DECISION SUPPORT SYSTEMS IN REAL ESTATE: HISTORY, TYPES AND APPLICATIONS

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ABSTRACT

This chapter deals with decision support systems that are used in the real estate industry. The focus lies on so-called model-driven decision support systems (DSS), i. e., systems that model human decision behavior and are designed to help people make better decisions.

After an introduction on decisions, decision-making, and decision support in the real estate industry, section 2 outlines the historical development of DSS in general. In the beginning, the systems had only one goal or criterion in focus, later DSS emerged for multiple goals or criteria, which are the standard today. Now, it can be said that there is a third generation, in which human behavior is included in the system's design. This is an important evolutionary step for DSS to meet the expectations placed on them, especially regarding effectiveness, cognition, and user acceptance.

Section 3 presents the different types of DSS. Many classifications can be found in the literature; we follow a common classification based on the type of support, according to which DSS can be driven by models, communication, data, documents, or knowledge. Model-driven DSS such as scoring and Analytic Hierarchy Process (AHP) are discussed in detail.

Not all types of DSS are applied in real estate, and DSS do not exist

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for all real estate activities, as revealed by the extensive research we present in section 4. Section 5 attempts to evaluate the different types. The conclusion is somewhat disillusioning, as most of the DSS developed so far are hardly applicable for making complex real estate decisions, only for certain subtasks.

The chapter concludes with an outlook, in which we indicate where the limits of traditional DSS lie in the real estate industry and what a roadmap for the research and development of behavioral DSS might look like.

1. INTRODUCTION

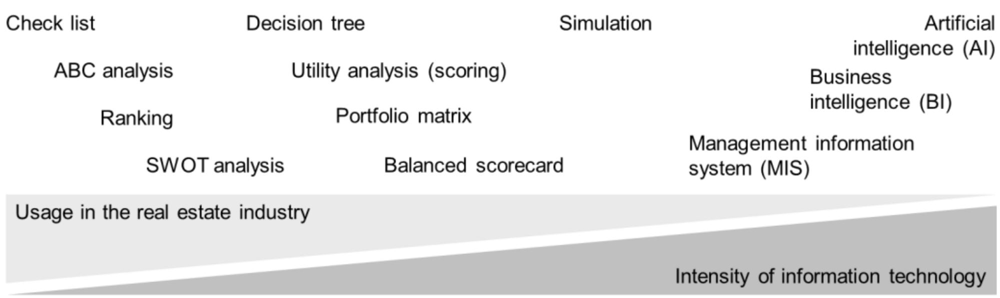
The real estate industry is not the preferred field of decision support system (DSS) developers and DSS are not the preferred instruments of real estate managers. This may be because the assets involved are too heterogeneous, the decisions too complex, and the decision-makers too conservative. And yet, if you look hard enough, you can find many examples for DSS in real estate. Their number has increased in recent years due to the growth in data resources, technological advances and insights into human behavior. Further growth is likely if software developers gain a better understanding of how decisions are made in the real estate industry, real estate managers more readily accept technical decision support, and more researchers work on bringing both sides together. This article intends to contribute to the latter task by giving an overview of the state of development of real estate DSS.

Before we delve deeper, it is necessary to define some key terms. In a field of research that is fed from many disciplines, it is particularly important to strive for a clear language.

One possible definition of a decision is “a choice that you make about something after thinking about several possibilities”. This definition from the Cambridge Dictionary is of only limited use for complex decisions such as those typical for real estate. In such complex decisions, the choice is embedded in upstream and downstream steps that must be considered when developing support measures—in contrast to spontaneous or stereotypical decisions. It is therefore usually better to use the term decision-making: ”A decision process that includes problem identification, selection of criteria, development of alternative solutions, identification of the best alternative based on specified criteria, planning of implementation, and review of the outcome.” (Krieger and Lausberg 2021, p. 2f.)

Real estate decision-making processes can be very complex and lengthy. Drivers of complexity include the number of decision factors and stakeholders. In larger property developments, for instance, both can easily reach triple digits, which clearly exceeds the limited human capacity for information processing and problem solving. Therefore, human beings need decision support, i. e., measures to improve human decision-making—from simple flow charts to complex process models, from standard operating procedures to training programs, from checklists to tools with built-in artificial intelligence (AI) (Krieger/Lausberg 2020). If a tool in a broader sense is used for this purpose, e. g., a schema or a computer system, we call it a decision support instrument or decision aid. This excludes, among others, training and process charts. Thus, a decision aid (DA) is a tool that supports people in making decisions. A few examples are given in Figure 1 and are discussed in more detail in Sections 2 and 3 of this chapter. The differentiation is in part difficult because toaday everything can be computer-aided, even a simple checklist. However, at least for simulations and other sophisticated tools, the use of computers is indispensable.

Figure 1. Examples for decision aids common in the real estate industry



It can be assumed that the usage of DA and the intensity with which information technology (IT) is used for this purpose are reciprocally related, as indicated by the two gray triangles in Figure 1.[1]

According to Power et al. (2011), a decision support system (DSS) is a computer-based information system that increases the effectiveness of the user in making complex decisions. This results in three key requirements for DSS: Firstly, they must be “computer-based,” i. e., developed in the form of software. This excludes decision models that can be solved by mental arithmetic. Secondly, they must be ”effective”. By this we mean that a result obtained by means of DSS should be better than one obtained without (Lausberg and Krieger 2021). In other words, a DSS should improve decision quality. Thirdly, DSS must be created for “complex decisions,” e. g., those in which there are many decision factors or in which the decision situation is constantly changing (Funke 2012). This requires a model to represent the various decision elements such as objectives, decision factors, linkages, and restrictions. In our terminology DSS in a broader sense are computer-based systems, which do not aim at improving the decision quality (instead, for

[1] This is not to say that it is a causal relationship or that the relationship must always be like this. Forms of AI, for example, are already included in many widely used applications such as internet search engines. On the other hand, pure forms of AI such as neural networks are rarely used to support the solution of real estate decision problems.

example, at increasing the efficiency) or which do not contain a decision model (only, for example, prepare information in a way that is suitable for decision-making).

As we will show, there are many types of DSS with very different IT intensity and distribution. Accordingly, real estate DSS would be classified in Figure 1 in a broad area to the right of the center.

Finally, the term real estate industry should be defined. According to a narrow, internationally common definition, the real estate industry includes the companies and private individuals that help to manage, administer and broker real estate. This definition excludes many actors—firstly, those responsible for development, planning, construction, and demolition, i. e., mainly construction companies and architects. Secondly, it excludes companies that provide services along the life cycle of real estate, such as financing, investment, valuation and consulting services. In this chapter, we use the broad definition that includes these areas. Thus, a real estate DSS is a computerized information system that enhances the user's effectiveness in making complex real estate decisions.

What DSS are available to decision-makers in the real estate industry today? That is the research question we want to answer in this chapter. To answer the question, we conducted an extensive literature review to explain the historical development first and to systematize the existing types. Then, we searched literature databases and the internet to find DSS that are applicable in practice and already in use.

Our motivation is to close the gap that we perceive exists between the real estate industry and other industries regarding the use of DSS, in order to increase decision-making quality. The gap is probably due in large part to the special features of real estate investments. These include being unique, indivisible, illiquid, long-term, capital-intensive, associated with high transaction and search costs, and management-intensive (for a detailed comparison, see Trippi 1990). This makes real estate decisions complex, unstructured, and thus challenging for the use of DSS.

2. HISTORICAL DEVELOPMENT

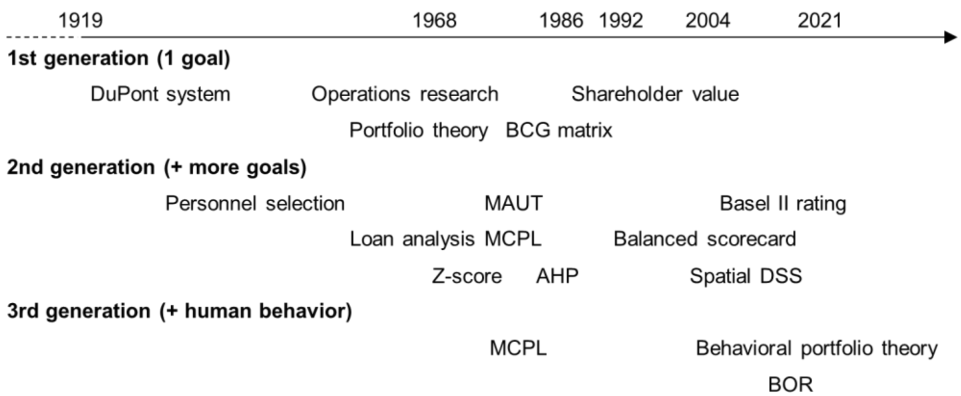
In order to understand the historical development of real estate management DSS, it is advisable to look at it from different perspectives, at least from the point of view of decision theory, (business) informatics and real estate.[2]

Decision theory

"Managerial decision theory deals with the choices a manager should make in an ideal world (normative approach), does make in the real world (descriptive approach) or should make in the real world (prescriptive approach)." (Lausberg and Krieger 2021, p.1; for a detailed comparison see Bell et al. 1988) These three approaches have their roots in neo-classical microeconomics (normative), behavioral science (descriptive) and behavioral economics (prescriptive). In the history of decision theory, many decision aids have been developed—roughly speaking in three generations, which are shown in Figure 2 and explained in the next section. "At first, decisions were analyzed with regard to a single monetary target variable such as value, gain or return. This turned out to be too simplistic for most practical applications. Later, target systems were created, which also included non-monetary, qualitative goals such as the market position of a company. This required incorporating the preferences of the decision-makers because the best alternative could not be calculated based on quantitative data only. Even later, insights from psychology and other disciplines were used to understand the preferences and integrate human behaviour in the models." (Lausberg and Krieger 2021)

[2] Other views, such as those of game theory or organization theory, are not discussed here because a complete presentation of decision theory is not the aim of this chapter. Thus, our account of the historical development is necessarily incomplete.

Figure 2. Historical development of decision aids from the viewpoint of decision theory



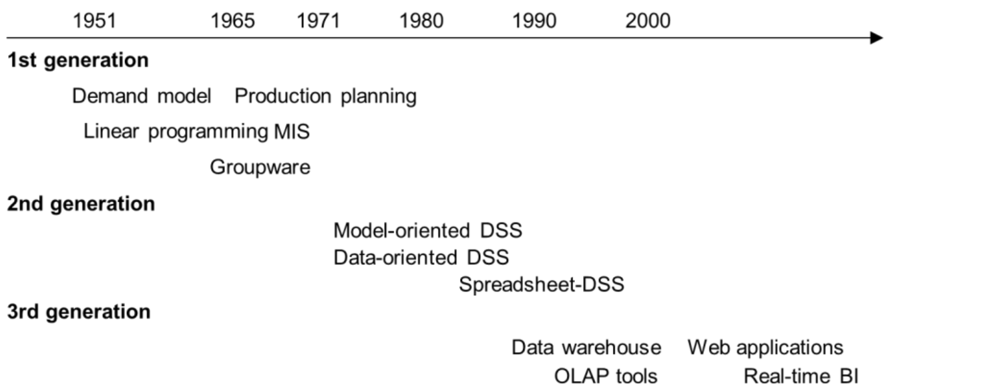
The division into generations is not quite coherent because the earlier generations still exist and the generations mix. For example, decision-making tools for only one goal are still used and newly developed today, and Operations Research (OR) methods are applied to multi-goal systems. Furthermore, there are other classifications of generations depending on the perspective, for example by Brans (1996).

Informatics

The development from the perspective of (business) informatics has already been presented in detail elsewhere, e. g., by Daniel J. Power in his books and on his personal website[3]. According to Power (2013, pp. 7-11) the origins of DSS can be traced back to 1951, when Lyons Tea Shops developed a software that used weather forecasts to help determine the demand for certain goods. In the mid-1960s the first video-conferencing system was invented which later led to group DSS, and experiments in the field of production planning were carried out that led to management information systems (MIS); see Figure 3.

