviation and Beta. These indicators are calculated for our portfolios as well as for the human-managed Large Cap, Midcap and Small Cap mutual funds chosen for comparison. Based on market capitalisation of all stocks in our portfolios, the performance of Low Risk portfolio is compared with Large Cap funds, Moderate Risk portfolios with Midcap funds, High Risk portfolio with the top ten Small cap funds and Very High Risk portfolio with the following ten Small Cap funds. This comparison determines whether our automated risk assessment based SB portfolios constructed for Robo Advisors outperform human-managed peer funds. **RESULTS AND DISCUSSION**

The performance analysis results of our portfolios and a comparative analysis with traditional mutual funds are given in Table 5

Table 5: Performance Analysis of Robo Advising SB portfolios (April 2020-March 2023)

Performance Measures	LOW RISK PORTFOLIO	LARGE CAP MF	MODERATE RISK PORTFOLIO	MID CAP MF	HIGH RISK PORTFOLIO	SMALL CAP MF (1-10)	VERY HIGHRISK PORTFOLIO	SMALL CAP MF (11-20)
Annualised Return	**16.39%**	25.01%	**45.31%**	32.39%	**58.43%**	36.86%	**73.31%**	33.32%
Sharpe Ratio	**0.97**	1.23	**2.71**	1.71	**3.14**	1.98	**3.16**	1.66
Sortino Ratio	**1.70**	1.99	**4.71**	2.70	**5.32**	3.12	**5.29**	2.59
Treynor Ratio	**0.21**	0.21	**0.60**	0.33	**0.76**	0.42	**0.79**	0.35
Standard Deviation	**12.52%**	16.93%	**15.17%**	16.40%	**17.33%**	16.19%	**21.89%**	17.36%
Downside Deviation	**7.16%**	10.41%	**8.72%**	10.43%	**10.20%**	10.26%	**13.06%**	11.27%
Beta	**0.58**	0.97	**0.68**	0.86	**0.71**	0.81	**0.88**	0.84

Note: Source: Computed by authors

Table 5 shows the results of performance analysis of the developed portfolios and comparison with human-managed mutual funds

Table 6: Risk assessment and SB mapping results for robustness test

(April 2017-March 2020)

Risk category	Number of stocks after first level screening	Final number of stocks after second level screening
Low Risk	70	38
Moderate Risk	154	32
High Risk	139	36
Very High Risk	69	36

Note: Source: Compiled by authors

Table 6 shows the number of stocks in each risk category after first and second level of screening for the period April 2017 to March 2020 to test for robustness

Our results shown in Table 5 are aligned with the risk return characteristics of each risk category. It is seen that the annualised return is the least for Low risk category and it gets higher for each of the other categories with the maximum return for Very High Risk category, in accordance with the principle of 'High risk High return'. A similar trend is seen in all the return indicators. The Standard Deviation is lowest for Low Risk category and increases to reach the highest value for Very High Risk category. The other risk indicators of Downside Deviation and Beta also show the same trend.

Table 5 also shows the results of the comparative analysis with human managed funds. The return indicators of the Low Risk portfolio are slightly lower than those of Large Cap funds. However, it must be noted that the investors of this category focus on lower risk rather than higher returns. The values of all the three risk indicators of the Low Risk category are much lower than those of Large Cap funds, indicating the suitability of our SB portfolio for investors with low risk appetite. In the Moderate Risk category, all the performance indicators show clear outperformance of our automated SB portfolios as the return indicators are higher and risk indicators lower. This implies that the portfolio is most suited and optimal for investors willing to take only moderate risk in equity investment. As most of the retail investors across the globe would fall into this risk category, the results have an important implication for the Robo Advisors, who can benefit from higher AUM using our unique portfolio construction model. In High Risk and Very High Risk categories, investors seek higher returns and are willing to take higher risk. The return indicators of these portfolios are higher than those of the Small Cap funds. The Sharpe and Sortino ratios having values much higher than one (3.14, 3.16 and 5.32, 5.29) clearly indicate that the returns of our automated SB portfolios more than compensate for the high risk taken by investors in these categories. The results of performance analysis provide evidence that SB portfolios formed using our unique framework would be better investment choices for equity investors. It emphasises that the effective and novel use of AI/ML based models could outperform human-managed portfolios, remove cognitive biases of human managers, and reduce transaction costs, making Robo Advising affordable to all investors.

5. TEST OF ROBUSTNESS

In order to check if our SB portfolios perform consistently, we applied the same framework for a different sample period, which did not include any major recession, pandemic phases or geo-political tensions as witnessed in our initial sample period. The period used for the robustness test was the three years prior to our initial sample period, beginning April 1, 2017, and ending March 31, 2020. Through the same two step screening process using market capitalisation, impact cost and daily volatility in the first level and SB factor mapping in the second level of stock screening, we constructed four portfolios for the four risk categories identified earlier. This sample period consists of 741 trading days. The 500 stocks constituting Nifty 500 as on the last day of the sample period were chosen and after removing stocks with missing data for the sample period, the final number of stocks available for portfolio construction was 432. The number of stocks obtained in each level of screening is shown in Table 6. It is seen from Table 6 that the number of stocks was more or less in line with that of the initial results where each portfolio had about 30 to 40 stocks. This portfolio size is comparable to that of most traditional mutual funds. The performance of these portfolios was also compared with the Large, Mid and Small Cap mutual funds selected in the initial analysis. The results of our analysis are shown in Table 7.

