An Intelligent System for Automated Portfolio Management using Semantic Bayesian Networks

Literature Review

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ABSTRACT

Portfolio management is a phased decision-making process used by investors to build a profitable portfolio of financial securities. This process is achieved through manual evaluation of multiple erratic factors, and the initial share evaluation phase involves identifying suitable securities for investment. Semantic Bayesian networks (SBN) are a class of Artificial Intelligence techniques that support explainability in intelligent systems. Drake proposed an intelligent decision support system (IDSS) for share evaluation using SBNs. This paper reviews the literature to examine IDSS solutions for portfolio management, ontologies and BNs. Our review revealed that current systems primarily incorporate black-box AI techniques and do not provide adequate support. Secondly, there is a lack of research investigating SBNs in the finance domain. We conclude that further research is required to investigate the application of SBNs to share evaluation.

CCS CONCEPTS

• **Computing methodologies → Probabilistic reasoning**.

KEYWORDS

share evaluation, portfolio management, intelligent system, ontology, bayesian network

1 INTRODUCTION

The stock market is a dynamic, non-linear and chaotic system. This results in investment professionals assessing and evaluating multiple factors, including contradictory information when deciding whether a share is investable for inclusion in an investment portfolio [17]. Intelligent systems incorporate Artificial Intelligence (AI) techniques to automate tasks and support human decision-making. The INVEST system, proposed by Drake [17], is one such intelligence system that incorporates ontologies and Bayesian networks to support decision making for share evaluation on the JSE. Ontologies are used to formally encode unstructured expert information into a representative, machine-understandable form [68], while Bayesian networks (BN) are useful in the financial domain as it represents uncertain, ambiguous or incomplete knowledge. Furthermore, they have the ability to convey how an investment decision is reached [15]. This characteristic can be classified as a glass-box approach; it allow users to understand automated decisions by explaining predictions [58] as opposed to black boxes. Black-box approaches are characterized when a system is unable to provide insight into the reasoning it has used when transforming inputs to corresponding outputs [16] and is therefore uninterpretable [24] by humans. Approaches that are in the middle of the spectrum are classed as grey-box [1]. This work will extend Drake's work to perform share evaluation on the JSE using a combination of ontologies and Bayesian networks to provide decision support.

This literature review will explore five key areas of particular importance to the research objectives. This includes a discussion on the share evaluation and portfolio management through the stock market, modern portfolio theory and share evaluation approaches. Secondly, we explore Intelligent Decision Support Systems, encompassing intelligent systems including their constituent AI Techniques and system designs, and results and limitations thereof. This is succeeded by intelligent decision support systems for portfolio management. Thereafter, ontologies will be reviewed, with a specific focus on financial ontologies, succeeded by a discussion on Bayesian networks for general modelling and share evaluation. The final section will include methods for ontology, Bayesian network and system validation.

2 SHARE EVALUATION AND PORTFOLIO MANAGEMENT

2.1 Stock Market

The stock market is a platform where buyers and sellers connect to make trades on listed securities, which give the shareholder a unit of ownership of a publicly-traded company. This platform works through a network of exchanges [17], known as the stock exchange. As a means of capital generation, their shares are listed on the stock market [2] through an Initial Public Offering (IPO) process. Share prices are determined by supply and demand for each listed stock, therefore buyers and sellers aim to buy stocks at a lower price, and sell at a higher price, where the difference of these prices is the profit gained from the investment. A key determinant of portfolio performance is the excess return, or alpha measure [25]. This is the returns earned by the portfolio relative to earnings of a benchmark [17], an example of which is the FTSE/JSE All Share Index.

2.2 Overview

Portfolio management is a process whereby an efficient portfolio is built through correct investment choices, with the initial phase consisting of share evaluation [51]. In the share evaluation process, investors select securities that possess advantageous risk-return characteristics [71] [17]. The shares selected based on these criteria are then used in the second phase of portfolio management: portfolio selection. Portfolio selection entails using weighting to find the most beneficial way to incorporate available securities in a portfolio [20], such that risk is minimized and return is maximised

[54]. The main objective of this process is to maximise an investor's utility, or return [71] [43].

2.3 Modern Portfolio Theory

The Efficient Market Hypothesis (EMH) is an investment theory that states that securities on the financial market efficiently reflect all available information about individual stocks [38] in an unbiased and expeditious way [6]. The EMH stems from random walk theory and declares that subsequent stock price changes are independent of the previous [38]. The implication is that uninformed investors using random selection for stocks will benefit from the same return as educated investors [38].

However, counterarguments in the literature [39] have evidenced that market inefficiencies exist. This inefficiency manifests in a stock price that is unreflective of its true value, given that all publicly available and relevant information is not fully reflected in the price [69] [17]. The consistent inefficiencies provide an opportunity for economic exploitation by investors. Investors exploit these market inefficiencies to earn profits from their capital investments. Heymans and Santana [29] have claimed that the JSE all-share index is weak-form efficient where prices reflect all past market information [37].

