

Explainable AI for Enterprise Product Portfolio Decision-Making: Effects of Data Quality, Transparency, and Managerial Control

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ABSTRACT

This is research highlights that inaccurate and incomplete data, as well as lack of algorithmic transparency, may negatively affect decision-making accuracy and effectiveness. Therefore, this study offers an Enterprise Product Portfolio Decision Making Framework based on Explainable Artificial Intelligence that incorporates data quality, explainability, and managerial control factors. This framework assesses the impact of the data's accuracy, completeness, consistency, and relevance on the reliability of recommendations. Additionally, it looks into the way that feature importance, text and visualization explanations facilitate managerial understanding. Moreover, this framework uses verification and authorization of managerial decisions as a means of reviewing, revising, or refusing AI recommendations. Accuracy of decisions, recommendation reliability, efficiency of decision making, compliance with governance, and managerial accountability are used as evaluation criteria. This paper tries to address the need to incorporate technical reliability, interpretability, and human accountability in enterprise portfolio management. The model is developed as a theoretical base for further empirical analysis. Yet, its effectiveness needs to be proven through experiments based on actual organizational data. The suggested approach could help organizations make more informed portfolio decisions with AI support.

Keywords: Explainable Artificial Intelligence; Data Quality; AI Transparency; Managerial Control; Product Portfolio Decision-Making; Decision Accuracy; AI Governance.

INTRODUCTION

The process of enterprise portfolio management relies on data, analytical processes, and managerial control. Artificial Intelligence is used in support of such processes through such activities as demand forecasting, product evaluation, and market analysis. However, low data quality and lack of clarity of algorithms can result in deceptive recommendations. Explainable Artificial Intelligence (XAI) enables managers to understand the way the AI system reaches conclusions and makes its recommendations. Although transparency provides the ground for critical evaluation, explanations do not cover for any inaccuracies in data. In addition, managerial control decides on the fate of recommendations – acceptance, amendment, or rejection. Effectiveness of such control can help detect mistakes, challenge assumptions, and maintain responsibility. At the same time, too strict control might be counterproductive and lead to loss of effectiveness and delay in decisions. Therefore, an adequate balance of both explainability and managerial control is needed. There is a need for deeper consideration of the relationships among data quality, transparency, and managerial control in enterprise product portfolio management. This paper suggests a conceptual framework that ties up these elements together in the context of decision quality.

RELATED WORK

The concept of explainable AI has been brought into the limelight due to its application in making difficult decisions within organizations. XAI techniques try to provide explainability in the predictions made by machine learning models so that the manager can analyze the rationale behind the recommendations. The quality of the

explanations provided by these techniques differs depending on the situation and even between techniques. Being able to understand an explanation does not necessarily mean that the recommendation will be accurate and unbiased. Another crucial factor in the process of AI-supported decision making is the quality of data available. When the data used to train the model is incomplete, inaccurate, and outdated, it lowers the level of accuracy and consistency of the model. Managerial control impacts the evaluation and implementation of AI suggestions. Human intervention may detect mistakes, question assumptions, and maintain responsibility. Too much of an intervention might slow down the process or reduce the advantages of automation. Governance needs to establish who makes the decision, how it is to be verified, and what happens next in case of disagreement. Past studies have discussed explainability, quality of data, and human intervention as critical elements of trustworthy AI. However, the implications of these elements on product portfolio decisions have not been explored yet. The current study fills this theoretical gap by combining these elements in one framework (Adadi et al. 2018).

