Boosting The Market Competitiveness Of Artificial Intelligence Forecasting-Based Portfolio Management Products Through Fuzzy Quality Function Deployment

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Abstract: - In recent years, econometric predictions in the finance sector have gained popularity. Traditional methods have proven inadequate for these predictions, due to the frequent adoption of artificial intelligence. In this study, the aim is to create an FQFD model for artificial intelligence forecasting-based portfolio management products, intending to provide firms with a strategic direction. Significant attributes for customer requirements are identified through collaboration with experts and literature review. Initially, a survey is conducted among portfolio holders who actively monitor their investments. Based on the survey results, key attributes for customers are definitively determined using the Multiple Linear Regression method. Engineering characteristics to meet these requirements are similarly sourced from articles and expert consultations. The relationship between important customer attributes and engineering characteristics is established using the Fuzzy Quality Function Deployment method. According to this relationship, the best engineering characteristic is identified. The primary contribution of this study has no similar research has been conducted previously. Hence, it provides firms considering the development of such products with high quality and competitive advantage in the market.

Key-Words: - AI forecasting-based portfolio management products, Multiple Linear Regression, Fuzzy Quality Function Deployment, Marketing Analysis, Robo-Advisory, Fintech Strategy, Product Development, Artificial Intelligence in Finance, Portfolio Management

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1 Introduction

1.1 Background Information

Over the years, there have been numerous technological advancements aimed at easing people's daily tasks in life, and one of these advancements is robots. With the development of artificial intelligence (AI), robots, which were once more primitive, have advanced. AI involves programming machines to think and act like humans, solving problems similarly but often more quickly, significantly [1]. AI is used in many fields, from assisting students with their homework in education to diagnosing illnesses in the healthcare sector. Another application area is data prediction. Data relevant to the field to be utilized is collected. Predictions regarding how future events will unfold are made using appropriate AI techniques with the collected data [2]. In the field of finance, AI techniques are frequently used in forecasting future prices of financial instruments, stock market forecasting, and developing portfolio optimization models based on outputs [3].

Generally, when making these predictions in this sector, machine learning and deep learning techniques come into play. Although deep learning is a subset of machine learning, they have different methodologies. In a broad sense, machine learning encompasses a group of algorithms capable of automatically creating predictive models through the identification of patterns within data [4]. On the other hand, Deep learning permits computational models comprised of multiple layers. The deeper layers near the data input acquire basic features, whereas the upper layers acquire more intricate features built upon the features from the lower layers [5].

Financial models provide a convenient way to represent financial data, known as time series, which refers to numerical data points observed sequentially over time. Before making predictions using these techniques, traditional methods such as autoregressive integrated moving average (ARIMA), exponential smoothing, etc., are used. These methods face difficulty in accurately studying financial time series due to their non-linear and nonstationary patterns [6]. In this sector, the utilization of AI methods has made it more feasible to make risk predictions.

1.2 Literature Review

Predictions based on AI are particularly significant in portfolio management. There have been numerous studies conducted in this field. The aim of these studies is to accurately predict the future of the assets to be invested in as much as possible. Hence, in many of them, different models have been compared to find the one that yields the closest results in forecasting. The authors in [7], have utilized Artificial Neural Networks and Support Vector Machines in their research. Before training on monthly stock datasets, cleansing was performed, such as removing erroneous and duplicate data. They trained these 3 models with cleansed datasets. After making predictions with these models, they have examined which model performed the best, meaning which one was closest to the actual and provided the highest returns. Besides comparing the models among themselves, these have also been compared with traditional forecast methods. The authors in [8], employed deep reinforcement learning for portfolio management. After dataset cleansing and training the model on the dataset, they tested it and presented that it provided much more accurate predictions compared to methods such as Moving Average Reversion and Robust Median Reversion.