[3] Source: http://dssresources.com/ (accessed 10 June 2021).

Figure 3. Historical development of decision aids from the viewpoint of business informatics



Source: Adopted from Power (2013, p. 8)

The beginning of the second generation was marked by the differentiation between MIS for well-structured decisions and DSS for unstructured decisions. By the early 1980s, DSS were accepted as a class of information systems with sub-classes such as data-oriented and model-oriented systems for purposes such as financial modelling and strategy development. In the mid-1980s personal computers were introduced, which greatly expanded the scope and capabilities of computing technology. New classes of DSS were developed, such as spreadsheet-oriented systems, which enabled users without programming skills to analyze data and to model decisions. This is one of the characteristics of the third generation, which is still in existence today. Further milestones in the DSS history were the invention and spreading of data warehousing, Online Analytical Processing (OLAP) tools as well as web-based applications. Today, Business Intelligence (BI) software enables decision-makers to analyze data in real-time. This takes decision-making to a new level, at least in areas where the analysis of large quantities of constantly changing data is paramount. (Power 2013, pp. 8-13)

Real Estate

From the perspective of real estate research and practice a presentation of DSS should begin with three influential articles by American scholars that were published around the same time: In the late 1980s Gregory B. Northcraft and Margaret A. Neale initiated fundamental considerations on real estate decisions, Julian Diaz III began his research on decision-making in real estate appraisal, and Robert R. Trippi published an overview of computer-aided systems to support real estate decisions (Northcraft and Neale 1987;

Diaz III 1990; Trippi 1989). At that time, some DSS were already in use in the real estate industry, e. g., spreadsheet models for investment analysis (for an overview see Trippi (1990)). Most of them focused narrowly on the selection phase in the decision-making process or on individual tasks with low complexity and short time frame (Trippi 1990, 52f.). The software developed by Trippi, on the other hand, aimed to help top management with strategic decisions (Trippi 1989, p. 48). In the period that followed, the technical progress was also evident in the real estate industry. For example, OLAP tools spreaded quickly in portfolio management. However, many applications have not got beyond the status of prototypes (for an up-to-date overview of real estate DSS, see section 4). In our opinion that this is less due to the complexity of the decisions, but rather due to the fact that most real estate decisions are human decisions. For example, in many large housing companies still employees and not computers decide whether the rent for a particular apartment is increased. The decision is very easy to model on the basis of mathematical rules and legal regulations, but since real estate is a social system in which people live and work, many non-economic factors have to be considered. Another example are acquisition decisions. Compared to rent increases, a different phenomenon can be observed here, namely the deviation of the actual decision-making behavior from the norm behavior, for example because a decision-maker trusts his intuition more than rational decision-making rules. For us, therefore, the human factor is the essential distinguishing feature to other sectors such as the manufacturing industry. The cited articles by Northcraft/Neale and Diaz opened the field for behavioral research in the real estate industry. Some progress has been made since then, but we are still a long way from deciphering the human factor in real estate decisions.

In this section, we concentrate on the perspective of decision theory because the associated concept of decision-making models is the most comprehensive. If the analysis is narrowed down to computer systems, chances are that tools will be left out, which were not originally developed as computerized models, e. g., portfolio models; if the perspective of the real estate industry is taken, the fact that many DSS are independent of the sector will be ignored.

2.1. First generation

In traditional, neoclassical managerial economics, the profit target was dominant for a long time. That is, it was assumed that the maximization of absolute or relative profit, i. e., the return on investment, was always the highest goal for a company. This corresponded to the idea of the rational investor and was very practical because business problems could be clearly defined and mathematically solved in this way. In practice, this dominance probably never existed. From the middle of the 20th century, more and more empirical studies (e. g., by Kaplan et al. (1958)) showed that companies in reality usually pursue several objectives—and that profit is often not one of them. In addition, new management methods were introduced that explicitly assumed multiple objectives, e. g., "management by objectives" (Drucker 1954), and heterodox schools of thought undermined the dominance of the neoclassical paradigm (e. g., Rothschild (1947)). This led to the multi-objective systems that prevail today, as described in section 2.2.

Nevertheless, from the second half of the 20th century until today, single-objective systems have been and are still developed, especially in Management Science and OR. They have their justification both on the enterprise level (if a company wants to committ itself to one goal), and on the operational level (if the system focuses on the optimization of certain indicators). In the following, a few of the best-known target systems will be presented.

A very simple target function is to maximize the rate of return on capital, better known as the Return On Investment (ROI). In formula notation:

$$\text{ROI} = \frac{\text{Return}}{\text{Total Capital}} \rightarrow \text{Max!} \tag{1}$$

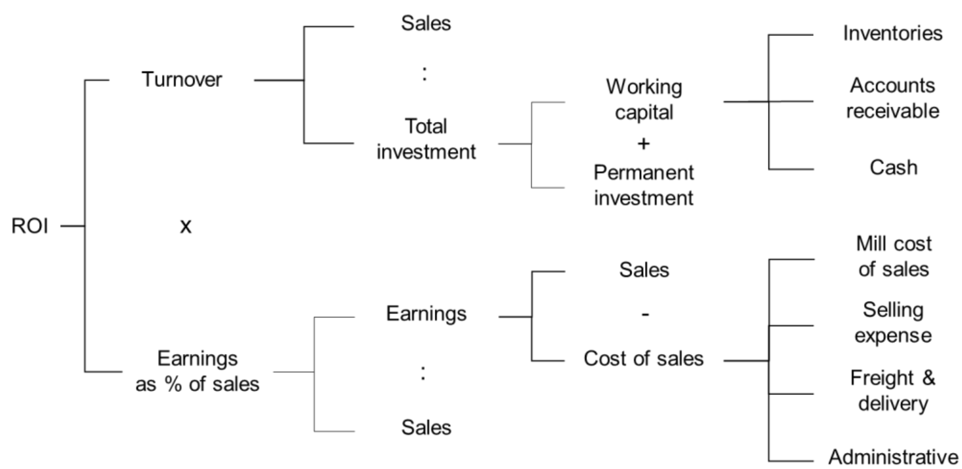
This is not yet a decision aid. For that at least clues on the alternatives are needed, e. g., whether the ROI should be increased by a higher return on sales or a faster capital turnover. For this purpose, the above formula can be broken down into two indicators, profit margin (operating ratio) and turnover (stock turn):

$$\text{ROI} = \frac{\text{Earnings}}{\text{Sales}} \cdot \frac{\text{Sales}}{\text{Total Investment}}$$

$$= \text{Profit margin} \cdot \text{Turnover} \rightarrow \text{Max!} \tag{2}$$

This was the basic idea behind the DuPont system of financial control, which serves the analysis of profitability and which was introduced in the US chemical company DuPont in 1919 (Laitinen 1999, p. 80). Today it is probably the best-known business ratio model. It comprises hierarchically structured ex-post key figures, which are derived from the overall objective of ROI maximization. The DuPont system has evolved over the decades, for instance, when the return on equity became more important in the 1970s and when the shareholder value concept emerged in the 1980s. Today, ROCE (Return on Capital Employed) or EVA® (Economic Value Added) for example, are known as target figures based on this concept. Furthermore, there are attempts to transform the DuPont system to an ex ante model, which is more suitable for supporting decisions than a purely analytical tool (Laitinen 1999).

Figure 4. The DuPont system of financial key indicators



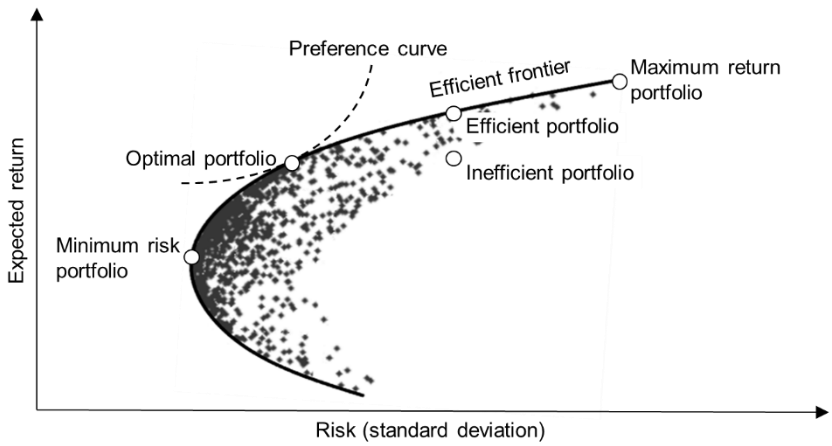
Source: Adopted from Davis (1950, p. 7)

In the real estate industry, such models are also in use—with necessary adjustments. A typical adjustment is to pay more attention to the main drivers, which in the case of real estate companies are mainly the fixed assets.

In the period between the introduction of the DuPont system and the shareholder value approach, OR emerged, a discipline where decisions are prepared with the help of quantitative methods. Many applications have been developed since the 1960s, especially for business functions such as production and logistics. In the real estate industry, OR is almost unknown even today. At best, there are publications in peripheral areas such as the optimization of land use or overlaps with other industries such as logistics.

One of the most important corrections of the pure profit target was the inclusion of uncertainty or risk. Neoclassical theory has produced a number of decision models for this purpose, the best known is probably the portfolio selection model by Markowitz (1952), as described and depicted in countless textbooks on this subject

Figure 5. The Markowitz model for portfolio decisions



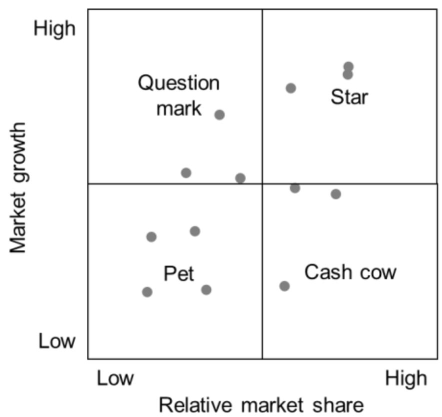
Source: Adopted from https://financetrain.com/lessons/modern-portfolio-theory/ (accessed 10 June 2021)

According to portfolio theory, one can determine the optimal composition of a portfolio from the expected return and standard deviation of the available assets, the covariances of these assets, and the risk-return preference of the investor. The optimal portfolio is the one where the efficient line and the highest possible preference curve touch. On closer inspection, it becomes clear that this approach does not represent the optimization of two objectives, but the ratio of return to risk becomes the new objective. This can be expressed by measures such as the Sharpe ratio, the Z-score or the variation coefficient.

Although portfolio theory was originally developed for securities and has strict premises, the model has been applied to real estate portfolios quite frequently—with limited success, as it has been shown that the transfer to real estate is problematic and can lead to incorrect results (Viezer 2010). One reason for this is that volatility is not an appropriate risk measure for real estate (Lausberg et al. 2020).

Integrating two objectives into one is a common way to reduce the complexity of decisions. This creates new opportunities for the representation, analysis and solution of decision problems. A good example of this are matrix charts, for example the growth share matrix of Boston Consulting Group (BCG). The matrix is based on the idea that new products go through a typical life cycle in which they ideally develop into stars. Once this position has been reached, a company's goal should be to maintain this position, e. g., by taking advertising measures to secure its market share. Furthermore, a company should strive for a balanced product portfolio in which sufficient products are available in all life cycle phases. (Reeves et al. 2014)

Figure 6. The BCG growth share matrix for portfolio decisions



Source: Adopted from https://www.bcg.com/about/our-history/growth-share-matrix (accessed 10 June 2021)

BCG's matrix and McKinsey's similar 9-box matrix have often been applied to real estate portfolios (e. g., by Bone-Winkel (1994) and Kołodziejczyk et al. (2019)). As with Markowitz's model, the exact replication must fail because of the underlying premises and the special features of real estate investments. However, this does not mean that the models are not useful for the real estate industry. On the one hand, they can be modified to fit reasonably well (see Section 2.3); on the other hand, the models can serve as an "engine of inquiry" (Viezer 2010), i. e., to verify insights gained with other methods.