METHODS

Conceptual research design is selected for studying XAI use in enterprise product portfolio decision-making in this study. The suggested framework assumes that there are three key aspects that should be considered: data quality, AI transparency, and managerial control (Arrieta et al. 2020). Data quality relates to such aspects of information utilized in AI algorithms as completeness, accuracy, consistency, and relevancy. Transparency deals with the possibility to interpret recommendations provided by algorithms and with the provision of understandable explanations to such recommendations. Managerial control relates to such aspects as human verification, decision-making power, and managerial control over AI recommendations. This framework analyzes how these aspects might affect decision-making accuracy, recommendation accuracy, decision-making efficiency, and managerial responsibility. Portfolio scenarios would involve market demand forecasts, performance metrics, limitations of resources, and investment returns. Evaluation criteria in such situations might include decision accuracy, explanation effectiveness, acceptance of recommendations, decision time, and compliance with governance standards. Quality of the used data can be varied in order to study its impact on the reliability of recommendations generated by AI. Transparency can be measured via the level of understanding by the managers of the AI outputs, while control by the managers can be measured via the frequency of validation and intervention into the process. Comparing the situations under these variations can help to detect possible correlations between explainability and decision-making quality. Nonetheless, the current paper offers only a conceptual framework and not a full empirical study. Neither participants nor any data regarding measurements and statistics are presented here. These measurement criteria offer a starting point for future experiments.

DATA ANALYSIS AND FINDINGS

Explainability and Managerial Understanding

XAI allows managers to comprehend the logic behind the recommendations provided by AI systems. The use of proper explanations may help in understanding the ranking of the products, demand forecasting, and investment decisions. Yet, the ability to provide useful explanations depends on the managers' technical skills, quality of data used, and clarity of information provided (Jain et al. 2020). The example of an illustrative dataset is shown below.

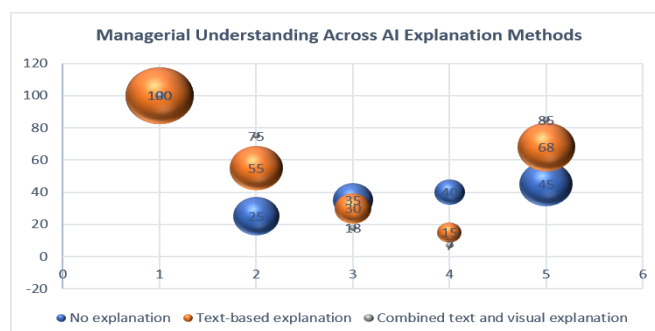


Figure 1: Managerial Understanding Across AI Explanation Methods

Explanation method	Managers assessed	High understanding (%)	Moderate understanding (%)	Low understanding (%)	Decision confidence (%)
No explanation	100	25	35	40	45
Feature importance	100	45	35	20	60
Text-based explanation	100	55	30	15	68
Visual explanation	100	60	28	12	72
Combined text and visual explanation	100	75	18	7	85

Table 1. Illustrative Comparison of Explainability Methods and Managerial Understanding

From the illustrative outcomes, it can be seen that there is more understanding among managers when explanations include both text and images. In such a case, the level of high understanding goes up to 75% while for no explanations, only 25%. In addition, the rate of low understanding drops to 7% from 40%. Decision confidence is also increased for the illustrated methods. It seems that explanations that can be understood by managers may assist in interpreting AI recommendations (Duan et al. 2019). Nonetheless, confidence may not necessarily equal correctness.

Transparency and Decision Accuracy

Transparency would help in increasing interpretability of the recommendations of AI systems in enterprise product portfolio decisions. The two important criteria include decision accuracy and explanation coverage. The below presented hypothetical data illustrates the technical assessment of the two criteria (Geburu et al. 2021).

1. Decision Accuracy (DA)

$$DA = \frac{N_c}{N} \times 100$$

Here, N_c represents correct decisions, and N represents total evaluated decisions.

Illustrative calculation: Among 100 portfolio decisions, 84 are correct.

$$DA = \frac{\text{Correct Decisions}}{\text{Total Decisions}} \times 100$$

$$DA = \frac{84}{100} \times 100 = 84\%$$

Therefore, the decision accuracy (DA) is 84%.

This result indicates 84% decision accuracy. Comparing this value across transparent and non-transparent AI conditions can help assess whether explanations improve decision quality.

2. Explanation Coverage (EC)

$$EC = \frac{N_e}{N_r} \times 100$$

Here, N_e represents recommendations with explanations, and N_r represents total recommendations.