Even though the models exhibit good performance in the studies, they may not achieve the same level of success in every dataset, particularly in the finance sector where data fluctuates. The authors in [9], have proposed a model called the deep reinforcement learning based Long Sequence Representations Extractor - Cross-Asset Attention Network in their research. They discovered that when these models have been trained and tested with highly fluctuating data, they are much more suitable for portfolio management. The authors in [10], discovered that long short-term memory networks are suitable for financial time-series forecasting.

In addition to accurate forecasting, there has been a trend towards providing recommendations in recent years. This stage is referred to as robo-advisors. According to the authors in [11], robo-advisors are not only easily accessible and cost-effective but also provide superior risk-adjusted returns to investors. The authors in [12], investigated the impact of users' past investment performance on their adoption of intelligent advisers in their study. According to the research findings, they provided recommendations for enhancing the adoption of intelligent advisers in various criteria, such as design.

While there have been numerous studies in the literature, there is a notable absence of research on the application of Fuzzy Quality Function Development (FQFD) methodology to AI forecasting-based portfolio management products. Hence, the primary contribution of this study is to offer a strategic direction for companies aiming to develop an AI forecasting-based portfolio management product, thereby enhancing quality and their marketing competitiveness.

The remainder of the study is organized as follows: In Section 2, the materials and methods selected in this research, including Multiple Linear Regression (MLR) and FQFD, are 4 elaborated. Section 3 provides calculations and theoretical explanations based on the MLR and FQFD. In Section 4, results and recommendations are presented based on the calculations. Finally, Section 5 provides a summary of the study.

2 Problem Formulation

2.1 Multiple Linear Regression

Multiple regression analysis methods are used to estimate parameters for a hypothesized, typically linear, relationship between a single dependent variable and multiple independent variables. The equation generally takes the following form:

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k + \in \quad (1)$$

where y represents the dependent variable, x_k denotes the kth independent variable, β_0 show intercept, β_i which is slope represents the coefficient to be estimated, and $\in$ represents the error term [13].

The calculation of beta values is necessary for establishing the equation. To find the kth beta values, a matrix x is created to add the relationship between independent values.

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}_1 - \ldots - \hat{\beta}_k \bar{x}_k \quad (2)$$

$$\in' \in = (y - x\beta_i)' \, (y - x\beta_i) \quad (3)$$

$$\widehat{\beta_i} = (x'x)^{-1} x' y \quad (4)$$

where y is a vector represents the actual values of the dependent variable. x is a matrix represent independent variables and their relationship. β_i is a vector represent the coefficients [14].

After constructing a regression model, one of the key measures used to evaluate its goodness of fit is likely the coefficient of determination, denoted as R-squared, which signifies the extent to which the model accounts for the variability in the response variable. A higher R-squared value suggests that the model provides a better fit to the data [15]. The formulas for calculating R-squared are as follows:

$$R^2 = 1 - \frac{SS_R}{SS_T} = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (5)$$

where SS_R is referred to as the Regression Sum of Squares which indicates how much the predicted (calculated) value $\hat{y}_i$ of the dependent variable deviate from the actual mean of dependent variable $\bar{y}$. SS_T is termed to as the Total Sum of Squares which is expressed as the deviation of the actual value of the dependent variable y_i from the actual mean of dependent variable $\bar{y}$.

Moreover, Additionally, subtracting SS_R from SS_T yields SS_E, which allows us to find the variance [14]. Variance can be calculated as:

$$\hat{\sigma}^2 = \frac{SS_E}{n - k - 1} \quad (6)$$

where n indicate that observation number.

To determine whether independent variables have a significant effect on dependent variables, a hypothesis is formulated for each independent variable. The null hypothesis (H_0) states that the kth independent variable has no significant effect on the dependent variable. The alternative hypothesis (H_1) indicates that the kth independent variable has a significant effect on the dependent variable.

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_n = 0 \quad (7)$$

$$H_1 : \beta_k \neq 0. \quad (8)$$

If the p-value, which from the F test, of the kth independent variable exceeds 0.05, then the null hypothesis is retained, indicating that a linear model in x does not contribute significantly to predicting y [16].