2.4 Share Evaluation Approaches

Two common share evaluation approaches performed by investors include the technical and fundamental approach. The technical approach focuses on using historical price movements to infer price forecasts [8] [36] and is based on the premise that regularities exist in historical stock statistics [65]. While the technical approach particularly focuses on historical price movement, the fundamental approach uses economic and financial factors such as profitability, quality, management and growth of shares [17] as well as other quantitative and qualitative factors [36]. Two recognised fundamental approaches include value investing and growth investing. These two approaches have been widely adopted by individual and institutional investors. [11].

Value investing involves investing in stocks that are trading at a value less than their intrinsic value, given that in the future, they will yield abnormal returns through the price reversals (undervalued stocks will rise and revert to intrinsic value) [35]. It is important to note that even though value investing is premised on the above, there is no universally accepted method of implementing value investing, therefore a variety of value measures are used in practice and academic research [35]. Growth investing is premised on the idea of investing in smaller companies, which are often categorized by strong earnings growth, research and development (R&D) intensity, and innovative technology [13] [35].

While empirical research shows that value investing earns higher returns than growth investing [11], Lev and Srivastava [35] assert that the value investing strategy has produced diminished returns in the past decade. Given this, Cronqvist et al. [13] assert that the choice of investment style does not entirely depend on returns, but is influenced by biological basis, behavioural bias, and investor's macroeconomic experiences.

3 INTELLIGENT DECISION SUPPORT SYSTEMS

In this section, we define an intelligent system, decision support system and explain the notion of explainability. We then discuss intelligent systems from different domains, and the prevalent AI techniques . This is followed by a presentation of decision support systems for portfolio management and concludes with a detailed discussion of the INVEST system.

3.1 Overview

A decision support system (DSS) support the decision making process through an interactive computer program which model data to identify and solve unstructured problems[50]. Given the powerful use of AI techniques, it has been applied in many domains resulting in intelligent systems (IS) being built and sparking the integration of intelligent systems with traditional decision support systems; resulting in an intelligent decision support system (IDSS) [50]. Goebel et al. [24] have identified the inability of practical application of AI to communicate effectively with a user. Thus, the need for explainability arises. Explainability entails making results and machine decisions transparent and understandable to the user [24]. DSS may incorporate the notion of explainability when providing decisions to its users.

3.2 Artificial Intelligence Techniques

3.2.1 Neural Networks. In our review of the literature, we found several intelligent systems that incorporate Artificial Neural Networks (ANN)-based models. Subhadra and Vikas [61] have designed one such intelligent system that uses a Multi-layer Perceptron Neural Network for diagnosing heart disease. The authors note the effectiveness of neural networks for practical applications in the literature [61]. This paper incorporates data mining techniques, which include a combination of statistical methods and machine learning (ML) algorithms to make decisions. The data mining aspect helps analyze symptoms, while ML is useful in predicting heart disease based on the analysis. Our review illustrates that data mining in the medical domain is commonly applied for the prediction of diseases. Shouman et al. [57] and Vikas et al. [64] incorporate the technique in their research, and their results demonstrate reasonable performance. Subhadra and Vikas system is advantageous given that it can predict the disease more efficiently while keeping costs at a minimum. The results demonstrated that the system produced the best predictions when compared to baseline ML models. We note that the reviewed research applies ANN-models to the medical domain, and thus the generality of the techniques are not validated.

Similarly to Subhadra and Vikas [61], Ahmad and Simonovic [3] have incorporated an artificial neural network approach in their the flood forecasting module for their intelligent Decision Support System for Flood Management (DESMOF). To develop the ANN model, input parameters are related to flood hydrograph characteristics to specifically address the characteristics of the Red River basin in Canada. This approach was effective, as the system is able to predict the peak flows with a 2% error rate. In contrast to Ahmad and Simonovic [3] modular design of their system, Roca et al. [10] use ANNs to predict the output current of the fuel cell in a precise manner using a hybrid architecture. We note that the hybrid architecture produced the best results [10]. Rajaee et al. [47] review models with the best performances for prediction quality of water. In their review, ANN is the prevalent AI technique for intelligent systems in this domain. This is followed by fuzzy-logic based systems, although there is comparatively less literature on the subject. Our search of the literature has yielded that ANN techniques are regularly applied for prediction tasks in the medical and environmental domains.

3.2.2 Fuzzy Logic. Saritas et al. [52] have designed a rule-based fuzzy expert system (FES) that simulates an expert doctor's behavior, using laboratory and other data to determine the possibility of a diagnosis of prostate cancer. It was observed that this system was rapid, economical and less risky than traditional diagnostic systems. We note that this system could be improved by utilising a neural network, and dually by increasing the knowledge rules [52].

In their research, Ghani et al. [23] also apply a fuzzy logic approach for measuring customers loyalty to a product. This research was novel and we note that the results from using this AI technique outperformed previous sentiment analysis- based approaches [26] [5]. Melin et al. [40] designed a hybrid model using modular neural networks and fuzzy logic to provide the hypertension risk diagnosis of a person. We note that the hybrid system had excellent performance when used to provide the final diagnosis to the patient, given the effectiveness of both techniques used. Given the excellent performance of Melin et al. [40] hybrid model, we concur with Saritas et al. claim that [52] incorporating neural networks will yield an improvement in performance.