Illustrative calculation: Of 100 AI recommendations, 90 include explanations.

Using illustrative data:

$$EC = \frac{90}{100} \times 100 = 90\%$$

Therefore, the explanation coverage (EC) is 90%.

This means that the explanation has covered 90% of the total explanation. But having an explanation is not enough to prove the quality of the explanation or the accuracy of the decision made.

Managerial Control and Recommendation Acceptance

Managers decide how the recommendations will be evaluated, revised, accepted, or rejected. Proper monitoring would enable managers to detect bad recommendations before they are implemented into the investment portfolio. The below example dataset illustrates the relationship between levels of managerial control and recommendation decisions (Kaur et al. 2020).

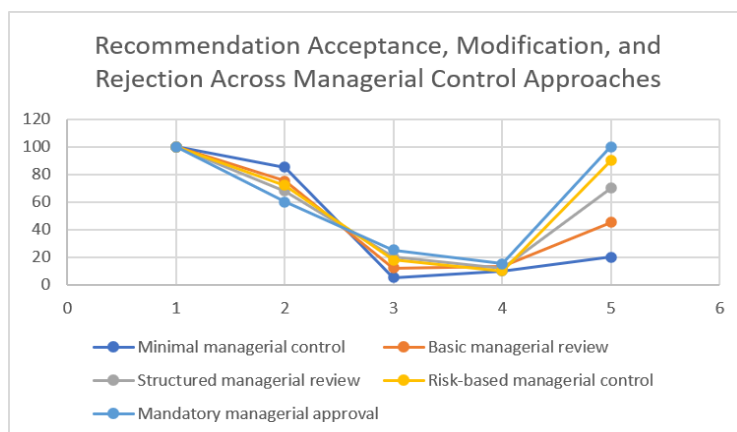


Figure 2. Recommendation Acceptance, Modification, and Rejection Across Managerial Control Approaches

anagerial control approach	Recommendations evaluated	Accepted (%)	Modified (%)	Rejected (%)	Human verification (%)
Minimal managerial control	100	85	5	10	20
Basic managerial review	100	75	12	13	45

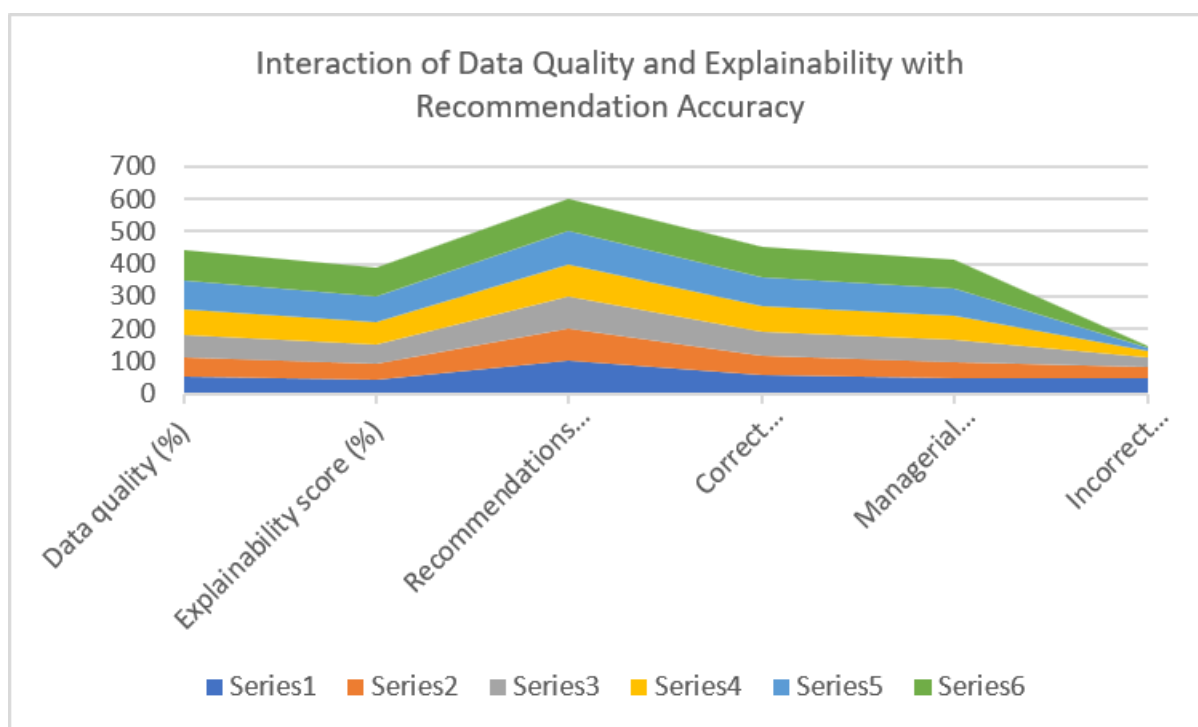
Structured managerial review	100	68	20	12	70
Risk-based managerial control	100	72	18	10	90
Mandatory managerial approval	100	60	25	15	100