2.2 Fuzzy Quality Function Development (FQFD)

Quality function deployment (QFD) is a technique for product development and quality assurance initially created to guarantee that “the Voice of the Customer” (VOC) resonates throughout all phases of the product development process [17]. The QFD process involves building one or more matrices, often referred to as Quality Tables. The combining of these matrices is known as the House of Quality (HOQ), where the left side represents the customer's desires and requirements (CR), and the top side represents the engineering characteristics (EC) provided by the development team to fulfill those desires and requirements. The matrix is composed of multiple sections or sub-matrices interconnected in diverse configurations, each containing information that is interrelated with others [18].

In recent years, fuzzy logic has been increasingly incorporated into QFD analyses [19]. Fuzzy logic has gained recognition for its ability to capture the semantics of linguistic terms. When conducting QFD, the use of fuzzy logic enables the representation of linguistic terms, thereby allowing different stakeholders to communicate in natural language [20]. Different types of fuzzy numbers exist for linguistic terms, with each potentially more appropriate for analysing specific ambiguous structures. These numbers are expressed as triplets like (x_l, x_m, x_u), where x_l and x_u represent the lower and upper boundaries of the fuzzy number, respectively, and x_m denotes the value that best represents the data. Triangular fuzzy numbers are frequently employed for quantifying linguistic data [21].

The fuzzy QFD (FQFD) application can be outlined in 7 steps [22].

Step 1: The initial step involves determining CR, also known as “whats” for the FQFD model. These can be identified through literature review and expert opinions. Multi-criteria decision-making methods (MCDM) or MLR can be employed to decide which of these identified requirements will be used in the study.

Step 2: After identifying the “whats”, the next step is to explore ways to transform CR into product value using various EC, also known as “hows”. Like the process of identifying “whats”, “hows” are determined through literature review and expert opinions.

Step 3: A FQFD model is created based on the “whats” and “hows” and experts are tasked with collecting data. Experts assign symbols to the relationship matrix, which are then transformed into triangular fuzzy numbers to accommodate the uncertainty of human thoughts.

Step 4: The customer's importance rating (CIR_{wh}) for each attribute “what” is calculated by multiplying the weights (W_k) from the importance rating scale with the frequency (F_i) of attributes, and then dividing each attribute by the total number of respondents (TR).

$$CIR_{wh} = \frac{\sum(W_k \times F_i)}{TR} \quad (9)$$

In the given context, $i = 1, .., n$ signifies the ith attribute, where k denotes the kth weight on the scale, and wh represents the “whats”.

Enumerate the values of CIR_{wh} for each “what”, also referred to as CR in the FQFD model.

Step 5: The relative weight (RW_h) for each “how” is calculated by multiplying the customer's importance rating (CIR_{wh}) of each “what” with the fuzzy number (FN_{wh}) assigned to it by the respondents, and then summing each “hows” individually to obtain the relative weight for that particular engineering characateric.

$$RW_h = \sum_{wh} (CIR_{wh} \times FN_{wh}) \quad (10)$$

where, wh represents the "whats", while h represents "hows" of the FQFD model.

Step 6: Since the relative weights are represented in triangular fuzzy numbers, the process of de-fuzzification involves converting these fuzzy numbers into crisp values. This can be done using the center of gravity method. These relative weights can be represented as $(l,\ m, u)$, where signify the lowest possible value, the modest possible value, and the ultimate possible value, respectively [23].

$$Defuzzified\ RW_h = \frac{(u-l)+(m-l)}{3} + l \quad (11)$$

Step 7: In the final step, the de-fuzzified relative weights (RW_{hj}) of each "hows" from all the FQFD responses collected from experts are taken, and the mean (M_h) is calculated. Then, the results of each "how" are normalized and ranked from highest to lowest value, with the highest value representing the final solution.

$$M_h = \frac{\sum_{j=1}^{r} Defuzzified\ RW_h}{TE} \quad (12)$$

$$Normalization = \frac{M_h}{\sum_{h=1}^{z} M_h} \quad (13)$$

where, TE is the total number of experts that responded to the FQFD model and ($j = 1, .., r$) represents the response of the jth expert. Where, ($h = 1, .., z$) represents the value of the HOW.