The aforementioned matrices are good examples of the first generation of DA for another reason. They are instruments that do not originate from (neoclassical) science, but from practice. Over time, many such methods and decision models have been developed, e. g., cost-benefit analysis, Delphi method and SWOT analysis (strengths, weaknesses, opportunities and threats). They are of high importance especially in the real estate industry because "real estate is not a number crunching exercise but is a series of problem solving opportunities which interface practical tools of applied social science with every major issue of our time […]." (Graaskamp 1976, p. 27)

Many of the decision models described so far do not require technical support because of their simplicity. But of course, digitization has not stopped here, so that today computer programs are available even for the simplest decision support tools, e. g., for performing a SWOT analysis. Examples of this are given in section 4. Furthermore, decision aspects have been integrated into other types of software, e. g., (real estate) portfolio management systems and management information systems, but these are not the subject of this paper. Both types can be described as DSS in a broad sense.

2.2. Second generation

As mentioned above, companies usually pursue several goals at the same time, which complement each other but can also be in conflict with each other. Other important business goals are, for example, sales and market share as quantifiable goals or reputation and securing independence as qualitative goals. In addition, there are non-economic goals, e. g., ecological and social sustainability, as well as goals of the people in the organization, e. g., a pleasant working environment and career advancement, which do not necessarily coincide with the goals of the organization.

As far as can be traced back, multi-objective systems were first established in personnel selection. In the middle of the 20th century, scoring methods spread in this field, which at that time already had a long tradition in education. Soon, the scoring method was also used for other business tasks, e. g., for choosing between competing projects or for assessing loans (Lausberg and Krieger 2020).

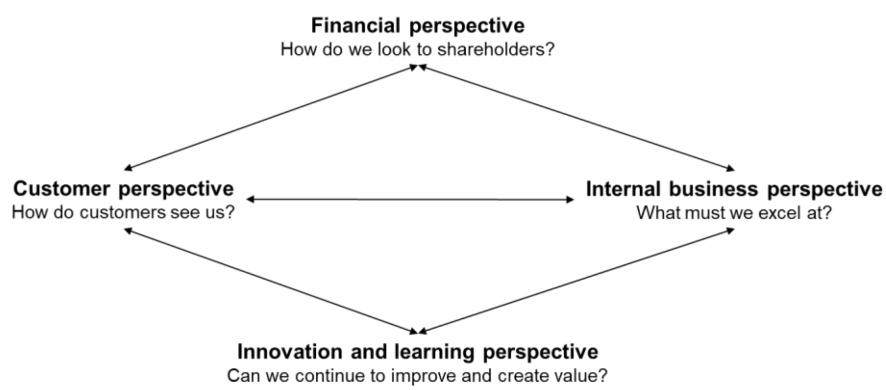
To this day, the financial services sector is an important driver of scoring systems. Important impulses came, for example, from the so-called Z-score by Altman (1968) and the rating methodology of the second Basel Accord ("Basel II"), which the Basel Committee on Banking Supervision set as a worldwide standard for measuring credit default probabilities in 2004.

At this point, it becomes obvious that there are some demarcation problems. At first sight, banks are concerned with only one objective, namely to make the correct yes/no decision, which is, in essence, a prediction about the probability of default (PD) and the loss given that the customer defaults (LGD), i. e., a 1st generation case. However, estimating PD and LGD is such a complex undertaking that its assignment to the 2nd generation seems reasonable. A similar demarcation problem between the 1st and 2nd generation exists with the models that originate from the expected utility theory. There are normative as well as descriptive variants, both with one and with several objectives. One example is the Multi-Attribute Utility Theory (MAUT). In a MAUT model, the utility of a decision alternative is calculated as the sum of the weighted partial utilities of all its attributes. The decision-maker should then choose the alternative that has the highest utility. This is similar for the other models from the family of MCDM methods (Multiple Criteria Decision Making, see Figure 9). According to Stewart (1992), it is not important that maximum utility represents a single goal, but that the criteria are diverse and imprecise: "The key philosophical departure point defining Multiple Criteria Decision Making (MCDM) as a formal approach to types of problem solving (or mess reduction), lies in attempting to represent such imprecise goals in terms of a number of individual (relatively precise, but generally conflicting) criteria." (Stewart 1992, p. 569)

While MCDM methods assume rational behavior, this is not the case with Multiple Cue Probability Learning (MCPL). Here it is accepted that people intend to proceed analytically and can orient themselves e. g., on attributes (cues) and probabilities, but that they also make mistakes and act intuitively ("quasi-rational") due to their cognitive limitations (Slovic et al. 1977, pp. 11-13).

Not all multi-objective systems strive for a unique solution to decision problems. In the "Balanced Scorecard" model by Kaplan and Norton (1992), for example, the four objectives ("perspectives") are placed on an equal footing. This may be frustrating for some decision-makers, but for others, the use of such an instrument enables holistic corporate management that corresponds to reality and is not limited to financial ratios.

Figure 7. Kaplan and Norton's Balanced Scorecard for strategic management

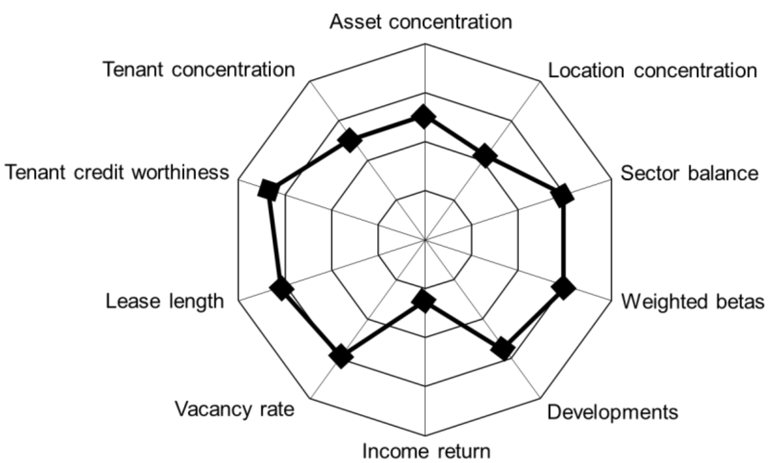


Source: Adopted from Kaplan and Norton (1992, p. 72)

An important feature of the second generation is the integration of multi-criteria decision models into geographic information systems (GIS) or—more rarely—the addition of the spatial dimension to MCDM systems. The term Spatial Decision Support System (SDSS) was coined for this in the early 1980s (Peterson 1993). Obviously, this is an important feature for real estate applications since every property has a spatial reference, and geographical aspects such as the distance to the city center or the infrastructure in a neighborhood are extremely important for their valuation. According to a current literature review, in recent years the technological development of GIS has advanced to the point where the incorporation of decision support features is easily possible or already taken for granted (Ferretti 2020).

The treatment of risks is also different in the 2nd and 3rd generations. Rather than expressing uncertainty about decision alternatives in terms of isolated risk indicators or lumping them together with expected return, other approaches have been taken here. Some methods are relatively simple (such as sensitivity and scenario analyses, discussed in Section 2.3), while others are highly complex (such as fuzzy MADM, presented in Section 3.2)—see Stewart and Durbach (2016) for an overview. Analogous to the Balanced Scorecard, there are also systems in which different risk metrics are placed next to each other, such as the RiskWeb of Blundell et al. (2005), presented in Figure 8.

Figure 8. Blundell, Fairchild and Goodchild's risk web for managing real estate portfolio risk



Source: Adopted from Blundell et al. (2005, p. 126)

As with the decision support tools of the first generation, special software has been created for those of the second generation, but decision models have also been incorporated into other types of (management) software. The first category includes, for example, applications for carrying out MCDM procedures, but also AI systems, which would not be possible without computer support.

2.3. Third generation

The third generation differs from the first two in that it not only accepts that humans have their own goals, which may differ from those of the organization, but it explicitly incorporates these goals as well as the behavior and idiosyncrasies of humans. We summarize this under the broad term Behavioral Operations Research (BOR), which can be defined as: "the study of the effects of psychology, cultural, cognitive, and emotional factors on our thinking and action with the use of (advanced) analytical methods and/or models to solve complex problems, support perplexing decisions and improve our ever-changing organizations" (Kunc 2020, p. 7). As the name BOR suggests, the roots of BOR lie in business OR and behavioral decision theory. Contrary to what Figure 2 suggests, there have always been links between these streams, for example, psychologists have also made important contributions to the development of MAUT procedures (Slovic et al. 1977, 21ff.).

At its core, BOR is about bringing together actual human problem-solving behavior and DSS (Kunc 2020, p. 7). To this end, emphasis is placed on model building using process-oriented research methods, which include, for example, case studies and action research (Kunc 2020, 3ff.). Kunc points out that three types of behavior are studied in BOR: "behavior in models, behavior with models and behavior beyond models" (Kunc 2020, p. 8). The first type examines the impact that human behavior can have on decision-making. In the second type, the focus is on models for decision-making in which information is used and processed. It should be noted that decision-makers often do not use all available information and simplify the calculations that lead to their decisions. This includes changes of cognitive functions and the effects of using a model on the behavior of a group. The third type is the behavior beyond models. Here, the impact on decisions is assessed after the models have been applied, so that the model can help embed routines, rules, or procedures into an organization (Kunc 2020, 8ff.).

An important topic in BOR is how managers can effectively lead their organizations in dynamic environments. System dynamics modeling can be used for this purpose. This is a common modeling method in the field of strategic planning; however, existing studies have hardly considered how the modeling processes affect the behavior of decision-makers (Kunc 2020, 15f.). Kunc further describes that BOR can improve the competencies and skills of decision-makers, for example, by applying similar models in different contexts. Thus, the effects of individual behavioral aspects can be investigated. Furthermore, known techniques relating to biases and heuristics should also be used to account for behavioral issues in and with models (Kunc 2020, 20). When these so-called debiasing measures, e. g., the well-known consider-the-opposite strategy (Mussweiler et al. 2000), are incorporated into a DSS, they can lead to more rational decision-making.

BOR bridges the gap between operations research and behavioral economics, which is based on the assumptions that investors do not always act rationally and do not primarily seek to maximize utility (Momen 2020, p.

41). BOR also differs from traditional operations research in terms of portfolio diversification and the inclusion of risk. These two characteristics will be briefly discussed, as they are particularly important for real estate applications.

- Markowitz (1952) formally formulated the principle of diversification for the first time. It represents the basic idea of the portfolio theory, which he founded. Portfolio theory assumes rational behavior and is therefore of limited use in practice. One reason for this is that people have difficulty interpreting covariances and probabilities correctly and therefore create separate "mental accounts" for different types of investments. This was first shown experimentally by Tversky and Kahneman and later empirically by others (Tversky and Kahneman 1981; Jorion 1994). As a way out, behavioral portfolio theory was developed by Shefrin and Statman (2000). Behavioral portfolio theory is structured like a pyramid in which each level contains defined goals. At the lowest level, the goal is to prevent financial disasters (e. g., by investing in government bonds or in prime properties), and at the highest level, the goal is to maximize returns (e. g., by investing in lottery tickets or opportunistic real estate investments) (Shefrin and Statman 2000, p. 141).

  To account for human behavior in portfolio diversification, it is possible to change individual elements or the structure of portfolio models, according to Momen (2020, p. 42). For the elements, one possibility is to use a risk measure such as the conditional value at risk, which better corresponds to the human perception of risk than the volatility used by Markowitz. In terms of structure, Momen et al. propose a model to link different mental accounts (Momen 2020, 50ff.).