3.2.3 Bayesian Networks. Das and Gosh [14] proposed semBnet, a variant of a BN using a multivariate prediction approach for prediction of meteorological time series data. Two major challenges regarding meteorological data is the complex spatial-temporal interrelationships between meteorological variables and the influence of various spatial attributes. Therefore, the key objective of the architecture is to incorporate spatial semantics as a form of domain knowledge in a standard BN. Das and Gosh identify a general limitation of BNs; a large amount of observed data must be available during training for a proper learning of the network to prevent strongly biased inference results full of uncertainty [14]. To adjust for this uncertainty, it has been noted that prior qualitative semantic knowledge about the domain may assist. Das and Gosh incorporate spatial semantics into the proposed BN model. semBnet was analysed both theoretically and empirically in comparison with linear and machine-learning models. We note that the presented results in tandem with their comprehensive evaluation validate their approach. In comparison to a standard Bayesian network, semBnet shows a 24% improvement in mean absolute percentage error (MAPE). This approach therefore highlights the significance of incorporating domain knowledge in meteorological time series prediction given the improved accuracy. We note that this approach can be applied to other domains in which expert knowledge may positively impact performance and predictive accuracy.

Similarly, Kim et al. [32] propose a system where a conversational agent uses semantic BNs to infer the intentions of the user in the context of retrieving information. We note that the agents that used semantic Bayesian networks showed better performance than the conversation agents that used standard BNs. We note that their findings concur with Das and Gosh's [14] results. Of the different AI techniques investigated in the literature, semBnet presented by Das and Gosh [14] is the most relevant to our objectives, given the use of BNs and a dataset with complex spatial-temporal relationships. To the best of our knowledge, the INVEST system is the only system utilizing a BN within the finance domain specifically for the problem of share evaluation.

3.3 System Design

This section seeks to identify prevalent software tools and system designs in current intelligent systems.

Archer and Ghasemzadeh [4] have designed an integrated framework for project portfolio selection. The framework consists of a modularised system, which makes it easier for different parts (e.g. the model management and database management module) to be easily replaced or changed. Archer and Ghasemzadeh [4] suggest the use of third-party packages and libraries for data storage to support implementation. Further, they propose that optimization tools and a Rapid Application Design methodology is adopted for user interface development. We note that not many systems are designed to provide a user interface, however is a potentially useful feature to include. Similarly, Samaras et al. [51], Ahmad and Simonovic [3] and Subhadra and Vikas [61] have designed their systems using a modular approach. In Samaras et al. contribution, each module represents the different phases of evaluation. This design decision improves the understandability of their system.

Haq et al. [28] introduced a hybrid intelligence system framework for the prediction of heart disease, which uses ML models. This hybrid modularised system combines of distinct ML classifiers to perform prediction tasks. Similarly, Peddabachigaria et al. [45] proposed a hybrid system for intrusion detection. The authors use a combination of conventional ML models (decision trees and support vector machines), and use an ensemble (stacking) method to combine these base models into more complex architectures. Their results demonstrate that hybrid system produced improved accuracy in comparison to evaluated individual approaches.

We note that different AI techniques have been used for distinct applications. However, our review of the literature shows that by using a hybrid architecture, it allows for different performant systems and techniques to be combined, which may in turn lead to increased performance and accuracy [45] [10] [40]. A notable limitation of the system design in the literature analysed is that only Archer and Ghasemzadeh [4] explicitly stipulated which tools would be utilised in the development process, while other authors had minimal mention of this subject. This is important for reproducibility; omitting this information creates difficulty in replicating the study results.

3.4 Decision Support Systems for Portfolio Management

Share evaluation requires that numerous factors are considered before a decision is taken. Therefore, a majority of decision support systems in the financial domain incorporate a multi-criteria decision-making framework [17]. Samaras et al. [51] designed a Multi-Criteria Decision Support System (MCDSS) that utilizes both qualitative and quantitative data as well as multi-criteria analysis methodologies. However, this system does not incorporate AI techniques and can not be classed as intelligent. The incorporation of AI technologies optimize the systems' response to the complicated and rapidly changing financial markets [50], and therefore are used in portfolio management systems. We will discuss these systems which incorporate different AI techniques in the context of portfolio management below.