3 Problem Solution

This section outlines how two methods are employed. Firstly, in section 3.1, MLR is presented to identify the criteria identified as "whats" in the HOQ. In section 3.2, after the selection of "hows", the calculations made according to the steps of FQFD are provided.

3.1 Multiple Regression Analysis (MLR)

First, the attributes important to customers of an AI forecasting-based portfolio management product are identified through literature review and expert opinions. The attributes are presented in Table 1 (Appendix) along with their descriptions and the referenced studies.

A survey is prepared based on the identified attributes. The survey is completed by 25 individuals who regularly invest and use investment instruments. These respondents are asked to assign a value between 0 and 5 to indicate the importance of the relevant attributes for them. The Importance Rating Scale, ranging from 0 to 5 points, is categorized as follows: Not Preferred, Very Slightly Preferred, Slightly Preferred, Moderately Preferred, Highly Preferred, and Very Highly Preferred. After completing the survey, respondents are asked about the probability of managing their portfolios through an AI forecasting-based portfolio management product, and they are asked to provide a value between 0 and 100 as a result. The frequencies of responses given to the surveys on important attributes are presented in Table 2 (Appendix).

The probability question in the survey is determined as the dependent variable, while attributes are designated as independent variables. To investigate the impact of independent variables on the dependent variable, MLR is conducted using Minitab version 22.1. The R^2 value which also known as the coefficient of determination, is calculated as 71.90%. This value indicates a highly robust regression relationship between the independent and dependent variables. The regression hypothesis is provided below.

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$
$$H_1 : \beta_i \neq 0 \quad for\ i = 1, .., 5$$

These hypotheses are formulated to assess the collective variance between the dependent variable and the independent variables. Essentially, the significance level between the array of attributes and the probability of customer preference is examined through an F test conducted at a significance level of 0.05. The outcomes of the MLR are presented in Table 3 (Appendix). It is evident that the p-value derived from the F test is considerably lower than the significance level of 0.05, indicating the rejection of the null hypothesis and acceptance of the alternative hypothesis. This implies that ith independent variable has a significant effect on the dependent variable.

Another crucial attribute is the variety of EC available to address various CR. These characteristics are determined by examining research papers and consulting the development team. Table 4 (Appendix) outlines some of these engineering characteristics along with references to relevant papers.

3.2 FQFD Calculations and HOQ Construction

The four critical attributes impacting customer selection are transformed into the FQFD model, as the house of quality. These represent CR ("whats") necessary for enhancing product quality and market value. Diverse EC ("hows") are identified using the method outlined in the second dataset, constructing a corresponding FQFD model. Two experts assign weights to the relationship and co-relationship matrix, which is prepared using three linguistic terms: "strong" "moderate" and "weak" The triangular fuzzy numbers corresponding to these terms are provided in Figure 1 (Appendix). This matrix allows for the calculation of the customer importance rating for each "whats" (CIR_{wh}) using Equation (9), based on weight frequency from Table 2. The relative weight for each "how" (RW_h) is calculated using the triangular fuzzy numbers assigned to these three linguistic terms using Equation (10), followed by defuzzification via Equation (11). A comprehensive FQFD model, expert feedback, and results from these equations are depicted in Figure 1 (Appendix).

According to CIR_{wh} calculations, the most significant attribute identified is performance which represents how close the forecasts of this product are to the actual values.

To determine the final ranking, the mean (M_h) of each HOW is computed by consolidating all the defuzzified relative weights obtained from the three responses ($j = 1, 2$), utilizing Equation (11), with TE set to two. Following this, the outcomes are normalized using Equation (12) and (13) and subsequently ranked in a descending manner. These results are displayed in Table 5 (Appendix).