- The second distinguishing feature is the consideration of uncertainty or risks. BOR is based on a fundamentally different understanding of risk than the neoclassical understanding described in sections 2.1 and 2.2. This is primarily due to the Prospect Theory of Kahneman and Tversky, according to which humans are not only risk-averse but also loss-averse (Kahneman and Tversky 1979). This has serious consequences for risk management, e. g., the need to apply alternative risk measures such as maximum loss. It is also worth mentioning that uncertainty in a decision situation can be so large that estimating probabilities of occurrence is not useful. When uncertainty reaches a level where probabilities are difficult to understand and quantify, even with careful problem structuring, it is defined as uncertainty. In this case, it is better to model uncertainty with the help of scenarios (Durbach and Stewart 2020, 76ff.).

Scenarios can also be used to facilitate strategic decisions and to gain a better understanding of causal relationships (Durbach and Stewart 2020, 80f.). However, scenarios can be influenced by heuristics and can be biased. That is why a scenario, when used in BOR models, is “a dimension of concern to be taken into account by decision-makers” (Durbach and Stewart 2020, p. 87).

Due to the complexity of the subject, the application of BOR is only reasonable with computer support. Here, however, it is evident that there is still a great need for research in the consideration of behavioral aspects, so that only experimental software has been developed so far. Greasley and Owen have developed a framework for this, which may be useful as a guide for future software development (Greasley and Owen 2016). In this context, it is important to recognize that the use of technical tools is of limited help. This becomes evident by looking at heuristics and biases. For debiasing, one can modify either the decision-maker or the decision situation (Soll et al. 2015). Various strategies have been developed to modify the decision-maker, including technological strategies such as the use of DSS. However, these are often not sufficient when applied individually; motivational strategies that seek to achieve greater effort from the decision-maker and cognitive strategies that optimize the decision-maker's cognitive abilities are needed as well (Lausberg and Dust 2017, 334f.). Three characteristics are crucial for the success of a DSS: ensuring effectiveness, the user's cognition and interaction with the system, and the user's experience (Krieger and Lausberg 2021, p. 16).

3. TYPES

3.1. Classification systems

DSS research has produced countless classifications. A few selected classifications are listed in Table 1. Holsapple and Whinston (1996), for example, distinguish DSS by how data are stored or processed in a DSS. According to their classification, there are spreadsheet-oriented, text-oriented, database-oriented, solution-oriented, rule-oriented and compound DSS. According to this classification, the DSS that is certainly the most widely used in organizations is Microsoft Excel, a spreadsheet system included in the Microsoft Office package (Statista 2021), for which a wide range of real estate applications is available. Among other things, this software has the advantages that it is easy to learn, it is globally used for a wide variety of applications, and it allows for complex extensions that can be used by virtually all employees in all real estate organizations.

All systems have specific advantages and disadvantages. Storing data in a spreadsheet-based DSS, for example, is easy for users as long as the amount of data is small. For larger data quantities, a relational database is advantageous, which in turn is not very user-friendly for calculating. Many DSS only allow the analysis of structured data, while a text-based DSS can also analyze unstructured text. In contrast, a solver-oriented DSS is able to process the data so that numerical problems can be tackled. In contrast, a rule-oriented DSS can support the decisions of a human decision-maker by making recommendations based on pre-defined rules. The compound DSS are hybrid systems that meet at least two of the described criteria.

Table 1. Selected classifications of DSS

Author	Criterion	Classification	Features
Bhargava & Power (2001, 230)	Mode of assistance	Model-driven DSS	"use formal representations of decision models and provide analytical support using the tools of decision analysis, optimization, stochastic modeling, simulation, statistics, and logic modeling"
		Communication-driven DSS	"rely on electronic communication technologies to link multiple decision-makers who might be separated in space or time, or to link decision-makers with relevant information and tools"
		Data-driven DSS	"help managers organize, retrieve, and synthesize large volumes of relevant data using database queries, OLAP techniques, and data mining tools"
		Document-driven DSS	"integrate a variety of storage and processing technologies to provide managers document retrieval and analysis"
		Knowledge-driven DSS	"can suggest or recommend actions to managers"
Haettenschwiler (2001)	User relationship	Passive DSS	aid the process of decision-making without producing explicit suggestions or solutions
		Active DSS	generate explicit suggestions/solutions
		Cooperative DSS	allow the decision-maker to modify, complete, or refine the decision suggestions/solutions generated by the system
Holsapple & Whinston (1996)	Orientation	Text-oriented DSS	store text-based data that can afterwards be accessed, utilized, and evaluated by the decision-maker
		Database-oriented DSS	store data in a structured way in a (relational or multi-dimensional) database so that it can be combined and retrieved in various ways
		Spreadsheet-oriented DSS	store data in files, which consist of spreadsheets that are easy to use for creating, viewing, and modifying the knowledge
		Solver-oriented DSS	help to analyze and solve numerical problems such as optimization and forecasting
		Rule-oriented DSS	give a recommendation based on a set of rules that mimic the decision-making behavior of a human expert
		Compound DSS	hybrid system that combines two or more the above mentioned structures
Hackathorn & Keen (1981)	Recipients	Personal Support	support only one user
		Group Support	support groups of users
		Organizational Support	support an organization as a whole

Source: Adopted from Mir et al. (2015, p. 405)

Further suitable distinctions come from Haettenweiler (based on the criterion of the relationship to the user) and Hackathorn and Keen (based on the criterion of the type of recipient). In the following, we will use the classification based on the mode of assistance by Bhargava and Power (2001) and Power (2001), respectively, which is referred to very often in the DSS literature—see Table 2.

According to this classification, there are five types: The first type is document-driven DSS, where the focus is on supporting the delivery of documents to decision-makers. Typical functionalities of systems in this class are ad hoc search, scanning, text mining, and analysis (Power 2013, 44f.). Examples are document management systems and virtual data rooms, which have become indispensable tools in parts of the real estate industry in recent years. Although not all programs on the market classify as DSS, some of the leading system do. The virtual data room Drooms, for instance, has a module that uses AI and optical character recognition (OCR) to identify important pieces of information in rental contracts and other texts, which allegedly helps individuals to make faster and better decisions (Drooms 2021).

Table 2. Characteristics of DSS-Types according to Power (2001)

	Keywords	Other names	Platform	Methods	Examples
Document-Driven DSS	document databases, document retrieval, document analysis	/	Client/server systems, web	search methods, storage and processing methods and technologies	search engines
Communications-Driven DSS	communications, collaboration, groupware	/	client/server systems, web	network technologies	chats software, document sharing, online collaboration, net-meeting systems
Data-Driven DSS	manipulation of a time-series of data, query a database, historical data	Retrieval-Only DSS Business Intelligence	mainframe system, client/server systems, web	data warehouse, on-line analytical processing (OLAP)	Executive Information Systems (EIS), Geographic Information Systems (GIS)
Model-Driven DSS	model manipulation, simulation, optimization, rule (expert) models, analyze decisions, multi-criteria, decision tree	Model-oriented, Model based, Computationally oriented DSS	stand-alone PCs, client/server systems, web	optimization and analytical methods, operational research methods (quantitative methods)	choosing between many options ("the best" alternative: "the best" meal, "the best" car), scheduling,
Knowledge-Driven DSS	expert knowledge (expertise), knowledgebase, knowledge engineering, knowledge discovery	Knowledge based DSS, Expert system	stand-alone PCs, client/server systems, web	intelligent decision support methods, data mining, artificial intelligence methods, knowledge discovery methods, heuristic methods	medical diagnosis, equipment repair, investment analysis, financial planning, vehicle routing, production control and training

Source: Nižetić et al. (2007, p. 3)

Communication-driven DSS typically support asynchronous and/or synchronous communication between the people involved. Typical functionalities include document and screen sharing, polling, and meeting recording capabilities. This class includes chat software, document sharing solutions, and video-enabled online meeting rooms (Power 2013, p. 41). Examples of such systems include Microsoft SharePoint and Google Workspace, which can be extended to include functions for the real estate industry.

Data plays a central role in many decisions. If a system focuses on supporting the processing of data, it is a data-driven DSS. Typical functionalities of these systems are ad hoc data filtering, alerting and triggering functions, data management, and reports (Power 2013, 42f.). Business intelligence systems, for example DeltaMaster (Bissantz 2021), used by several real estate companies, or the prototype risk management system developed by Valverde (2011), belong to this class.

In contrast, if formal descriptions of decisions or decision models are used, it is a model-driven DSS. Typical functions of these systems are the choice between multiple alternatives, moreover what-if analyses, scenario analyses, consideration of historical data, and backward analyses to plan back from a planned outcome (Power 2013, p. 48). Examples of model-driven DSS are presented in Sections 3.2 and 4.

Knowledge-driven DSS is the fifth type according to Power (2001). It provides knowledge generation and delivery support to decision-makers. Among other things, these systems provide the decision-makers with the opportunity to ask questions and have the reasons for a decision explained to them. (Power 2013, p. 46). As an example, a system that can identify the maturity level of construction companies' risk management and make suggestions to increase it based on literature and expert interviews (Zhao et al. 2016).

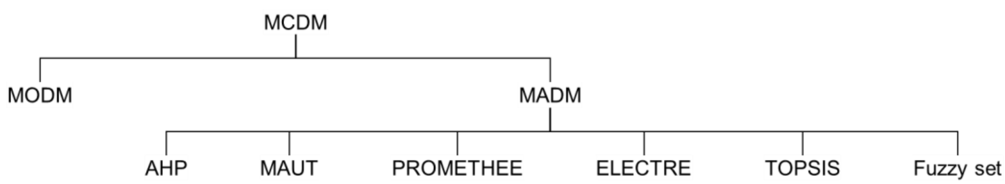
3.2. Model-driven DSS

When it comes to complex decisions, people reach natural limits that are caused, among other things, by the limited information processing capacity of the human brain. To compensate for the resulting decision errors and weaknesses, decision models have been devised to help people make decisions. The MCDM models (synonym: Multiple Criteria Decision Analysis, MCDA) can be roughly divided into Multiple Objective Decision Making (MODM) and Multiple Attribute Decision Making (MADM).

These two types differ primarily in the variables used and in whether the alternatives are predefined. In MODM, continuous variables are used, i. e., numerical values, which can exist in an infinite number. Because the models use functions with vectors, they are also called vector optimization models (Schuh 2001, p. 9). In the case of the MODM methods the alternatives are not given. It is thus attempted to develop alternative solutions by means of mathematical calculations and then to find the optimal one.

In contrast, MADM uses discrete variables, which are numerical values and can be counted. Compared to the MODM methods, the alternatives are given, so that an attempt is made to select an alternative as the solution for the decision problem. For this purpose, decision trees or matrices can be used. The best-known methods are briefly presented below, see Figure 9. For a detailed overview, see Wątróbski et al. (2019).

Figure 9. Selected MADM Methods



AHP is the abbreviation for "Analytic Hierarchy Process", which means that a complex decision is broken down into individual parts in a structured process in order to simplify the analysis (Saaty 1980). This is done in three steps. First, all criteria and all possible alternatives are identified, for example by brainstorming. In the second step, experts weight the criteria, usually. For each criterion, the alternatives are compared and evaluated in pairs. The third step is to rank the alternatives. (Rajaeian et al. 2017, p. 45; Schuh 2001, p. 23) A typical application area is the decision between different possible locations for a commercial property.

Unlike AHP, MAUT does not involve a pairwise comparison. MAUT is an approach to derive a utility function from people's preferences and to identify the optimal alternative by comparing it with the utility of offered goods (Keeney and Raiffa 1976; Fishburn 1970). This assumes that decision-makers have a precise idea of the utility of the alternatives and can also clearly formulate their preferences regarding risk, return, and other features. This is regularly not the case in practice, which is why utility is often derived from expert opinions, for example, on which attributes the utility of a property depends.

A pragmatic variant of MAUT is scoring, which is very common in practice. Scoring models are often theory-free and qualitative, i. e., they are not based on an explicit utility function and are limited to an ordinal utility measurement. However, this does not have to be the case—if higher demands are placed on scoring, e. g., when used for risk measurement, one can and should also follow theoretical guidelines and work quantitatively (Lausberg and Krieger 2021).