3.5 Intelligent Decision Support Systems for Portfolio Management

3.5.1 Correlation-driven ML algorithms. Li et al. [36] propose a system that utilise Correlation-driven Non-parametric learning strategy (CORN) for actively trading stocks. Through a correlation coefficient metric, CORN exploits effective statistical correlations in financial markets and reaps the benefit of non-parametric ML techniques. The CORN algorithm substantially achieves excess returns, and Li et al. ascribe its success to its use of statistical correlations to exploit hidden information in the market. Li et al. assert that this pattern matching approach achieves better performance than other pattern matching methods [36]. Despite the success of the system, Wang et al. [66] identified its inability to recognize risk and subsequently proposed RACORN-K, which penalizes risk when searching for optimal portfolios. Empirical results from this study indicate that the algorithm performs particularly well in high risk markets, addressing the key limitation faced in Li et al. work. Similarly to Wang et al., Sooklal et al. [59] designed a system to incorporate dynamic risk into the CORN-K algorithm, with two principal components. The first incorporates systematic risk, Beta (β), into portfolio optimisation which reflects the sensitivity of a portfolio to the overall market. The second component has the task of classifying the current market conditions into categories of bearish (trending-down) and bullish (trending-up). When markets were bearish, β allowed for high-risk portfolios to be penalized, while when markets were bullish, high-risk portfolios were rewarded. DRICORN [59] has the ability to leverage risk in varying market conditions, which Wang et al. had failed to address in RACORN-K, and therefore mitigated the issue of low investment returns especially in a volatile market. We note that the dynamic-risk approach [59] improved portfolio performance and provides a more robust system.

3.5.2 Bayesian Networks. Tseng and Gmytrasiewicz [63] implemented a probabilistic prediction and decision system for real-time portfolio management. The system uses a decision network to reach investment decisions, which is constructed using an Object Orientated Bayesian Knowledge Base (OOBKB). The system utilizes the notion of urgency when constructing the decision network to determine the level of detail which it should be constructed with, through assessing the level of urgency the investor is in. Through a user interface, the system provides the investor with a decision where the decision is more abstract if the level of urgency is high, and more detailed if the level of urgency was low. The model is able to incorporate real-time information sources, which has led to increased accuracy and responsiveness. The results indicate that the system has outperformed index benchmarks. We note that the system has been tested on 12 companies from the SP500 index.

Similarly to Tseng and Gmytrasiewicz [63], Demirer et al. [15] designed a decision support system for equity analysts using a BN. The proposed BN incorporates a combination of macro-economics and fundamental factors to determine return. Demirer et al. assert that the BN possess the ability to overcome the limitation faced by many analysts; not always knowing how an investment decision is reached (explainability) [15].

3.5.3 Fuzzy Logic. Yunusoglu and Selim [69] proposed a fuzzy rule-based expert system, where the system performs both share evaluation and portfolio construction. The system allows for user preference to be incorporated; similarly to Fasanghari and Montazer's system [19], it can be tailored according to the investor's risk profile and specific preferences by changing certain parameters. The profiles constructed outperforms the benchmark index in terms of all risk profiles. Although Yunusoglu and Selim assert that the user can understand the structure of the system, the system does not explicitly explain how a specific investment decision is reached. Similarly, Fasanghari and Montazer [19] have designed a fuzzy expert system for portfolio recommendation on the Tehran Stock Exchange. While the system also has the ability to consider investors' preferences through parameters, the stock market conditions and knowledge of previous recommendations, the system does not provide further support. The system shows the result scoring of all stocks, however it does not provide an explanation of how the decision was reached, suffering from the same limitation as Yunusoglu and Selim's study [69].

3.5.4 Genetic Algorithms. Fu et al. [21] designed a system using a ML-based framework for stock selection. This system classifies stocks using fundamental and technical features, labelled with respect to their Sharpe Ratio measure. A Genetic Algorithm (GA) is initially applied to select optimal features which are input into the ML models which predict the optimal portfolio. We note that Fu et al. use a GA in a quasi-preprocessing step, in comparison to Sharma et al. [55] who have integrated a GA with fuzzy goal programming (FGP) to form a hybrid DSS for portfolio management. In this framework, the GA is used to directly generate the optimal set of shares. We note that in both systems, GA has been used in tandem with another AI technique to obtain the best results. Specifically, Sharma et al. use FGP to include imprecise variables such as risk and return in the system. While Fu et al. do not incorporate any fuzzy logic in their approach, the authors evaluated Logistic Regression, Random Forest (RF), Deep Neural Network (DNN), and a stacked model for classification. Fu et al. results show that the portfolios predicted by the proposed models outperformed the market average. In particular, the RF+DNN hybrid model produced the portfolio that achieved the highest return.

We note that Fu et al. utilized black-box methods when preselecting the stocks to evaluate; the features that influenced the initial selection are not transparent to the decision-maker. Additionally, we note that Sharma et al. have provided a conceptual framework that has not been tested and validated. This is a significant limitation of their contribution.

3.5.5 Clustering. Clustering is an unsupervised ML technique that has been successfully applied in portfolio selection. Clustering allows for multivariate data to be placed into homogeneous groups

[34] for the purpose of evaluation. Additionally, clustering is useful in allowing investors to identify and incorporate the rapid changes inherent in financial markets [34]. Leon et al. [34] use clustering techniques which categorized assets (share evaluation), and thereafter applied optimization methods to each cluster, selecting the best assets from each category (portfolios selection). Similarly, Nanda et al. [43] design a system for portfolio management, which clusters Indian stock market data according to different clustering algorithms. An important result drawn from Leon et al. is that clustering-based portfolios were stable, which addresses the issue of volatility in financial markets.

