WORKING PAPER SERIES

# Artificial Intelligence and Fuzzy Logic in modern Human Resource Management

Thomas Spengler/Tobias Volkmer/Sebastian Herzog

Working Paper No. 10/2023

OTTO VON GUERICKE
UNIVERSITÄT
MAGDEBURG

FACULTY OF ECONOMICS
AND MANAGEMENT

Impressum (§ 5 TMG)
*Herausgeber:*
Otto-von-Guericke-Universität Magdeburg
Fakultät für Wirtschaftswissenschaft
Der Dekan

*Verantwortlich für diese Ausgabe:*
T. Spengler, T. Volkmer, S. Herzog
Otto-von-Guericke-Universität Magdeburg
Fakultät für Wirtschaftswissenschaft
Postfach 4120
39016 Magdeburg
Germany

http://www.fww.ovgu.de/femm

*Bezug über den Herausgeber*
ISSN 1615-4274

**Artificial Intelligence and Fuzzy Logic in modern Human Resource Management**

Thomas Spengler, Tobias Volkmer and Sebastian Herzog [1]

Abstract

The corporate environment is always characterized by a high degree of volatility, uncertainty, complexity and ambiguity. These aspects influence Human Resource Management (HRM) just like other areas of the company. In the context of decision problems, especially in HRM, it is not always possible to specify all the considered variables precisely. A suitable instrument to deal with such fuzzy conditions is Fuzzy Logic (FL).

This paper aims to give insights into this field and its possible applications in HRM. For this purpose, selected theoretical foundations from the areas of HRM, FL and Artificial Intelligence (AI) are presented first. Based on this, situations in HRM are shown in which it can be useful to include FL in decision calculations. These concern e.g. problems of personnel allocation or considerations on the segmentation of labor forces. The paper is aimed at both practitioners and scholars.

JEL: A20, A22, A23, C60, C61, C63, J21, J23, M12, M21, M51

Keywords: Artificial Intelligence, Data Mining, Demography Sensitive Personnel Policy, Digitization, Fuzzy Expert Systems, Fuzzy Logic, Fuzzy Scenarios, Human Resource Management, Leadership Styles, (Meta-)Heuristics, Simulation

---

[1] Thomas Spengler, Prof. Dr., thomas.spengler@ovgu.de; Chair of Management and Organization, University of Magdeburg, P.O. Box 4120, 39016 Magdeburg (Germany), Phone: +49 391 67 58440; Tobias Volkmer, Dr., Otto-von-Guericke-Straße 54, 39104 Magdeburg (Germany), Phone: +49 151 5154764775; Sebastian Herzog, M. Sc., sebastian.herzog@ovgu.de; Chair of Management and Organization, University of Magdeburg, P.O. Box 4120, 39016 Magdeburg (Germany), Phone: +49 391 67 52626.

# Contents

# 1. Introduction

Many countries and companies are currently and prospectively facing serious, sometimes turbulent changes in their socio-cultural, technological, legal-political and economic surrounding systems (Farmer/Richman 1970). Among others, these include demographic, information technological, value configurational or market structural shifts. Therefore, human resource management (HRM) has to deal with e.g. immense changes in age and qualification structures, increasing desire for work-life balance as well as decreasing employees´ career orientation. The surrounding systems represent a so-called VUCA environment, which means that they are highly volatile, uncertain, complex and ambiguous (Bennett/Levoine 2014, Mack/Kare 2016), so that intuition and sure instinct are not sufficient, but above all (economically) rational management is necessary. This requires methodologically well-engineered and scientifically sound procedures. Thus, mechanical instruments must increasingly be properly combined with human intelligence, i.e. artificial intelligence (AI) must be used.

In addition, the underlying logic should be multi-valued and not two-valued (true/false). Fuzzy logic (FL) is one of multi-valued logic approaches. The core of this article is the intersection of ① Human Resource Management,② Artificial Intelligence and ③ Fuzzy Logic. Consequently, three research fields can be considered as three disjoint sets ④ - ⑥ and four intersections ⑦ - ⑩. These ten sets are shown in the Venn diagram in fig. 1:

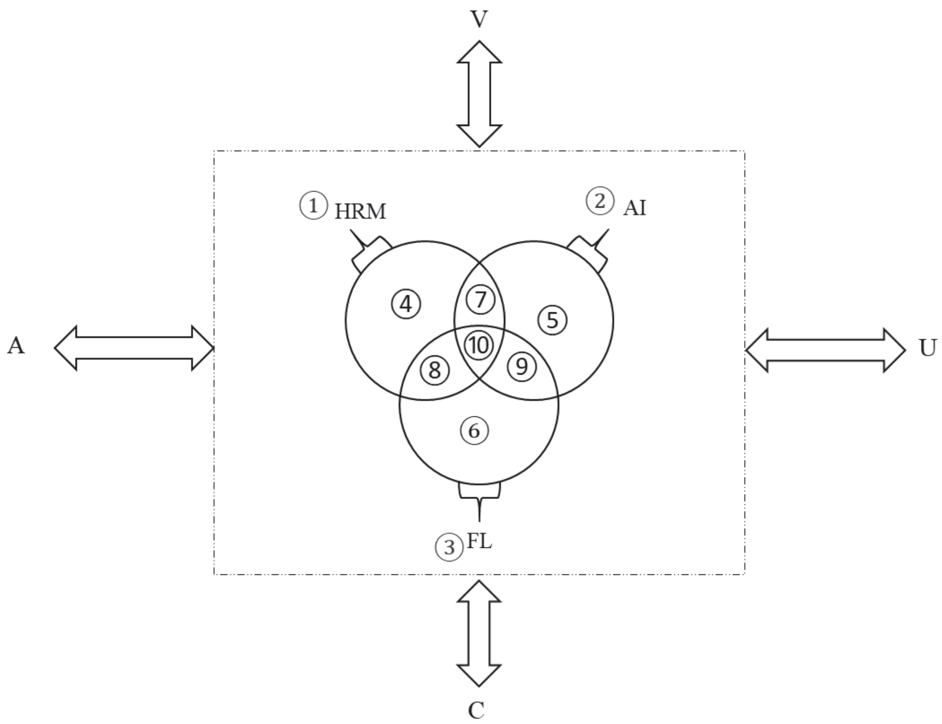


*Figure 1: Venn-Diagram of HRM, AI und FL under VUCA conditions*

In the following sections we mainly consider the sets ① - ③ and the intersection ⑩ due to capacity restrictions. In doing so, we are addressing a complex of problems that is not only urgent and challenging for business practice in the present, but also will be in the future.

## 2. Methodical and Systematical Basics of HRM, AI and FL

### *2.1. Human Resource Management (HRM)*

In our understanding, HRM serves to cope with two central problems, to attain and ensure the availability and functionality of personnel (Siegling et al. 2023a). The first problem deals essentially with covering concrete or abstract personnel demands, whereas the second is about the implementation or enforcement of expectations on personnel behavior. Personnel planning methods deal with availability problems, whereas functionality problems are faced within leadership. In personnel planning, three problem fields must be coordinated: personnel demands, personnel and personnel assignment. We understand personnel (demand) as type and number of available (required) employees, and assigned personnel as the number of employees of type $r$ who cover personnel demands of type $q$. We define the following symbols:

$Q \coloneqq \{q | q = 1,2, \dots, \overline{Q}\}$ set of personnel demand types, e.g. categories of jobs

$R \coloneqq \{r | r = 1,2, \dots, \overline{R}\}$ set of personnel types, e.g. categories of qualifications

$R_q \coloneqq \{r |$personnel types $r$ are capable of covering personnel demand type $q \in Q\}$

$Q_r \coloneqq \{q |$personnel demand type $q$ can be covered by personnel type $r \in R\}$

$PD_q \coloneqq$ personnel demand of type $q \in Q$

$P_r \coloneqq$ personnel of type $r \in R$

$AP_{rq} \coloneqq$ assigned personnel of type $r \in R$ for covering personnel demand of type $q \in Q_r$

$\mathfrak{P} \coloneqq$ power set

$\emptyset \coloneqq$ empty set

The explicit or implicit approach of personnel planning can be applied to coordinate these three problem fields (Siegling et al. 2023a). The explicit approach explicitly takes into account the assignment of personnel and ensures that the personnel demands are exactly covered by the assigned personnel (1) and that the number of assigned personnel cannot be greater than the personnel (2):

$$PD_q = \sum_{r \in R_q} AP_{rq} \;\; \forall \, q \in Q \qquad (1)$$

$$\sum_{q\in Q_r} AP_{rq} \leq P_r \; \forall \, r \in R \tag{2}$$

The so-called implicit approach does not explicitly consider the assignment of personnel, but only implicitly. At least one permissible personnel schedule can be derived from it (if there exists one at all). It requires that every partial personnel demand and any combination of partial personnel demands can at least be covered by sufficiently suitable employees (3):

$$\sum_{q\in Q^*} PD_q \leq \sum_{r\in \bigcup_{q\in Q^*} R_q} P_r \; \forall \, Q^* \in \mathfrak{P}(Q)\backslash\emptyset \tag{3}$$

Regarding leadership, instruments of directing, assessing and compensating personnel behavior are applied (Siegling et al. 2023a). Directing is primarily about formulating explicit or implicit behavioral norms (keyword: delegation problems, Bendor et al. 2001) and supporting employees adequately in performing their tasks. When assessing behavior (Roos et al. 2004), the desired and actual employees´ behavior is to be compared and, if necessary, deviation analyzes have to be conducted in order to determine the importance as well as the causes of and the person responsible for possible deviations. Behavioral compensation (Clark/Wilson 1961) means to formulate incentive systems containing incentives, reward criteria and criterion-incentive relationships.