Another method is PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations), where the preferences of the decision-maker are not known. Therefore, an attempt is made to rank alternatives based on preference degrees. A preference degree is a number between 0 and 1 and indicates how much one alternative is preferred to another. This is relatively easy for the decision-maker to evaluate. As a rule, the criteria used have an economic meaning, which also makes them relatively easy for the decision-maker to define. (Brans et al. 1986; Rajaeian et al. 2017, p. 45)

ELECTRE (ELimination Et Choix Traduisant la REalité) is an outranking method for which the decision-maker does not need to know his preferences, similar to PROMETHEE. ELECTRE is based on a pairwise comparison of alternatives, where each criterion is compared to all other criteria. A key feature of this method is that poor performance of one criterion cannot be replaced by good performance of other criteria. Each criterion can be weighted differently. For example, preference, veto, or indifference thresholds can be chosen for evaluating a criterion. (Roy 1968; Natividade-Jesus et al. 2007, 785f.)

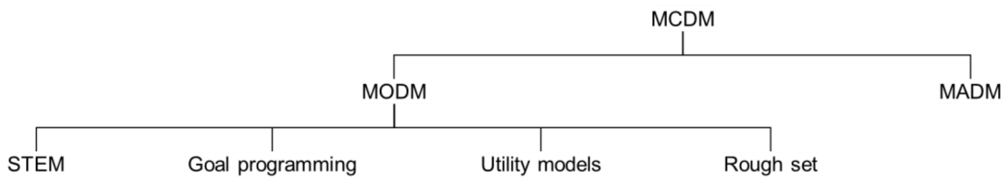
Another MADM method is TOPSIS (Technique for Order Preference by Similarity to Ideal Situation). Here, the alternatives are determined based on the geometric distance between the solutions. The ideal solution is the one that achieves the best values for all considered criteria. Just like the least ideal solution, it is usually not feasible in reality. The optimal alternative is the best compromise solution between these two extremes. The solutions found can then be ranked. TOPSIS thus makes it possible to neutralize a bad result in one criterion by a good result in another criterion. (Hwang and Yoon 1981; Natividade-Jesus et al. 2007, 785f.) An application example is the selection of a property manager. Each service provider is evaluated on the criteria of performance, expertise, price, and timeliness. The decision-maker first evaluates each criterion for each property manager. Then, using decision matrices, the ideal and least ideal solutions are calculated. The distances to the ideal solution and the least ideal solution are then determined. In the end, the result is a ranking of the property managers.

With the fuzzy set theory, there is a MADM method, which tries to represent the uncertainty and indetermination mathematically. For this purpose, formalized tools are used to find out how to deal with imprecision in decision problems. The evaluation is based on a linguistic judgment of the decision-maker, where indetermination and to some extent uncertainty arise due to different human perceptions. For this purpose, an affiliation function is defined for each criterion, which assigns a value between 0 and 1 to the alternative. The closer the value is to 1, the higher the affiliation. (Zadeh 1965; Rajaeian et al. 2017, p. 45) An example is the evaluation of a property in terms of location relative to the city center. If the property is located exactly in the city center, it is assigned a value of 0. If it is located on the outskirts of the city, it is assigned a value of 1. A value of 0.75 indicates that the property is closer to the outskirts than to the city center.

In some DSS, several of the above methods are used in one system. As an example, the software developed by Natividade-Jesus et al. (2007) should be mentioned. It is used to help decision-makers (in this case municipalities) to evaluate different development alternatives for buildings. This system uses TOPSIS and ELECTRE, among others (Natividade-Jesus et al. 2007).

A few well-known MODM methods will also be briefly presented below—see Figure 10.

Figure 10. Selected MODM Methods



The first MODM method presented is STEM (Step Method), which is based on linear programming using a target function. It tries to replace the optimal objective with the best compromise. Possible solutions are explored one after the other, interacting with the decision-maker. He should be guided to recognize good solutions and the relative importance of the objectives. The final decision is then the best compromise. (Lu et al. 2007)

Here is an example: When selling a property, the offers to buy should represent the solutions. In a first step, the offers are evaluated according to the criteria “offer price” and “time of sale” to see how the maximum can be achieved. In a second step, the criteria are evaluated according to the minimum result. In a third step the minimum is calculated from the maximum from the first step and in the fourth step, the maximum is calculated from the second step. In the fifth step, the decision (the compromise) results from the criteria vector that is closest to the positive ideal and furthest from the negative ideal. Then the decision-maker is asked to accept or reject this solution. If he rejects it, a relaxation process starts, i. e., a certain amount of relaxation of a satisfactory objective must be accepted to allow an improvement of the unsatisfactory ones. If the new solution does not satisfy the decision-maker either, the system repeats the process. (Lu et al. 2007, p. 24)

Another method is goal programming, in which decision-makers set goals for each criterion. The solution to be selected is then the alternative in which the deviations in all criteria from the defined targets are the smallest (Lu et al. 2007, 25f.). For example, for the sale of a property, the targets “at least $ 100,000” and “by February” can be defined for the two criteria “sales proceeds” and “time of sale”. The incoming offers are then analyzed according to how close they are to the two targets.

The Rough Set Theory tries to analyze unclear descriptions of objects. It assumes that each known object can be described by attributes. In contrast to the MADM method Fuzzy Set Theory mentioned above no affiliation function is used, but it is indicated whether the object belongs to a boundary set. To do this, the condition and decision attributes for each object are first determined. For example, the properties in a city can be considered as objects. For these objects, there are the decision attributes “location of the property” and “size of the property”. The value of the property can be considered as a decision attribute. With the condition “location”, there can be the values “city”, “city edge” and “periphery”. These then result in decision rules, such as “location = city” and “size > 10,000 m²”, which results in “high” for the value of the property. The decision rules are often described in if-then-form, and multiple decision rules define a decision algorithm. There may be dependencies between the condition and decision attributes. For example, it may be true that regardless of the size of the property, a “periphery” location always means that the value of the property is considered “low.” These dependencies are often derived from past values, which can then be used to make decisions for new properties. (Xu and Tao 2017)

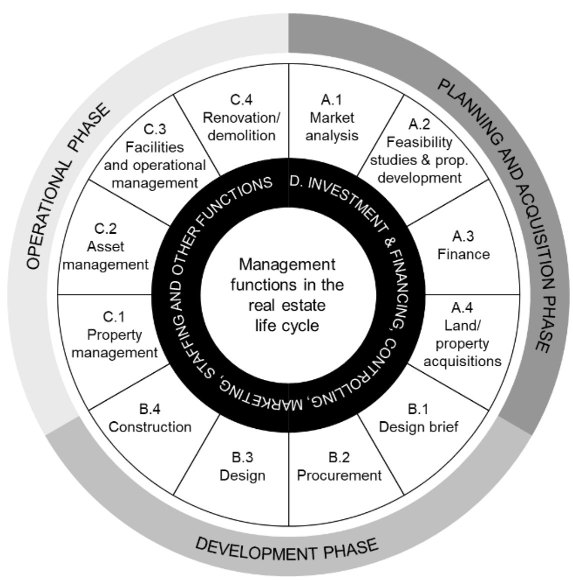
4. APPLICATIONS

The purpose of this section is to present the results of a literature and internet search that the authors used to identify academic and practical DSS applications for real estate management activities. As in the previous chapter, the focus here is on model-based DSS.

By "application" we mean, on the one hand, academic DSS developed for research purposes, usually available as prototypes and mostly described in scientific journals, and, on the other hand, practical DSS developed for commercial purposes and usually available in the form of software. We consider only those systems that directly support decision-making, and not indirectly, such as Enterprise Resource Planning (ERP) systems do.

We define "real estate activities" as all management functions that occur during the real estate life cycle, as shown in Figure 11. In addition to core activities such as property acquisition or asset management, these also include general business activities such as human resources management or controlling, provided they have special real estate-related features.

Figure 11. The real estate life cycle



Source: Adopted from RICS (RICS Royal Institution of Chartered Surveyors 2016)

The distinction is sometimes difficult, as the following examples show: In the construction sector, we do not include construction site logistics in our research field, but we do include defect management, because there is overlap here with the core real estate activity of property development. In facility management (FM), we exclude the optimization of technical building equipment, but not the selection of FM service providers, because this is a management activity. In the field of urban planning, we do not consider infrastructure and traffic planning and limit ourselves to real estate-related activities such as development and neighborhood planning. Finally, we leave out infrastructure buildings such as roads, bridges, ports, or pipelines and focus on private and commercial real estate such as single-family homes and shopping centers.

The basis for this chapter is the literature review by Krieger and Lausberg (Krieger and Lausberg 2021, esp. p. 25f.). There, we systematically searched the academic English-language literature for real estate DSS and analyzed 40 articles in more detail. We have now extended this literature base in two directions: First, we have defined the term DSS more broadly and added MADM procedures to the list of search terms. To do this we searched general articles on DSS (Burger and Malpass 2016; Elkosantini 2015; Razmak and Aouni 2015; Arnott and Pervan 2016) for real estate applications—in addition to searching relevant literature databases. Second, we searched the internet for reports of DSS being used in practice. This has increased the number of systems identified, but on the other hand, we cannot speak of a complete survey anymore because not every DSS used in practice leaves traces on the internet.

All findings were assigned to the 13 core real estate activities shown in Figure 11 (from A.1 to D.). In addition, a category "Other DSS" was created for systems that could not be assigned to any activity.

A.1: Market Analysis

Market analysis is probably the area in the real estate life cycle that has benefited the earliest and the most from digitization. Today, obtaining market information is no longer primarily a question of availability, but of price. There are countless providers in all major real estate markets who collect and evaluate market data and make it available for a fee (or free of charge, depending on the business model), usually via web-based applications with map functions. Examples of such systems are CoStar, Real Capital Analytics and Zillow in the USA, GfK/Regiograph, RIWIS and Sprengnetter in Germany. According to the distinction made above, these systems cannot be called DSS in the narrow sense, because they are limited to data analysis and do not include a decision model. Similarly, simulation models, such as Gretas[4] (Haeusler 2011), also belong to this category because they offer added

[4] Source: https://gretas-research.de/# (accessed 15 June 2021)

value in decision-making in addition to data analysis, but do not use any of the previously mentioned models. When decision support functionalities such as scoring are included, they are typically used to evaluate a specific site (see Section A.4). In the literature, market analysis systems are sometimes referred to as DSS (e. g., by Tidwell and Gallimore (2014)), but this is probably just due to a different definition of DSS.

Introne and Iandoli (2014) have developed an argument-based system for forecasting trends in the housing market. Using the system, evidence can be weighted and aggregated by the system to support evidence-based reasoning. In their research, they conclude that inexperienced users can use an argument-based decision-making system with little upfront cost. The authors point out that using the system does not change the way users think about a decision problem. Furthermore, the authors conclude that "decision performance [...] depends upon the ability of a user to use the tool and the performance of the belief aggregation algorithm" (Introne and Iandoli 2014, p. 88).