Table 7: Performance Analysis of Robo Advising SB portfolios for robustness (April 2017-March 2020)

Performance Measure	LOW RISK PORTFOLIO	LARGE CAP MF	MODERATE RISK PORTFOLIO	MID CAP MF	HIGH RISK PORTFOLIO	SMALL CAP MF (1-10)	VERY HIGH RISK PORTFOLIO	SMALL CAP MF (11-20)
Annualised Return	**1.99%**	-2.01%	**5.51%**	-7.25%	**-1.57%**	-9.23%	**-4.12%**	-14.88%
Sharpe Ratio	**-0.32**	-0.46	**-0.04**	-0.71	**-0.53**	-0.87	**-0.53**	-1.10
Sortino Ratio	**-0.49**	-0.63	**-0.06**	-0.94	**-0.78**	-1.14	**-0.81**	-1.43
Treynor Ratio	**-0.05**	-0.12	**-0.01**	-0.15	**-0.08**	-0.18	**-0.09**	-0.26
Standard Deviation	**12.65%**	17.35%	**13.89%**	18.13%	**14.53%**	17.25%	**19.28%**	19.37%
Downside Deviation	**8.31%**	12.67%	**9.90%**	13.57%	**9.89%**	13.05%	**12.63%**	14.98%
Beta	**0.78**	0.87	**0.93**	0.88	**0.91**	0.82	**1.15**	0.82

Source: Computed by authors

Table 7 shows the results of performance analysis of the developed portfolios and comparison with human-managed mutual funds for the period April 2017 to March 2020 as test for robustness

Table 7 validates the effectiveness of our Risk assessment based SB portfolios for Robo Advising and confirms the viability of our portfolio construction framework. It is seen from the results of a different time period that the annualised returns for all traditional funds were negative due to the overall market movements during the period. However, even during such a period, the portfolios of Low Risk and Moderate Risk categories still earn positive annualised returns, offering downside protection to risk-averse investors. While the Sharpe, Sortino and Treynor ratios for both Low Risk and Moderate Risk portfolios are negative, they are higher than those of traditional funds. This is in contrast to our earlier results where the return indicators of our portfolios were lower than those of traditional funds. This is an important result as it provides evidence that during unfavourable market conditions, our Low Risk and Moderate Risk indicators provide higher returns and lower risk compared to traditional funds and could thus serve as optimal investment choices for investors with relatively low risk appetite in the equity market. It means these investors need not turn to debt market for lower risk but can continue investing in our equity portfolios. The risk indicators for both portfolios are much lesser than those for the Large Cap and Midcap funds. The High Risk and Very High Risk portfolios have also earned negative returns during the period and the other return indicators are also negative. However, these values are higher than those of Small Cap funds with which they are compared. At the same time, similar to our earlier results, the risk indicators of these two portfolios are lower than those of Small Cap funds. This implies that even for investors with high and very high risk appetite, our SB portfolios for Robo Advising serve as better investment choices.

The performance analysis of our portfolios for a different period to test for the robustness and validity of our portfolio construction model thus provides strong evidence that our automated SB portfolios are optimal investment choices for all investors. The ML algorithms used in our SB portfolios have the ability to analyse voluminous data quickly and accurately, while the AI based Robo Advising platform can accurately solicit investor information, conduct risk profiling, and recommend our SB portfolios to investors.

6. CONCLUSION

This study develops a unique Security Risk Assessment based SB portfolio construction model to cater to the tech-savvy Gen Z retail equity investors interested in Robo Advising. These investors have been very active in recent years and are likely to change the face of retail investment market. However, there are no models to offer them equity portfolios based on their risk appetite through Robo Advising platform. Our study addresses the need to develop equity portfolios for investors belonging to the low, moderate, high, as well as very high risk categories. Our unique automated model takes each stock of the Nifty 500 index on India's NSE and assesses their risk level based on market capitalisation, liquidity and volatility. Each stock is then given a risk score and categorised into one of the four risk types. Using a novel risk scoring method, our model then maps SB factors to each risk category and selects stocks for these categories. We thus construct equity portfolios for retail investors belonging to each risk category.

We assess the performance of our portfolios using return indicators (Annualised return, Sharpe ratio, Treynor ratio and Sortino ratio) and risk indicators (Standard Deviation, Downside Deviation and Beta). We compare these with the performance of human-managed mutual funds. Our study brings out evidence that our SB portfolios outperform human-managed mutual funds in both the return and risk indicators. The results are robust when the same portfolio construction model is applied to Nifty 500 stocks during a different three-year period. The study thus shows that SB equity portfolios can be effectively constructed for each risk category and offered through Robo Advisors to cater to Gen Z retail equity investors.

Our study is unique in that while prior studies develop SB portfolios without considering the risk-appetite of investors, we develop portfolios for investors with varying risk appetite levels. The study is also unique in its methodology as it first assesses the risk of individual stocks and then creates ML algorithm-based automated SB portfolios by mapping SB factors to each risk category. While prior studies followed the traditional approach of associating debt portfolios to investors with relatively low risk appetite, and stocks for investors with relatively high risk appetite, this study develops SB portfolios of equity stocks for investors belonging to all risk categories. The study contributes to the evolving literature on Robo Advising as well as SB investing, especially in emerging markets like India, where they are still in a nascent and fast-growing phase. The study also adds to the growing literature on whether AI and quantitative models can replace human portfolio managers.

The study has important implications for Robo Advisors as they can offer SB portfolios constructed based on our framework to Gen Z tech-savvy investors willing to try unconventional investment choices at lower costs. The study has adequate potential to take Robo Advising to the masses by offering SB portfolios with better performance than human-managed portfolios at lower costs. The study also has important implications for policymakers as it brings out the need to develop a separate risk assessment method for equity investors with varying risk appetite.

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