4 Discussion

Table 5 reveals that the AI Model Selection and Training exhibit the highest value. Consequently, it is designated as the top EC since it adequately meets the majority of CR and translates them into product value. A summary of the primary outcomes from both approaches is provided in Table 6 (Appendix).

According to the results of the QFD method, AI model selection and training is identified as the most crucial EC for an AI forecasting-based portfolio management product. Due to the high-frequency nature of the datasets used for learning in the finance sector, models suitable for these datasets should be selected. Another crucial factor is determining whether long-term or short-term memory will be held in the models. Depending on this choice, forecasts can provide more accurate results. Additionally, conducting tests after model training is essential. If the predictions during testing are close to reality, the likelihood of the product's success increases. While all three identified EC criteria are crucial in product development, it is observed that model selection and training hold greater significance in product quality compared to others.

4.1 Future Directions

This study aims to provide a direction for firms aiming to develop AI forecasting-based portfolio management products to enhance their quality and market competitiveness. With the increasing prevalence of robo-advisors in recent years, offering an additional service to enhance product quality and market competitiveness. Conducting an FQFD study for the product with the added robo-advisor in future research will provide firms with a new strategic direction. Additionally, instead of using the MLR method for determining customer requirements, it is considered that one of the fuzzy MCDM methods could be employed. These methods can enable customers to use more natural linguistic terms instead of assigning numerical ratings while communicating.

5 Conclusion

In recent years, the improvement of AI has caused its acceptance in various sectors such as finance. Particularly in portfolio management, where assets exhibit non-linear and non-stationary patterns, it has been observed to outperform traditional forecasting methods significantly. This study aims to identify the requirements of customers for AI forecasting-based portfolio management products and provide a strategic direction to enhance quality and marketing competitiveness by addressing these requirements with the necessary EC. CR, including Analytical Capabilities, Performance, Acceptance by Users, Reliability, and Security, is determined through collaboration with experts and literature review. A survey is conducted among customers, querying these attributes and the probability of managing their portfolios through the product. Based on the survey results, where the attributes served as independent variables, and the probability question as the dependent variable, multiple linear regression was conducted. According to the regression results, indicated that Security is found no significant impact on the dependent variable. EC necessary to meet these requirements are also derived from literature and expert consultations, identified as Data Collection and Cleansing, AI Model Selection and Training, and Model Verification and Validation. To establish the relationship between each EC and each CR, found through multiple linear regression, the Fuzzy Quality Function method is employed. According to this relationship, AI Model Selection and Training emerged as the preferred engineering approach to increase the preference for AI forecasting-based portfolio management products in the finance market.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors used Chat GPT to edit the English language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

Table 1. The Attributes Important to Customers of an AI Forecasting-Based Portfolio Management Product

Attributes	Description	References
Analytical Capabilities	Ability to present forecasts in a clear and organized manner	Experts
Performance	Closing the forecasts are to the actual values	[24]
Acceptance by Users	The desire to use increases upon observing other users utilizing it	[25]
Reliability	Relying on an automated system	[26]
Security	Protecting user data against attacks	[27]

Source: created by the authors

Table 2. The frequencies of responses given to important attributes

Attributes / Weight Frequency	0	1	2	3	4	5
Analytical Capabilities	3	5	3	5	5	4
Performance	2	4	4	4	5	6
Acceptance by Users	4	5	5	5	4	2
Reliability	1	5	5	3	6	5
Security	3	4	6	6	4	2
The Probability of Managing Their Portfolio Through This Product						
Probability Range	0-30	31-50	51-70	71-80	81-90	91-100
Frequency	0	0	10	5	8	2

Source: created by the authors

Table 3. MLR Results

Attributes	F test	p-value	Decision of H_0	Selected for FQFD
Analytical Capabilities	8.050	0.011	Reject	Accept
Performance	6.600	0.019	Reject	Accept
Acceptance by Users	32.200	0.000	Reject	Accept
Security	4.080	0.058	Accept	Reject
Reliability	10.440	0.004	Reject	Accept