Forgionne also explored forecasting possibilities as early as 1996, using an economic model supplied by a DSS to try to predict the housing supply of the U.S. Army. His DSS, called HANS (Housing Analysis System), was intended to replace the previously error-prone and conceptually flawed segmental housing market analysis. The model used by the system was able to predict quantity, rent, and market share in a fully automated fashion. He points out that this model can be applied to other areas as well. As an example, he mentions urban planning, which attempts to predict the demand and supply of housing so that planning can be made for the necessary transportation and cultural centers as well as for residential, industrial, and commercial areas. (Forgionne 1996)

Another example is described by Del Giudice et al. who studied urban planning and designed an evaluation model based on the AHP process. This model uses key factors that determine the importance of real estate investment in a competitive urban context. They present a research design to study the investment decisions of different agents operating in the residential real estate market. In this context, investment decisions are influenced by a multidimensional set of factors, including environmental and social characteristics that may vary in different territorial contexts. (Del Giudice et al. 2019)

A system presented by Renigier-Bilozor is an example of the parallel use of MODM and MADM methods in a DSS. Here, the data mining system uses rough set theory (MODM) to support analytical processes and fuzzy logic (MADM) to reproduce expert knowledge in vaguely defined problems. Renigier-Bilozor emphasizes that the use of rough set theory as an analytical tool provides an alternative to traditional statistical analysis. The theory offers a wide range of applications in the field of real estate management. It is intended to support public management in reaching a compromise in a conflict situation. The system takes the role of an assistant to help the decision-maker to maximize the effectiveness of his decision and to shorten the decision time. The system was validated based on land ownership transactions in the Polish city of Olsztyn in 2010 and 2011. (Renigier-Biłozor 2013)

A.2: Feasibility Studies and Property Development

Market analysis is followed by real estate development, for which feasibility studies are a typical part of the process. This can be rewarding for the use of DSS due to the particularly complex decision situation. It is therefore not surprising that there is a lot of evidence for development DSS in the academic literature. For example, Pommer shows in her dissertation how decision support systems could be used almost throughout the entire property development process (Pommer 2007). However, this is not accompanied by widespread use of DSS in this sector of the real estate industry, possibly because the overall level of digitization in property development is not very high (Lausberg and Scheer 2020). Site analysis is an exception. Here, the market analysis systems mentioned in section A.1 are frequently used in practice. Some of these systems have integrated scoring and similar decision models that can evaluate locations according to user preferences. An example of this is the system for analyzing macro and micro locations from the provider 21st Real Estate[5].

Here, the systems can be distinguished according to the logical sequence, from spatial to urban to property development. Montibeller et al. (2006), among others, have studied spatial development and combine scenario planning with multi-attribute value theory (MAVT), a MADM method similar to the MAUT method presented in the third chapter. They describe its use with two case studies from Italy. One is about deciding whether industrial and commercial land is suitable for logistics or retail development. Another is to decide whether it is possible to convert land previously used for agriculture. They conclude that the use of the MAVT method is only appropriate if there is a dominant option in all scenarios. The authors point out that in real-world situations, this counterpart is an exception in strategic decision-making and, in particular, does not apply to the development of land. Consequently, each scenario should include different organizational priorities, and there may not be a clear dominant option in any scenario. (Montibeller et al. 2006)

As described in the third section, Natividade-Jesus et al. (2007) addressed the selection of appropriate locations for real estate in Portugal. Such

[5] Source: https://www.21re.de/lageanalyse-relas (accessed 22 April 2021).

a system must provide users (consumers, government agencies, municipalities, etc.) with a flexible and user-friendly environment based on formal methods with multiple criteria. In their system, they use TOPSIS and ELECTRE. To complement decision support, they propose adding a GIS so that users can locate properties. The authors point out that the system to be used must be efficient, effective, and easy to use because there is a large number of hierarchically structured attributes that are interrelated. They conclude that the method used is a promising approach for analyzing housing markets. (Natividade-Jesus et al. 2007)

Many other examples of site selection for a wide variety of purposes can be found in the literature (see, for example, Mosallaeipour et al. 2019; Aljohani and Thompson 2020; Kahraman et al. 2003; Burnaz and Topcu 2006; Lee 2014; Han and Kim 1990; McIntyre and Parfitt 1998; Haque and Asami 2014). The authors mostly use MADM procedures. A distinctive feature here is the use of a group-based DSS for site selection by Cebi and Kahraman (2010).

Systems for property development in the narrow sense are also well documented (see, e. g., Leelarasamee 2005; Natividade-Jesus et al. 2007; Coutinho-Rodrigues et al. 2011; Li et al. 2005; Arentze et al. 1996; Padhi et al. 2015). Hoffmann et al.'s research on location analysis with reference to corporate real estate management strategy is also worthy of mention (Hoffman et al. 1990). Amarullah and Simanjorang and Ashaf et al. describe the selection of shopping centers and single-family homes, respectively, using the AHP method (Amarullah and Simanjorang 2020; Ashaf et al. 2019). Interesting approaches for future applications include the integration of Monte Carlo simulation and the combination of Spatial DSS and BOR systems (Hosny et al. 2012; Haupt 1995; Ferretti 2020).

A.3: Finance

The third core activity is the financing of the property. Here, DSS have a relatively long tradition, as already mentioned in section 2.2. In addition to systems that support companies in granting or taking up loans, this section also deals with valuation systems because a valuation is regularly a prerequisite for real estate financing. The leading providers of valuation software, e. g., Argus in the U.S. and Sprengnetter in Germany, have partially incorporated scoring for individual circumstances, but not higher-order decision models. That this can be done differently was already shown by Rossini in 2020, when he presented a DSS prototype, which works with components of artificial intelligence and in particular with the application of neural networks (Rossini 2000). In this context, the author investigates how an application for real estate forecasting is possible. A rule-based expert system and the Artifical Neural Networks method, whose procedure is similar to that of the human brain, were used. In addition, the author also presents other possibilities for the application of AI in real estate valuation. (Rossini 2000)

Real estate valuation is not only the field for which most DSS have been developed (Krieger and Lausberg 2021); it is also the field in which behavioral economists are most active. One reason for this is probably that property valuations lend themselves well to experimental research—for example, one can change the valuation process or the valuation technique for the experimental group and then compare the value obtained with that of the control group. This has not yet resulted in third-generation DSS, or BOR applications, being on the market for valuations. However, experimental programs are reported in the literature. At Nürtingen-Geislingen University, for example, it was investigated whether the evaluation accuracy can be improved by means of built-in decision support tools. This is of particular importance because appraisers of real estate often do not realize that they are making decisions, but at the same time they use software systems that do not support decision-making. For example, systems available on the market can process information using financial modeling, data analysis, or plausibility checks, but they do not help appraisers decide which data source can be trusted or which comparative data should be used (Lausberg and Dust 2017, 331f.). In an empirical study, Lausberg and Dust were able to show that their DSS can be used to reduce the anchor effect and increase the valuation accuracy, thus effectively supporting the reviewer in his or her decisions (Lausberg and Dust 2017, p. 337). However, a later, similarly designed experiment did not yield such clear results, indicating a need for further research (Evans et al. 2019).

Another study comes from Valverde; his tool, which spans multiple application areas, also addresses borrowing (Valverde 1999). Brauers and Zavadskas (2011), on the other hand, develop a DSS for bank lending. Their system aims to make the decision as objective as possible, for which they combine three individual methods. There is a wealth of other proposals in the literature, most of which use MADM methods (McCluskey and Anand 1999; Greer and Murtaza 2003; Kaklauskas et al. 2007; Kettani and Oral 2015; Kettani and Khelifi 2001; Czernkowski 1990; Gonzalez and Laureano-Ortiz 1992; Kilpatrick 2011; Larraz 2011; Moore 1992; Musa et al. 2013). An example of the use of a MODM method can be found in the study by Manganelli et al. (2018). The study by Bunyan Unel and Yalpir (2019) describes the forecasting of values in the context of a real estate appraisal. Belsky et al. (1998) address how to use GIS as a DSS in mortgage financing.

A.4: Land/Property Acquisitions

The next activity in the RICS scheme of the real estate life cycle is land and property acquisition. For this purpose, Kilic et al. describe a GIS-based system for planning land acquisition for realizing urban and public projects in Croatia. The system uses the PROMETHEE and AHP methods. (Lin et al. 2020)

Lin et al. (2020) use the Fuzzy Multiple Criteria Decision Making (FMCDM) technique, a method based on fuzzy logic, to reconcile the quality and housing valuation of real estate. Its aim is to provide the real estate broker with a tool that improves the coordination between seller and buyer. The purchase of a property is essentially characterized by comparisons and trade-offs between different property characteristics. Thus, starting from the pricing strategy, price and quality can be reviewed, leading to an improvement in the brokerage results of the real estate agents. The authors conclude that the use of the method can increase brokerage performance compared to conventional approaches. (Lin et al. 2020)

The use of DSS in investment analysis is described by Mantogiannis and Katsigiannis (2020). They have created a system for the Private Rented Sector in the UK, i. e., for private individuals who buy properties for letting. Since real estate investment requires the consideration of several qualitative and quantitative criteria as well as the different, sometimes conflicting, interests of stakeholders, their system is broad in scope. First, suitable criteria were selected in a multi-stage process, then experts assessed the non-financial aspects and the financial ones were calculated using Monte Carlo simulation. Then, four real investment alternatives were ranked using an AHP model. The authors conclude that the system helps investors to make better-informed decisions. Furthermore, the authors emphasize that their DSS can be applied to other types of uses without much modification. (Mantogiannis and Katsigiannis 2020)

Otay and Kahraman (2015) describe a similar system for investment analysis. Hsu et al. (2014) also use MADM methods, but in the area of bid selection. Wang (2005) describes investment analysis for government institutions. The approach of Festervand et al. (2001) lies in the marketing domain. Finally, two studies should be mentioned, which can be used to support negotiations in a land or property sale (Urbanavičienė et al. 2009; Zavadskas and Kaklauskas 2009). An example of a commercial system for supporting real estate purchases is ArcGIS Business Analyst by Esri.[6]

B.1: Design Brief

After the planning and acquisition phase has been completed, the design

[6] Source: https://www.esri.com/en-us/arcgis/products/arcgis-business-analyst/overview (accessed 23 April 2021).

phase begins. This includes the design of a site, such as the distribution of building masses and landscaped areas on a site, as well as the development of a concept. Different concepts are needed by property developers for large projects, e. g., for traffic, usages, or legal agreements, so that they can brief their partners or apply for building permits.

Yepes et al. (2021) compared different methods such as TOPSIS, ELECTRE, and AHP, first theoretically and then through a case study, in order to use them to find the most sustainable construction option for a residential building. They conclude that the simplest methods Simple Additive Weighting (SAW) and Complex Proportional Assessment (COPRAS) are well suited as a first approach to solve the problem. However, they are not ideally suited because there were quantitative, qualitative, and semantic variables that were not optimally mapped. The two direct evaluation methods, TOPSIS and VIKOR[7], were found to be very useful when the optimal ideal and non-optimal ideal solutions are known. The authors point out that both methods are well suited for selecting an alternative within a Pareto limit for an optimization problem with multiple objectives. In contrast, the two outranking methods ELECTRE and PROMETHEE can be used very well to classify alternatives by degree of dominance by pairs. The methods are also very useful for discrete multi-attribute decision-making problems. Finally, the utility/value method MIVES[8] obtained good and significantly different results from the other methods, mainly due to the possibility of prioritizing the criteria. (Yepes et al. 2021)

In another study, Adnan et al. (2015) investigated tenant preferences. The authors used the AHP method to analyze the relative importance of the main factors selected by office tenants in Kuala Lumpur, Indonesia. To do so, they identified 26 factors in four main categories (location, leasing, building, and finance) with expert assistance. The use of the AHP method led to the evaluation of the relative importance given to each category to reveal the different preference patterns. The authors conclude that among the sectors studied (finance/banking, IT & media, oil & gas), the preference differences were marginal for most factors, but significant for some. (Adnan et al. 2015)

B.2: Procurement

With the information from the design phase, the procurement of the required products and services can be started. For the real estate industry, hardly any studies can be found for procurement. This could be because—from a managerial point of view—the purchase can be seen as a part of the

[7] The acronym comes from the Serbian language and means Multi-criteria Optimization and Compromise Solution.
[8] The acronym comes from the Spanish language and means Integrated Value Model for Sustainable Assessments.

investment or of operations. Thus, the decision support systems mentioned in section D and other sections partly cover procurement too.