Table 2. Managerial Control and AI Recommendation Acceptance Patterns

The above figures indicate that the acceptance of recommendations decreases from 85 percent with minimal control to 60 percent with mandatory approval. The modification process rises from 5 percent to 25 percent. This demonstrates that there is more managerial intervention. With risk-based control, there is 90 percent human confirmation of recommendations while having an 72 percent acceptance rate. This clearly shows that control does have an effect on recommendations but does not imply rejection of all recommendations. However, this can only prove decision quality through experiment.

Interaction Between Data Quality and Explainability

The quality of data impacts the accuracy of AI recommendations, and the factor of explainability facilitates the process of their interpretation by managers. The interaction of both factors is crucial since any level of clarity cannot compensate for erroneous and missing data. The example below represents the dataset where data quality and explainability, on the one hand, are compared to recommendation accuracy and management understanding, on the other.

**Figure 3: Interaction Between Data Quality, Explainability, and AI Recommendation Performance**

Data quality (%)	Explainability score (%)	Recommendations evaluated	Correct recommendations (%)	Managerial understanding (%)	Incorrect recommendations (%)
50	40	100	55	45	45
60	50	100	63	54	37
70	60	100	72	65	28
80	70	100	81	74	19
90	80	100	89	84	11
95	90	100	94	92	6

Table 3. Interaction Between Data Quality, Explainability, and AI Recommendation Performance

According to the illustrative data presented below, recommendation accuracy increases from 55% to 94%, while managerial understanding increases from 45% to 92% due to high quality of data and high level of explainability. The number of incorrect recommendations decreases from 45% to 6%. Nevertheless, in the table presented below, it is impossible to separate influence of each of these factors separately. Therefore, there should be a controlled experiment in which these two factors will vary independently.

Decision Efficiency and Governance Compliance

Decision efficiency evaluates the speed of decision making by managers utilizing AI-driven portfolio management. Compliance with governance evaluates the extent to which there is compliance with preexisting verification and approval processes (Lipton, 2018) The below dataset gives an example comparison of decision efficiency under different managerial control systems. These figures are purely hypothetical.