Source: created by the authors

Table 4. The Characteristics Important to Development Team of an AI Forecasting-Based Portfolio Management Product

Engineering Characteristics	Description	References
Data Collection and Cleansing	The process of rectifying errors, addressing omissions, and resolving inconsistencies in collected data.	([28] ; [29] ; [30] ; [31])
AI Model Selection and Training	The process of selecting the most suitable model and feeding it with training data to achieve the desired results through optimization.	([32] ; [33] ; [34])
Model Verification and Validation	The process of verifying and validating the accuracy and effectiveness of the model to determine whether it meets the requirements.	([35] ; [36] ; [37])

Source: created by the authors

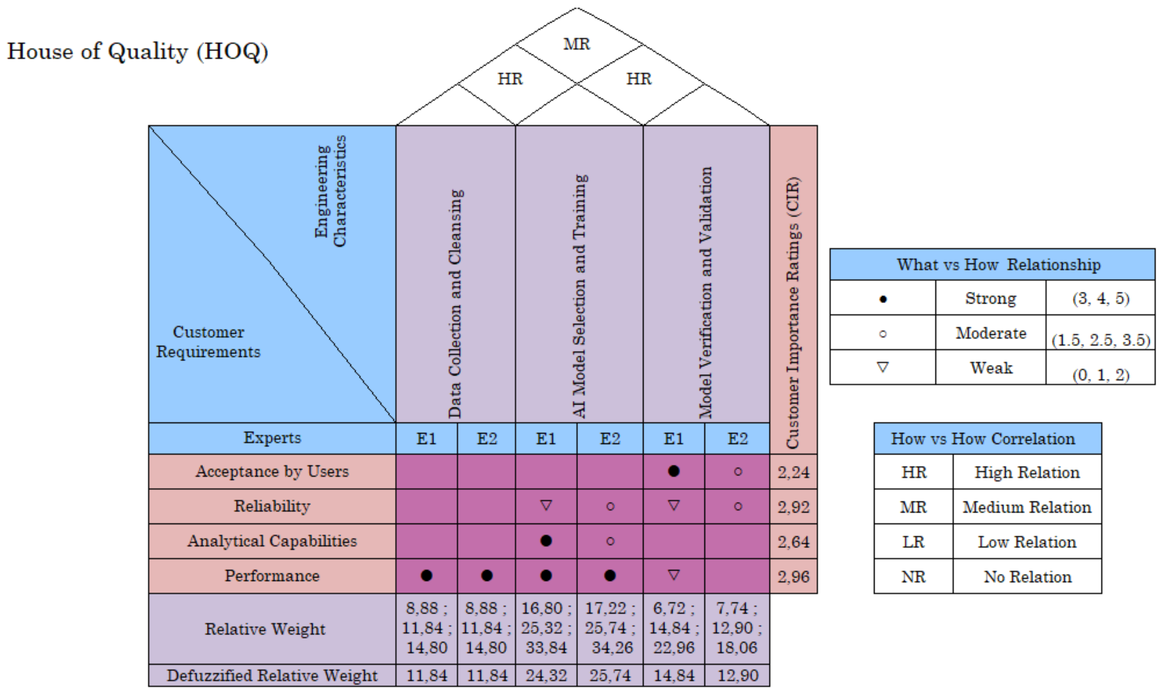

Fig 1**:** House of Quality (HOQ) of Product
Source: created by the authors

Table 5. FQFD Final Results.

HOW's jth Response	Data Collection and Cleansing	AI Model Selection and Training	Model Verification and Validation
Defuzzified RW_{h1}	11.84	24.35	14.84
Defuzzified RW_{h2}	11.84	25.75	12.90
Mean	11.84	25.05	13.87
Normalized	0.23	0.49	0.28
Ranking	3	1	2

Source: created by the authors

Table 6. Summary of the Main Finding

MLR Results	FQFD Results
Analytical Capabilities Performance Acceptance by Users Reliability	AI Model Selection and Training

Source: created by the authors