Here a study of Phillips et al. from the year 2007 should be mentioned. This study deals with the decisions in the procurement process of the public sector. This has many special features such as the long-term nature of the investments and the strict tendering and award guidelines. In their study, the authors developed a software tool that combines AHP and MAUT with a method to consider all costs and benefits of the entire life cycle (Whole Life Costing) in a systematic and economical way. The approach used represents the process for evaluating and ranking contractors and takes into account preferences and beliefs. The authors conclude that the uncertainty factor in decision-making can be best considered with AHP and MAUT. Furthermore, the authors point out that the system is suitable for many other types of projects, such as maintenance and repair contracting or residential modernization programs (Phillips et al. 2007, p. 71).

Dörr recently published another interesting study. As part of her doctoral dissertation, she examined contracting for new construction by non-property firms. The author selected the AHP method for prioritizing alternatives and the TOPSIS method for evaluating them. However, no proprietary software was created as part of the work. (Dörr 2020)

B.3: Design

The design of the property and its surroundings is the domain of architects, interior designers and landscape architects. Their activity consists mainly of designing and planning and thus takes place outside the economic sphere, which is the subject of this chapter. For an overview of the DSS used there, see Leeuwen and Timmermans (2006). However, for the real estate industry, it is important to consider the IT systems that are used at the interfaces between architecture and economics. These are mainly software packages, which digitize the design and planning process—for instance Building Information Modeling (BIM), which can later be used by facility managers and other real estate professionals—, but also for the business tasks of architects such as accounting for construction projects. However, these systems do not primarily support architects in making decisions, but rather their clients. Visualization of design variations using virtual reality glasses, for example, can significantly increase the effectiveness and efficiency of such decisions (Juan et al. 2021).

A more classical approach using the well-known DSS has been taken by Jalaei et al. (2015). They describe how decisions related to the continuation or abandonment of proposed buildings can be supported in the conceptual phase. One of the challenges here is the optimal selection of sustainable materials to meet project requirements while ensuring good design. With their DSS, designers can select the optimal building components for projects based on owners' priorities and sustainability criteria. For this purpose, TOPSIS was used as an objective weighting method. The authors conclude that by using the DSS, an optimal alternative could be selected, which resulted in an advantage in terms of acquisition costs and life cycle costs. (Jalaei et al. 2015)

B.4: Construction

The construction of the building concludes the development phase. For this phase, too, only a few studies can be found, because most decisions are of a technical nature and thus excluded from our definition. But of course, the standard methods of decision support are applicable here as well. The study by Brauers et al. (2008) should be mentioned, in which the Multi-Objective Optimization on The Basis of Ratio Analysis (MOORA) method is described for the construction and maintenance of real estate in Lithuania. The MOORA method attempted to rank contractors objectively. The method in this case consisted of two components, the ratio analysis and the dimensionless measurement. The authors found that the best contractors were not those with the lowest costs. Rather, the size of the company was very important. This study can also be assigned to the preceding Phase B.2 Procurement or the subsequent Phase C.1 Property Management. (Brauers 2008)

The DSS of Khumpaisal et al. (2010) has a different task. Using a case study of the major international airport London Heathrow, the authors show that the Analytic Network Process (ANP), another MADM method, is an effective tool for assessing the risks of a construction project and thus arriving at better decisions (Khumpaisal et al. 2010).

C.1: Property Management

In the RICS scheme, the operational phase of a property begins with property management. Van Reedt Dortland et al. (2012) describe a DSS for a flexible real estate strategy for healthcare organizations such as hospitals to adapt to future uncertainties. An example of such commercial building management decisions is the case when a department needs additional space. In this case, it is necessary to determine whether an additional investment should be made, for example, to add an extra floor. An alternative might be to expand the hospital elsewhere, which entails quite different considerations. The real options approach was chosen to describe flexibility and its consequences for corporate real estate management; furthermore, the scenario planning approach was used. (van Reedt Dortland, Maartje et al. 2012)

The maintenance management of properties has been addressed by Taillandier et al. (2017). In their study, building components were to be examined over a limited period of time with a limited budget with respect to several, often conflicting, objectives such as service quality, customer satisfaction, and regulatory requirements. For this purpose, the authors modeled a multi-objective multi-dimensional knapsack problem, and solved the optimization problem using the MOPSO (Multiobjective Particle Swarm Optimization) metaheuristic method. The decision maker's expected score and the actual score for each component were used as the basis to minimize the difference between the two values. The authors note that they did not use a weighting system, but such a system or a more complex aggregation method such as ELECTRE can be incorporated into the model as an element of the knowledge base. The system was applied to a building stock of a large French company. (Taillandier et al. 2017)

The same author (with other co-authors) has also worked on decisions of housing companies (Taillandier et al. 2014), more specifically on multi-year planning for maintenance and modernization of buildings. Other decisions typical of property management include leasing and contracting with facility managers. For tenant selection, Yau and Davis (1994) developed the prototype for a DSS.

C.2: Asset management

Asset management is responsible for ensuring that the owner's real estate and other assets are managed in the best possible way. It is superordinate to property management and focuses on the portfolio, not the individual properties. Therefore, it makes sense that most DSS in this field have portfolio management as their subject. An early study was by Trippi (1989). One objective of his study was to identify how key decisions to acquire, modify, and dispose of real estate assets are made and can be improved. On this basis, he developed the prototype of a DSS, which he later offered commercially. In the article, the author concludes that the use of a DSS is important because virtually all potential actions—due to long-term implications—create planning problems that must be resolved in the decision-making process. Among the success factors in developing DSS in asset management, Trippi cited the in-depth understanding that software developers must have of the subject matter and the ability to make the DSS operational on a variety of host computers in a short period of time. (Trippi 1989) The second success factor is negligible today because it has become a given in software programming.

A number of studies address how DSS can be used to increase the performance of real estate portfolios, which typically involves the use of econometric methods. One such study dates back to 2006. Ellis and Wilson describe a rule-based DSS that would have enabled Australian investors to outperform the market and randomly constructed portfolios for the period studied. (Ellis and Wilson 2006). Similar studies come from Simoni (2011) for Swiss and Valverde (2010) for US investors.

Risk management is also very important in asset management. Researchers have often shown that DSS are also useful for risk identification. For example, in 2019, Thilini and Wickramaarachchi conducted a study in Sri Lanka in which they analyzed risk factors for commercial real estate development using social, economic, environmental, technological, and political criteria. To do so, they used the ANP. The authors conclude that the permitting process, climate change, and natural disasters are the risk factors with the greatest impact on development. (Thilini and Wickramaarachchi 2019)

In a recent study conducted in 2021, Gupta and Newell examined the portfolio management of unlisted real estate funds in India throughout their life cycle with a focus on risk assessment. The authors also used MADM methods. They emphasize that understanding risk transformation in real estate portfolio management across life cycle stages is critical to formulating strategies for minimizing, transferring, and mitigating risk in the particular real estate portfolio. They conclude that entry and transaction risks are the most important risk factors in the investment phase. (Gupta and Newell 2021)

An example of a commercial system is @Risk from Palisade.[9] At its core, it is a software for Monte Carlo simulations, but the product family of the "DecisionTools Suite" can also be used for other purposes such as data analysis and decision trees.

C.3: Facilities and Operational Management

In the operation of the property, FM must be performed permanently. There are many IT systems on the market for this activity, but according to our internet research, none of them belongs to the category of DSS. Some DSS are described in the literature, but probably they have remained prototypes. The selection of FM service providers is addressed in a 2013 study by Tamosaitiené et al. They identified a set of evaluation criteria to guarantee successful selection. These include general management, safety, cleaning and building characteristics. For their case study, the authors use a game-

[9] Source: https://www.palisade.com/decisiontools_suite/ (accessed 23 April 2021).

theoretic approach and employ the Levi 3.0 software developed by Zavadskas et al. (2002) for multi-criteria decision support in construction. (Tamošaitienė et al. 2013)

Banaitiene et al. (2008) studied the life cycle of a property. The methodology proposed by the authors allows the decision-maker to develop alternatives and evaluate the qualitative and quantitative aspects. They foresee four steps for this purpose: Determination of the weights of the criteria, evaluation of the life cycle parts of a building based on the established system of criteria, design of the alternatives of the building and evaluation of the alternatives. The COPRAS method developed in the study was applied in the second and fourth steps. (Banaitiene et al. 2008)

Pun et al. (2017) applied a DSS with AHP and fuzzy logic to determine the most efficient maintenance strategy for building systems. One of their goals was to minimize downtime. Using their system, they derived weights of the criteria and evaluated the alternatives. In contrast to the simple AHP, pairwise fuzzy comparison matrices were used here. The authors conclude that by applying the system, the property manager can be given a clear direction for formulating various maintenance plans in facility management. (Pun et al. 2017)

C.4: Renovation/Demolition

The last activity in the life cycle of a property is the renovation or—if this is no longer economically viable—the demolition of the property. There are hardly any publications related to DSS on this phase. One of the few is the study by Shen et al. (2019). This is about a system that helps to modernize buildings. Because of the heterogeneity of real estate, it is difficult to determine the optimal combination of measures, especially since such diverse and vague information as climate forecasts and life-cycle costs must be taken into account there. The authors applied their software to an old building at the University of Pennsylvania that needed energy retrofits. (Shen et al. 2019)

Furthermore, a study by Nesticò and Somma (2019) should be mentioned, which deals with historic preservation in historic buildings. In it, the authors compared the AHP, ELECTRE, TOPSIS, and VIKOR methods. As a result, the authors see that with AHP, the problem could be reduced to the essential components, and the problem could be solved more effectively. The authors point out that for a correct implementation of the hierarchical analysis algorithms, a rigorous selection of the evaluation criteria and sub-criteria, as well as the corresponding indicators, is essential. (Nesticò and Somma 2019)

D: Operations

As early as 1998, Peterson described a conceptual framework for the development of an enterprise-wide SDSS for housing companies. Peterson concluded at that time that real estate decisions could benefit significantly from systems that support spatial decisions—and there are many in real estate (Peterson 1998). Other authors limit their concepts to individual activities of real estate companies, e. g., risk management or marketing & sales (see below). However, neither company-wide nor specific systems have become common practice, so that most of the applications we present in this section are merely prototypes.

One of the systems that cover several life cycle stages is the DSS of Valverde (1999), which was mentioned above. It consists of sub models that cover some of the key real estate decisions, for example whether to sell a property or how to finance it (Valverde 1999). Zavadskas et al. (2010) take a different approach. Their system supports prospective buyers throughout the purchase process, including negotiating with the seller. Kaklauskas et al. (2013) present a crisis management model that spans different lifecycle phases. This is intended to identify and mitigate the effects of the recession on the construction and real estate sectors. To this end, the authors have established, among other things, a model for setting priorities and a model for determining project utilization levels. (Kaklauskas et al. 2013)

For real estate risk management, Lowe and Standard presented a dynamic financial analysis model that was actually in use at a reinsurance company as early as 1997 (Lowe and Stanard 1997). Valverde (2011) has also built a DSS for risk management in the real estate industry. This is a BI system, but nothing is known about its application in practice.

In a study from 2020, Gleissner and Oertel conceptualize a comprehensive DSS for risk management of real estate transactions. The authors emphasize the need for quantitative risk analysis and risk aggregation at the portfolio and company level. Among other things, they recommend that a DSS should be part of the risk management unit in any organization. (Gleißner and Oertel 2020) Parts of their concept are already implemented in the software of the German consulting company FutureValue.[10]

As mentioned above, there are quite a few DSS studies dealing with real estate selection. A few papers look at the selection decision from the other side, namely from the point of view of companies that want to offer real estate in the best possible way (Kaklauskas and Gikys 2005; Kaklauskas et al. 2001). Another study that should be mentioned is by Hossein et al. (2013) who describe the design of an expert system for real estate recommendations

[10] Source: http://www.futurevalue.de/

using fuzzy logic. Fuzzy logic is used instead of Boolean logic, and the system can derive the conclusions from user input and fuzzy inference processes. Moreover, fuzzy rules and the membership functions form the knowledge base of the system. (Hossein et al. 2013)

Other

In addition to the systems described above, there are other DSS on the market that were not developed specifically for the real estate industry, but can be used for decision-making problems of all kinds, regardless of the industry. These include general statistics, mathematics and simulation programs such as SAS[11] (Statistical Analysis System), R[12] and Anylogic[13]. There are also programs such as VisiRule[14], which can be used to develop your own DSS without having to write your own program code, or Decisi-o-rama[15], an open-source library for MAUT applications in the Python programming language.