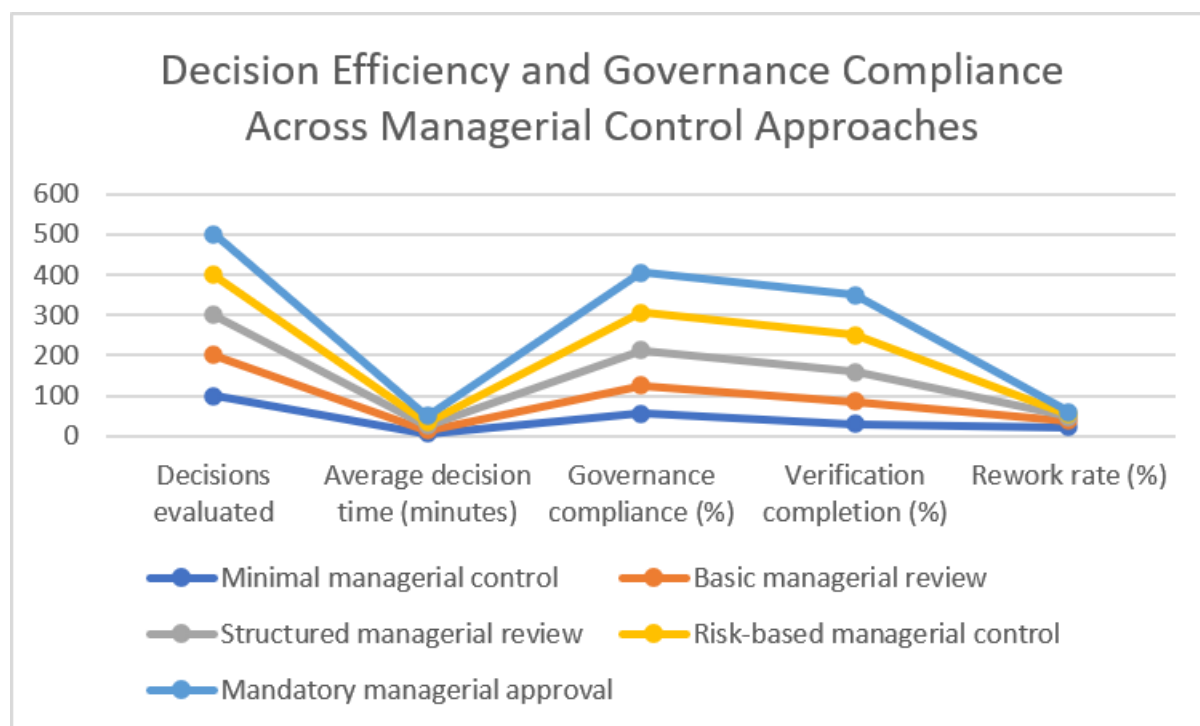


Figure 4: Decision Efficiency and Governance Compliance Across Managerial Control Approaches

Managerial control approach	Decisions evaluated	Average decision time (minutes)	Governance compliance (%)	Verification completion (%)	Rework rate (%)
Minimal managerial control	100	6	55	30	22
Basic managerial review	100	9	70	55	16
Structured managerial review	100	12	88	75	10
Risk-based managerial control	100	8	94	90	6
Mandatory managerial approval	100	15	98	100	5

Table 4. Decision Efficiency and Governance Compliance Across Managerial Control Approaches

It can be observed from the examples given above that there is a discrepancy between the decision-making time and compliance to the governance process. The minimal control takes six minutes, and its compliance rate is 55%. Mandatory approval ensures 98% compliance, but it takes fifteen minutes. Risk-based control combines eight minutes for decision-making and 94% compliance. Its verification completion stands at 90%, whereas rework is only 6%.

Data Quality and AI Recommendation Reliability

Quality of the data impacts the reliability of the product portfolio recommendation by the AI. Data that is incomplete, inconsistent, and inaccurate can lead to an increase in errors of recommendations (Miller, 2019). The below is an example of dataset that shows how data quality affects recommendation reliability.