3.5.6 Summary. In this subsection, we critically discuss and compare the aforementioned techniques. A summary of the techniques is detailed in table 1. ML models are advantageous when learning from data and adapting to changes in the financial market [34]. We note that correlation-driven ML algorithms perform well as they exploit hidden information in the market [36]. However, this approach did not incorporate many stock-related factors in portfolio optimisation, whereas the GA approach [21], clustering approaches [34] [43] and BN approaches do [62] [15] [17]. Furthermore, BN approaches allow for the simple adjustment or addition of share evaluation factors to the network at any point [15].

Both the fuzzy [69] [19] and [34] clustering approaches consider investor preferences in their system which is an important aspect in portfolio management.

We note that the majority of IDSS reviewed in the portfolio management space are black-box. The correlation-driven non-parametric models are black-box methods and therefore does not constitute a true decision support system for portfolio selection. Additionally, although GA [21] [55] and clustering-based [34] [43] frameworks are able to provide decisions with reasonable success; there exists no explainability for these decisions. Demirer states that BN approaches are not black-box expert systems [15], and therefore both frameworks provide some level of explainability to users for decisions provided i.e. glass-box approaches. We note that both the fuzzy approaches [69] [19] are classified as grey-box approaches, therefore are not fully explainable support systems such as glass-box approaches, however, incorporate explainability more than black-box approaches. A notable gap in the literature identified is the lack of explainable decision support systems (glass-box) for portfolio management.

We note the copious use of return and risk adjusted return metrics for evaluation. Specifically, the Sharpe Ratio is the most prominent metric used in systems reviewed followed by equal usages of Annualized Percentage Yield, Treynor ratio, Maximum Drawdown and Annual Return. We note that despite the importance of using the Omega ratio asserted by Leon et al. [34], it was the only paper to use this ratio in the reviewed literature.

While portfolios produced by the above systems incorporating different AI techniques had the ability to outperform the benchmark, we note that none of the above systems, with the exception of DRICORN [59] have been tested on stock market data from the JSE. Other stock markets may exhibit different dynamics relative to the JSE. Drake [17] has designed a true IDSS for share evaluation on the JSE which will be discussed in the subsequent section.

3.6 INVEST System

3.6.1 Introduction. Drake [17] proposed the *INVEST* system to support medium-term realistic share evaluation decisions for investment professionals flexibly. The decisions implemented in the system consists of both factual and heuristic knowledge. In Drake's work, she reasoned with expert knowledge with respect to share evaluation under the value investing approach. The *INVEST* system is composed of two key AI components: an ontology and a BN. Even though these components are separate, the system has been designed to support user query through the cohesion of information inputs and outputs across the components, presenting a cohesive system design for decision support for share evaluation.

3.6.2 System Overview. The system consists of interactive components which allow the user to query the system for investment decisions and explanations thereof. The designs follows a glass-box approach as opposed to black-box methods utilized in other systems within the financial domain. The *INVEST* ontology represents expert knowledge on share evaluation through concepts across the entire system, while the BN represents heuristic expert knowledge. A final investment recommendation is reached through causal knowledge.

While this system and its relevant components have been comprehensively explained conceptually, it is difficult to assess its implementation and validation. The research does not clearly illustrate how the system will map to concrete software classes. Additionally, there exists inconsistencies between the textual and diagrammatic descriptions of the system. This causes ambiguity, and clarity could be improved to support future implementation and testing.

3.6.3 Invest Ontology. The *INVEST* ontology supplies investment professionals with a clear structure of useful information and articulates concepts and properties, which are required by the BN as evidence. Drake has designed the ontology, consisting of eight classes, which are generic to share evaluation processes. The ontology has been designed and populated with instance data using the Protégé-OWL tool. When designing the ontology, Drake utilized concepts from the Financial Industry Business Ontology (FIBO) and the SONAR financial ontology. These ontologies will be discussed in a subsequent section of our review.

The classes along with subclasses are well-documented and explained, which enables it to be reproduced with ease. Additionally, the ontology mechanism provides for the ability to add or remove factors from the model, making it easily extensible.

3.6.4 Bayesian Networks. The BN supports investment professionals in their investment decisions. Drake has designed three decision networks, which correspond to the three sequential steps in the decision making process: Value Evaluation, Quality Evaluation and Investment Recommendation. The Investment Recommendation Bayesian Network reflects the decision process performed by investors: evaluating whether the price is reasonable and the quality of the share, thus providing an investment recommendation for a specific share.

The coupling of the ontology and BN in this system addresses the main limitation of an ontology: it does not provide a mechanism to handle uncertainty. The BN provided the mechanism to handle the uncertainty inherent to share evaluation decision making.