Another category is formed by special OR software that can also be used for real estate management purposes. They cover the first two of the three generations described earlier; we could not find any standard software for the third generation. The majority seem to be systems that contain simple decision aids such as decision trees, SWOT analyses or scenario analyses. For the second-generation systems, the majority seems to be in the field of MAUT and especially AHP applications (for a comprehensive overview see Weistroffer and Li 2016). Examples are CEPA[16], MindView[17], WinDASI[18], Super Decisions[19], Workday Adaptive Planning[20], Expert Choice Comparion[21], GMAA[22], Visual PROMETHEE[23] and AHP Priority Calculator[24].

[11] Source: https://www.sas.com/en_us/home.html (accessed 13 June 2021).
[12] Source: https://www.r-project.org/ (accessed 13 June 2021).
[13] Source: https://www.anylogic.com/ (accessed 13 June 2021).
[14] Source: https://www.visirule.co.uk (accessed 23 April 2021).
[15] Source: https://github.com/j-chacon/decisi-o-rama (accessed 13 June 2021).
[16] Source: https://economics.uq.edu.au/cepa/software (accessed 23 April 2021).
[17] Source: https://www.matchware.com/swot-analysis-software (accessed 23 April 2021).
[18] Source: http://www.fao.org/policy-support/tools-and-publications/resources-details/en/c/1199436/ (accessed 23 April 2021).
[19] Source: http://www.superdecisions.com/ (accessed 23 April 2021).
[20] Source: https://www.adaptiveplanning.com/products/scenario-planning-software-what-if-analysis (accessed 23 April 2021).
[21] Source: https://www.expertchoice.com/comparion/applications/general-decision-making/ (accessed 23 April 2021).
[22] Source: http://mayor2.dia.fi.upm.es/dasg/gmaa (accessed 13 June 2021).
[23] Source: http://www.promethee-gaia.net/software.html (accessed 13 June 2021).
[24] Source: http://bpmsg.com/ahp-online-calculator/ (accessed 13 June 2021).

5. EVALUATION AND CONCLUSION

DSS have a long history, which is likely to continue for some time to come. As described in Section 2, business management tools have been developed for about 100 years to help people make decisions. One can identify three generations here according to the variety of decision objectives. In systems of the first generation, which still exists today, there is only one goal, e.g., profit maximization. This narrow view leads to application and acceptance problems in the real estate industry, because here many decisions are complex, do not have a mathematically determinable, optimal solution and concern several goals. The performance measurement systems, portfolio models, or analytical tools used in practice are often decision support systems or DSS in the broad sense, but not DSS as defined by Power et al. (2011), according to which such a system must be computer-aided to increase the user's effectiveness in making complex decisions.

Second-generation DSSs assist users in making decisions that have multiple attributes or where multiple goals are pursued in parallel. At their core, these are MADM and MODM systems, although there are a number of other useful decision aids and DSS, such as the well-known Balanced Scorecard. The third generation differs from the first two in that it explicitly incorporates human behavior. This is particularly important for decisions in the real estate industry, because here people make all important decisions and affect other people, especially those who live and work in the properties. We refer to the third generation systems as BOR-DSS, because it is characteristic that in this case known B(ehavioral) methods, e.g. debiasing, are combined with known OR methods, e.g. simulations.

A fourth generation is not yet in sight. For that, BOR is still too young, too little developed and too little applicable in practice. Moreover, for that, business administration is still far too much in a paradigm shift, where the replacement of the neoclassical paradigm of rational decision-making is in full swing, but a new one is not yet in sight. Behavioral economics, neuroeconomics, environmental economics, and other approaches have undoubtedly enriched business studies, but no approach has yet been able to provide a similarly comprehensive theory of individual and organizational decision behavior. Thus, DSS also lacks a clear direction in which to develop over the long term. In the short to medium term, the potential is probably highest in the area of BOR. There is still a great deal of research and development to be done here, as outlined by Greasley and Owen (2016), who provide a framework for this.

There are promising academic approaches to third-generation DSS. However, there is a lack of practically usable DSS, at least if one focuses on model-driven DSS as we do. According to Power's (2001) classification, as explained in Section 3, in addition to model-driven systems, there are communication-driven, data-driven, document-driven, and knowledge-driven systems. For all five types, there are possible applications and examples of use in the real estate industry.

This was the subject of the main part of this chapter. In section 4, we have shown that there are DSS for the entire life cycle of a property, covering perhaps not all, but all key decisions. There are particularly many systems for the first life cycle stages of market and site analysis, property development, and financing. For other stages, such as the construction phase, we were able to identify only a few DSS. However, this is also because technical decisions dominate over business decisions here and we did not consider systems for this.

Another finding from our research is that most of the DSS presented are (resp. have remained) prototypes. There are some tools used in practice, but these are mostly DSS of a simple nature or those that do not specifically address real estate business decisions with their many specifics. From our market studies conducted over the past 20 years (Lausberg and Scheer 2020; Lausberg and Krieger 2014; Lausberg 2010), we know that while the software packages available on the market help with decisions, they do not do so on the basis of models. Their focus is usually on solving functional tasks such as analyzing portfolios, accounting for rent receipts, planning maintenance, providing information relevant to decision-making, etc. Enormous progress has been made in this area in recent decades, thanks in part to digitization, which is encompassing all areas of life. However, this has not led to real estate management decisions being supported by a model-based DSS as a rule today. This can be seen in the example of feasibility studies. In itself, the decision between two or more properties lends itself perfectly to modeling, but when the programs popular in this part of the industry are analyzed, one finds that they do not include decision models. Thus, the discrepancy between the prototypes from academic studies and the standard programs used in the real estate industry is considerable. Decision makers are therefore usually forced to either read academic papers and adapt the prototypes to their own needs, or settle for the lack of decision support provided by of-the-shelf software. Most seem to take the second path!

These important findings answer the research question posed at the beginning. Undoubtedly, much has been achieved within the last 30 years, as a comparison with the overview article by Trippi (1990) shows. Nevertheless, much remains to be done. For the outlook, we try to answer two questions:

- What is inhibiting the development of DSS?
- What direction should DSS research and development take to improve decision quality in real estate?

On the first question: Most real estate decisions and all the really important ones, such as the one about buying a property, are human decisions. This distinguishes the real estate industry from many other industries where the optimal alternative can often be determined mathematically. For example, when planning a factory, a classic use case of OR, there are human concerns such as health and safety regulations to consider, but the main concern is that the machines produce optimal output. This makes support by a DSS relatively straightforward, even though the business problems to be solved can be mathematically complex. When planning a property, in contrast, determining the best solution requires a deep understanding of the behavior of the people in and around the property (from the decision maker to the potential tenants to the neighbors). Since human behavior is characterized not only by reason but also by intuition, preferences, and biases, a rational behavior model is not sufficient-and for good models of bounded rational behavior, our knowledge is not yet sufficient, which we see as the biggest obstacle. Technically, this is where MADM and MODM reach their limits. They are well suited for some decisions, but not for those that are too "fuzzy". For this, there are special DSS and AI tools that replicate the way the human brain works. Some further developments can be expected here in the future. Also, general technological progress (e.g., quantum computing) and the increasing user-friendliness of IT tools (e.g., in BI systems) should lead to better real estate DSS. However, we doubt that the greatest developmental step for real estate DSS will take place on the technical level because development of multi-attribute analysis methods is already relatively advanced (Arnott and Pervan 2016).

Instead, we expect that real estate DSS will benefit much more from a greater focus on behavioral research and development, whose potential is far from exhausted. To this end, we see the following need for research and development (cf. Krieger and Lausberg (2021, pp. 22-24)), which leads to the answer of the second question. We believe that it is important to advance DSS research and development along the following lines:

1) Explore the actual behavior of decision makers in more detail. This primarily requires interdisciplinary basic and applied research with contributions from business administration, psychology, sociology, neurology, and other disciplines. Furthermore, the research should be more realistic, for example working with experts instead of students as test persons and with real properties instead of made-up cases.

2) Find out more about decision-making processes in organizations. A process audit should first identify the places in the processes where decisions are made. This is not trivial because the people involved

are often unaware that a decision is being made. Then the actual decision-making behavior and the decision-making support must be analyzed. Only then, it is possible to proceed to the development or adaptation of DSS. (Power 2013, 115ff.)

3) Represent the decision situation more realistically. Many DSS assume an unrealistic decision situation. For example, they assume a situation of certainty, although there is uncertainty about future developments, which suggests a risk calculation. Or, they assume uncertainty even though there is complete uncertainty, which does not suggest conventional risk measurement.

4) Demonstrate the effectiveness of systems. In many DSS prototypes by academics, we have the impression that they achieve a mathematical but not an economic solution to a decision problem. Effectiveness is often neglected, such as the extent to which the use of a system creates a competitive advantage (Power 2013, p. 101). This can only be determined through applied, empirical research.

5) Further develop existing systems. Developing a DSS model or even a working prototype is already a major achievement from a scientific perspective. However, this is not sufficient for practical use. In this respect, we would like to see the developers of the many prototypes mentioned above continue their work consistently with the help of programmers, engineers, sales people and other experts. Furthermore, we hope that the existing standard programs will also be further developed—in this case, with the addition of decision support functions—in order to expand the range of DSS from a different direction.

However, research and development alone will not lead to a higher quality of management decisions in real estate. After all, there are already many tools on the market. But the tools must not only be improved, they must also be applied, and in our opinion, this is another problem. The acceptance of OR methods in the real estate industry and, thus, of many DSS is rather low. This is possibly due to a lack of knowledge about the possibilities, perhaps also due to the unwillingness of many real estate professionals to apply quantitative methods, but certainly also due to a lack of training in this field. Here, we see the professors and other teachers under obligation to strengthen the topics of decisions, decision support and decision support systems in teaching.

LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
BCG	Boston Consulting Group
BI	Business Intelligence
BIM	Building Information Modeling
BOR	Behavioral Operations Research
COPRAS	Complex Proportional Assessment
DA	Decision Aid
DSS	Decision Support System
ELECTRE	ELimination Et Choix Traduisant la REalité
ERP	Enterprise Resource Planning
EVA	Economic Value Added
FM	Facility Management
FMCDM	Fuzzy Multiple Criteria Decision Making
GIS	Geographic Information Systems
HANS	Housing Analysis System
IT	Information Technology
LGD	Loss Given Default
MADM	Multiple Attribute Decision Making
MAUT	Multi-Attribute Utility Theory
MAVT	Multi-Attribute Value Theory
MCDA	Multiple Criteria Decision Analysis
MCDM	Multiple Criteria Decision Making
MCPL	Multiple Cue Probability Learning
MIS	Management Information System
MIVES	Integrated Value Model for Sustainable Assessments
MODM	Multiple Objective Decision Making
MOORA	Multi-Objective Optimization on The Basis of Ratio Analysis
MOPSO	Multiobjective Particle Swarm Optimization
OCR	Optical Character Recognition
OLAP	Online Analytical Processing
OR	Operations Research
PD	Probability of Default
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluations
RICS	Royal Institution of Chartered Surveyors
ROCE	Return on Capital Employed

ROI	Return on Investment
SAS	Statistical Analysis System
SAW	Simple Additive Weighting
SDSS	Spatial Decision Support System
STEM	Step Method
SWOT	Strengths, Weaknesses, Opportunities and Threats
TOPSIS	Technique for Order Preference by Similarity to Ideal Situation
VIKOR	Multi-criteria Optimization and Compromise Solution

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