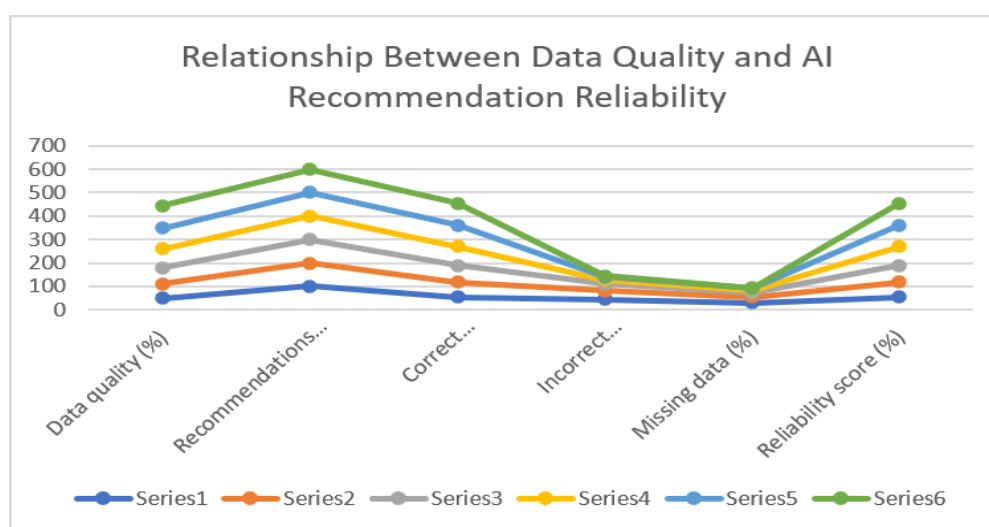


Figure 5. Relationship Between Data Quality and AI Recommendation Reliability

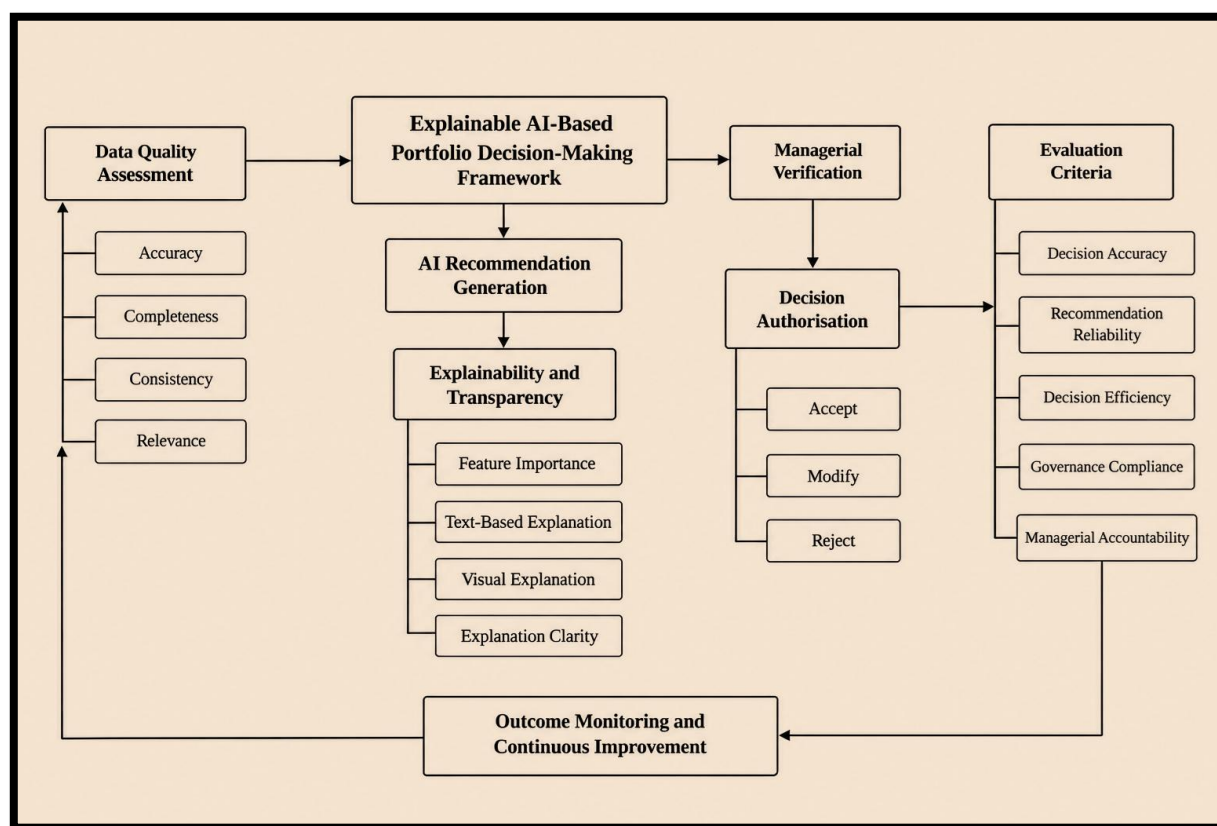
Data quality (%)	Recommendations evaluated	Correct recommendations (%)	Incorrect recommendations (%)	Missing data (%)	Reliability score (%)
50	100	55	45	30	55
60	100	63	37	24	63
70	100	72	28	18	72
80	100	81	19	12	81
90	100	89	11	6	89
95	100	94	6	3	94