Table 1: Reviewed Literature for DSS in Portfolio Management

Reference	AI Technique	Support	Evaluation Metrics	Key Findings
[36]	Correlation-driven ML algorithms	Black-box	Annualised Percentage Yield (APY), Sharpe Ratio, t-statistic	Exploits hidden information in underlying stock market movements through the statistical correlation
[66]	Correlation-driven ML algorithms	Black-box	Sharpe ratio, Maximum Drawdown (MDD), Accumulated Return	Risk aversion penalty when searching for optimal portfolios
[59]	Correlation-driven ML algorithms	Black-box	Cumulative Return (CR), Annualised Percentage Yield (APY), Maximum Drawdown (MDD), Sharpe Ratio	Incorporates dynamic risk
[63]	Bayesian Network: Decision network using OOBKB	Glass-box	Annualized Return, URG(t) [63]	Incorporates real time information sources Abstracts decision model detail based on level of urgency
[15]	Bayesian Network	Glass-box	-	Can easily be updated when new information becomes available Provides feedback on forecasts
[17]	Semantic Bayesian Network	Glass-box	Annual Return, Compound Annual Return, Average Annual Return Treynor Ratio, Sharpe Ratio	Novel framework Addresses a gap in the literature
[69]	Fuzzy logic	Grey-box	Treynor ratio, Sharpe ratio, Jensen's alpha, Information ratio (IR)	Shows better performance in the risk averse investor case Can be tailored to investors risk profile
[19]	Fuzzy logic	Grey-box	Expert Evaluation	Determined stock evaluation factors through interviews with experts Ranks stock based on fundamental criteria ratios and risk
[21]	GA with ML techniques	Black-box	Accuracy, Precision, Recall, True Positive Rate (TPR), False Positive rate (FPR)	Uses GA as a quasi-preprocessing step to select optimal stocks Ranks stock based on fundamental and technical features
[55]	GA and FGP	Black-box	-	GA used to generate the optimal set of shares Incorporates imprecise variables as Fuzzy goals Conceptual framework that has not been tested
[34]	Clustering	Black-box	Omega Ratio	Clustering based portfolios were stable; has the ability to deal with volatile financial markets
[43]	Clustering	Black-box	Intra-class inertia, Average Return	Used valuation ratios and timely stock returns as factors for stock selection

Drake's evaluation of the ontology and BN produce promising results. This system does not utilize black-box methods, and thus does not suffer from the shortcomings that our review has highlighted. The system has the facility to effectively provide decision support for investment decisions. This system addresses a gap in the research, but note that it is a conceptual design and has not been robustly evaluated. The *INVEST* system presents a promising opportunity for future investigation.

4 ONTOLOGIES

4.1 Introduction

Ontologies are used to encapsulate background domain knowledge in a machine understandable form [68], which is of particular utility for intelligent systems. Struder [60] defined an ontology by amalgamating two popular ontology definitions by Gruder and Bost [27]. Struder states that an ontology is a formal, explicit specification of a shared conceptualization [27]. Furthermore, ontologies may be lower-level or upper-level. Upper-level ontologies consist of concepts or terms that are generic and independent of a specific domain [22], and provide a basis for the development of a lower level ontology. The Resource Description Framework (RDF) is a standard model for data exchange on the web, while the RDF Schema is a semantic extension. The Web Ontology Language (OWL) is an extension of RDF, which describes a domain in terms of classes, properties and individuals on the web. OWL provides a larger vocabulary of data models in comparison to RDFS [68]. Both Drake [17] and Yang et al. [68] have employed this framework to represent their relevant ontology.

4.2 Financial Ontologies

In the financial domain, there are two common problems relevant specifically to share evaluation that are solved using ontological techniques. These problems are: Web Content Management and Automated Analysis and Decision support [17]. Ontologies in the context of Web Content Management provided financial professionals a means to integrate heterogeneous data sources from the web, ensuring that the data is in a format that can easily be used to perform meaningful analysis [17]. Several ontologies and taxonomies have been developed for Web Content Management, to eliminate data quality problems pertinent to online financial information.

4.2.1 XBRL. eXtensible Business Reporting Language (XBRL) is a taxonomy for business and reporting data, allowing businesses to generate reporting data directly from their financial data [42]. This provides a technical framework for machine-readable financial reports, and its use is required from many publicly listed entities [31] [17]. The taxonomy documents consist of an XML Schema that describes the concepts of financial reporting, while the relationships between these concepts are depicted using a collection of associated linkbases [31]. While XBRL may improve information quality regarding the dissemination of financial data, it does not provide information relevant to holistically assess a company [31]. Thus, investors cannot directly use XBRL data in the decision making process, especially when making inter-firm comparisons [31] [12].

4.2.2 SUMO. Suggested Upper Merged Ontology (SUMO) is an upper-level ontology used to represent concepts and the relationship between them in the financial domain [31]. Extensions of SUMO include SumoF and SumoS, where SumoF has a focus on banking and investment and SumoS has a focus on representing e-commerce services [17].

4.2.3 FIBO. A widely used and well-documented upper-level ontology in the financial industry is the Financial Industry Business Ontology (FIBO), which contains semantic linking between financial concepts [46]. FIBO was designed with the intention of mitigating ambiguation in the financial industry [17] and to be used as a reference model to create further financial models [46]. An ontology in FIBO can be represented either through a formal description of the concepts and their interconnections in OWL or through their description in a natural language using financial industry dictionaries. In practice, the FIBO ontology consists of a set of ontologies that are divided into modules and sub-modules. Specifically, the Foundation module forms as the basis for other models extensions and includes general concepts which are necessary to denote financial concepts, however, not solely applicable to the financial industry.

4.2.4 FIBO Extensions.
An extension of FIBO include the Global Fund Reporting Ontology (GFRO), which facilitates efficient and improved financial reporting by reducing disparities between domain specific databases and FIBO ontologies [9]. Another extension of FIBO is the creation of an ontology of the financial domain of Russia (RFIBO), which served as a basis to develop numerous ontologies for varying branches within the financial sector [46].

4.2.5 Lower-Level Ontologies.
Whilst the previous sections discussed higher-level financial ontologies, numerous lower-level financial ontologies exist. An ontology-based framework has been developed to facilitate the management of Big Data specifically in the financial industry by Du et al. [67]. Additionally, Mellouli et al. [41] define and ontology to represent financial headline news. Their ontology specifically represents reliable news and thus is not reflective of imprecise knowledge [41]. Salah and Mohamed [49] have developed an ontology specifically for investments, with the intention of integrating with an expert system to provide intelligent financial assistance to various users.

4.2.6 FAST.
In the context of automated analysis and decision support, the Fundamental Analysis System for Trading (FAST) [48] [17] presents a detailed and robust ontology model in the finance domain. FAST incorporates several ontologies, including a financial ontology containing financial data and financial reasoning ontology paired with a reasoning tool to reach investment decisions. However, we note that this does not account for the uncertainties in the decision-making process.

A limitation of the ontologies identified is the re-usability and ability to replicate these ontologies, given the lack of sufficient ontology engineering documentation. The re-use and extension of upper-level ontologies is still emergent, however a promising approach to represent data in the financial domain. We note that Mellouli et al. [41] have emphasised the inability of an ontology to deal with uncertainty, as their system only dealt with reliable knowledge.

4.3 Ontology Rules

The Semantic Web Rule Language (SWRL) combines sub-languages of OWL with sub-languages of the Rule Markup Language and has powerful rule capabilities representation in comparison to OWL [70], reducing the expressivity limitations of general rule representation in OWL. Financial rules in FAST [48] are developed using SWRL [48].

While ontologies are useful in representing knowledge in a particular domain, their use is bounded as they have no mechanism to deal with uncertainty and temporality. This supports the investigation of ontology and Bayesian network-based systems for financial domain applications.

5 BAYESIAN NETWORKS

5.1 Introduction

BNs are graphical, decision modelling tools [15] that encodes a representation of probabilistic knowledge within a domain [33]. BNs provide a mechanism to deal with the inherent uncertainty in many domains, and therefore often integrated into ontology-driven models. It is modelled as a Direct Acyclic Graph (DAG), with causal links (arcs) between variables (nodes). Each non-root node has a conditional probability table (CPT) associated with it. This is quantified using Bayes's formula to obtain conditional probabilities.

Bayesian inference utilizes Bayes theorem to compute and update probabilities in the network as more knowledge becomes available in the domain, making Bayesian networks easily adaptable [7].

5.2 Modelling

Demirer et al. [15] describe the process of constructing a BN in three steps: Firstly, creating a graphical representation, which involves identifying relevant variables and relationships (independence) between them. Secondly, specifying probability distributions between dependent variables. Lastly, updating the model given new knowledge or evidence in the domain (inference). Drake [17] and Shenoy and Shenoy [56] apply this phased approach to construct BN for portfolio risk and return. Considering the construction of BN, we note that an accurate graphical representation with relatively imprecise probability distributions performs better than a poor graphical representation with precise probability distributions [15].

The nodes in the BN correspond to random variables, which may take on different states, namely discrete (e.g. boolean) or continuous [68]. Deciding whether to use discrete probability models or a combination of both discrete and continuous present an important modelling decision [15]. Drake [17], Tseng et al. [62] and Demirer et al. [15] all chose to discretize continuous variables. Demirer et al. [15] note that this is to make the model more amenable to the addition of evidence. Our review of the literature indicates that this is the preferred approach specifically in the financial domain, given that continuous distributions are normally used to estimate economic data and returns [15].

5.2.1 Semantic Bayesian Networks.
Semantics can be incorporated to improve the utility of a BN. semBnet [14] incorporates spatial semantics as a form of domain knowledge in the network which improves the prediction accuracy [14]. This resulted in improved modelling of spatio-temporal inter-relationships among meteorological parameters. Although this was applied to a different domain, the model proposed is generic. Additionally, semantics may be incorporated in the network through constructing an ontology. Drake [17] has used this approach to semantically enrich the *INVEST* BN, by mapping factors in the ontology to variables in the BN. Drake's [17] semantic BN is a notable example in the finance domain, as semantic BNs remain an unexplored area in the literature.