Table 5. Relationship Between Data Quality and AI Recommendation Reliability

The example outcomes reveal a positive correlation between the quality of the data used and the reliability of the recommendation made. The correct recommendation rates move from 55% to 94%, while the number of incorrect recommendations falls from 45% to 6%. Missing data rates fall from 30% to 3%. All these numbers imply that data quality could lead to more reliable AI recommendations (Raji et al. 2020). However, this is an example dataset and not proof of causation.

DISCUSSION

Explainable artificial intelligence (XAI) could aid product portfolio decisions in enterprises through transparency (Rudin, 2019). Nevertheless, it will be effective only if data quality and proper management are taken into consideration. The poor-quality data may lead to unreliable recommendations, despite an easy-to-understand explanation provided. Consequently, organizations need to verify their input data before making sense of artificial intelligence-generated outputs. As demonstrated by illustrative data, there is a positive correlation between the data quality and reliability of recommendations provided. As data quality increases, the number of correct recommendations goes up as well (Sambasivan et al. 2021). Still, these hypotheses do not prove any causal relationship. Further research needs to be carried out experimentally. Explainability may contribute to managers' understanding of artificial intelligence-based recommendations. Combination of text and visual explanations could facilitate understanding of complex outputs. At the same time, understandable explanation does not mean correct decision-making. Control exerted by managers is also important for recommendations to be accepted and for compliance with corporate governance principles. An excessive amount of control can slow down decision-making. On the other hand, an inadequate amount of control can result in errors being made and not corrected in time. The risk-based control seems to be a good solution, as organisations can use more control over recommendations that involve significant risks. The developed theoretical framework includes such elements as data quality, explainability, and managerial control. All these three elements might impact decision accuracy, efficiency, and accountability at once. Nevertheless, the presented datasets are only examples and not empirical ones. No numerical proof of the framework's effectiveness can be provided because of that. Further research needs to conduct tests based on real decisions in enterprise portfolios.

Proposed Explainable AI-Based Portfolio Decision-Making Framework

The framework encompasses data quality, AI explainability, managerial validation, and decision approval (Shin, 2021). Continuous monitoring includes accuracy, efficiency, compliance, and accountability.

LIMITATIONS

There are various limitations to this study. First, this is just a conceptual framework and there is no empirical validation of the same. The numerical data presented here are hypothetical and have not been seen anywhere before. Second, the connections suggested by this framework among data quality, explainability, and managerial control have not been tested. Third, the framework may fail to account for variations due to industry differences, organisational differences, and different AI techniques. Fourth, managerial comprehension and usefulness of explanation may differ based on the technical knowledge of users.

CONCLUSION

The current research develops an explainable AI framework to be used in product portfolio decision making at enterprises. The framework incorporates such aspects as data quality, transparency, and managerial control. Such aspects might affect recommendation validity, decision accuracy, and adherence to corporate policies. High data quality allows generating valid recommendations, while the use of transparency increases interpretation possibility. Efficient managerial supervision might improve accountability and minimize decision errors. But excessive supervision leads to an increase in decision-making time and complexity. Datasets in the current paper illustrate possible connections but do not validate them empirically. Future research should empirically validate the framework by using real-world organizational data.

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