5.3 Share Evaluation

Tseng et al. [62] propose an approach for share evaluation using a decision network (also termed influence diagram) with a focus on conceptual model refinement. A decision network is an extension of a BN, specifically with utility functions and variables representing decisions [17], where its value is not determined probabilistically, but rather is computed to satisfy an optimization objective [62]. The decision network has three types of nodes: chance nodes, utility nodes and decision nodes. The process for the creation of the decision model by Tseng et al. [62] was adopted by Drake [17] when designing the *INVEST* system. BNs have been used for portfolio risk and return, as demonstrated by Shenoy and Shenoy [56] and Olbrys [44]. In both studies, the authors employ the use of BNs to forecast portfolio return based on an equally weighted portfolio of preselected stocks. To the best of our knowledge, we state that there is a significant lack of literature investigating the application of BNs to the share evaluation problem.

6 VALIDATION

This section briefly discusses prevalent methodologies and metrics for ontology, Bayesian network and system validation.

6.1 Ontologies

Du and Zhou [18] propose two ways of evaluating an ontology: (1) Evaluating its internal content and structure, (2) Evaluating its role in facilitating applications it was designed to aid. In their study, the latter case was adopted [18]. Additionally, Drake [17] also utilises the second approach by outlining usage examples and identifying how the ontology serves the broader *INVEST* system.

Maache and Touahria [49] utilise the Racer inference engine for the Semantic Web as a technique for testing their ontology. This inference engine is used specifically used for consistency validation (properties of satisfiability and coherence), and the classification tests (subsumption). Additionally, the Protégé-OWL tool vends plugins to execute tests on an ontology [53]. Maache and Touahria [49] demonstrate the use of these plugins to validate and verify the conditions of their ontology. This testing is performed prior to the ontology application. Although some validation and testing techniques are present in the literature, many authors tend to omit these details, which significantly weakens the claims presented in their contributions.

6.2 Bayesian Networks

BNs may be validated both qualitatively and quantitatively. Qualitative evaluation involves the structure being analyzed by domain experts, ensuring that it is accurate and comprehensive. The performance of prediction can be evaluated quantitatively in terms of statistical error metrics [14]: root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). In his review, Jiang [30] similarly finds that the aforementioned regression metrics are most prevalent in the literature. We note that many systems identified in the literature within the financial domain tend to omit statistical evaluations, and rather evaluate the system performance holistically. Although omitted, error metrics are a necessary component of a comprehensive evaluation procedure that validates performance and robustness. The omission of comprehensive evaluation in the reviewed literature weakens the validity of the presented system performance.

6.3 System Evaluation

Table 1 presents a summary of evaluation metrics used in literature we have reviewed. Jiang [30] finds that the existing literature commonly uses both return and risk-adjusted return metrics to evaluate the performance of financial models. We note that this is consistent with the the evaluation metrics presented in table 1.

7 CONCLUSIONS

This literature review examined several concepts and techniques relevant to intelligent systems for portfolio management. The main objective of portfolio management is to maximise investor return [71] [43], where excess return is a key indicator of portfolio performance [25].

We have reviewed intelligent decision support systems (IDSS) across multiple domains and found that ANNs are the prevalent AI technique used for prediction in both the medical and environmental domain. The literature suggests that designs incorporating hybrid architectures result in increased performance and accuracy [45] [10] [40]. We then reviewed the literature on IDSS for portfolio management, and found that the foremost limitation faced by these systems is the the lack of explainability. Whilst these systems produced reasonable performance, they did not provide adequate decision support. This is an undesirable consequence of black-box frameworks and a notable weakness in the current literature. We note that BNs are useful for building explainable systems [17] [63] [15]. Additionally, after reviewing the literature, we note the importance of incorporating dynamic risk in portfolio management, to prevent sub-par returns in a volatile market. We have reviewed ontologies, which are useful for representing knowledge in a particular domain and are often represented using the web ontology language (OWL) [17] [68]. The literature has evidenced that there are several popular ontologies specifically developed for the financial domain. These ontologies are able to successfully represent expert knowledge. We note that a limitation of ontologies is the ability to deal with uncertainty, and we thereafter discussed BNs, modelling methods and their applicability to share evaluation.

We found that semantic BNs are yet to be explored in the financial domain. We have concluded that to the best of our knowledge, the INVEST system is the only application of semantic BNs to share evaluation in the context of portfolio management. In our discussion of validation, our review found that return and risk-adjusted return metrics, specifically the Sharpe ratio, are more commonly used to evaluate financial system applications [30] as opposed to only statistical methods. Ontologies can be evaluated either by evaluating its internal content and structure or through evaluating its role in facilitating applications it was designed to aid [18]. Furthermore, we found that BNs are evaluated both qualitatively through expert evaluation and quantitatively using statistical methods.

In conclusion, we have identified two principal gaps in the literature reviewed. The state-of-the-art intelligent decision support systems do not provide adequate decision support. Secondly, there is no application of semantic BNs to the portfolio management problem, and specifically share evaluation on the JSE, other than Drake's work [17]. Drake has proposed a novel framework, however, without an implementation no empirical results could be obtained. Future research should focus on implementation and robust testing of the system, and further investigation of Bayesian networks for intelligent decision support systems for share evaluation in the context of portfolio management.

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