### *2.2. Artificial Intelligence (AI)*

We want to keep the introduction to AI brief in this article and consider AI as an area in which, primarily, action and decision-supporting (often machine, computer-aided) systems are constructed in order to integrate human intelligence in the preparation and execution of decisions. Among others, these especially include so-called rule-based expert systems (Liao 2005, Tan 2017, Tan et al. 2016), whose development require not only decision theory but also concepts from mathematics and (often) computer science. In this context, rules are constructs of if-then relationships in which a conclusion is derived from one or more premises (inference). Therefore, the so-called modus ponens (Dubois/Prade 1991, Mamdani 1981, Zimmermann 1987) is often applied: $(a \wedge (a \Rightarrow b)) \Rightarrow b$, e.g. with

$a \coloneqq$ an employee is motivated

$b \coloneqq$ an employee is productive

Read: An employee is motivated $(a)$ AND IF an employee is motivated, THEN he or she is productive $(a \Rightarrow b)$ so the employee is productive $(\Rightarrow b)$.

In addition to a suitable inference mechanism, an appropriate database for $a$ and $b$ is needed in order to be able to measure and assess the level of motivation and productivity, whereby these represent crisp values in classical systems.

In addition, among others, Chatbots, Machine Learning, Artificial Neural Networks and Deep Learning also count as AI.

### *2.3. Fuzzy Logic (FL)*

We indicate above, that we often act in a VUCA world. This trend will increase rather than decrease in the future, so that the pressure to develop suitable instruments will also prospectively increase. In VUCA worlds, we are dealing with ambiguity. We want to distinguish ambiguity in the narrower sense from ambiguity in the broader sense (Metzger/Spengler 2019). Ambiguity in a broader sense concerns situations of uncertainty occurring in combination with situations of fuzziness. Traditional (economic) literature considers ambiguity in the narrower sense as indeterminacy concerning only the environmental forecast. In such situations is only known that one of several possible environmental states will occur, but it is unknown which one (Knight 1921). In situations of risk (complete ignorance), one can (not) assess their probability of occurrence.

Between these two extreme situations of uncertainty there is a number of other situations in which not totally nothing, but also nothing precise is known about the probabilities of occurrence (see e.g., Camerer/Weber 1992, Choquet 1954, Curley et al. 1986, Einhorn/Hogarth 1986, Ellsberg 1961, Fox/Tversky 1995, Franke 1978, Frisch/Baron 1988, Ghirardato et al. 2004, Gilboa/Marinacci 2016, Gilboa/Schmeidler 1989, Hurwicz 1951, Kahn/Sarin 1988, Kofler 2001, Kofler et al. 1984, Kunreuther et al. 1995, Schmeidler 1989, Slovic/Tversky 1974, Wald 1949). In such cases possibilities, beliefs, plausibilities, probability intervals or capacities have to be evaluated.

While in risk situations probability measures, which are based on restrictive $\sigma$-additivity conditions are applied, in mixed situations other measures based on the general $\lambda$-fuzzy measure (Sugeno 1974) are needed.

The $\lambda$-fuzzy measure $Fu_\lambda$ is defined on an algebra $\mathfrak{F}$, if $Fu_\lambda(A \cup B) = Fu_\lambda(A) + Fu_\lambda(B) + \lambda \cdot Fu_\lambda(A) \cdot Fu_\lambda(B) \quad \forall A, B \in \mathfrak{F}$ with $A \cap B = \emptyset, \lambda > -1$. It can be easily shown that for $\lambda > -1$ this is always a fuzzy measure, for $\lambda = 0$ additive and therefore a probability measure, for $\lambda < 0$ subadditive and for $\lambda > 0$ superadditive, for $\lambda \geq 0$ a belief measure and for $-1 < \lambda \leq 0$ a plausibility measure.

In cases of ambiguity in the narrow sense fuzzy measures are used to assess the future occurrence of events and therefore phenomena of uncertainty are considered. Whereas phenomena of fuzziness are concerned with the events themselves, e.g. when personnel demands are assessed as «high», a working time system as «appropriate», incentives as «motivating» or employees as «productive». These terms are considered as vague, imprecise or ambiguous. This is where the fuzzy set theory comes into play.

Let $X = \{x\}$ be a crisp set and $A$ be a subset of $X$ ($A \subseteq X$). In the classical view it can be clearly determined which elements $x \in X$ belong to $A$ and which do not.

The theory of fuzzy sets initiated by Zadeh (1965), which we will call the traditional fuzzy set theory, relaxes the construct of the crisp set based on bivalent logic.

In this context, a fuzzy set $\tilde{A}$ on $X$ is defined as a set of ordered 2-tuples $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\}$ with $\mu_{\tilde{A}}: X \to [0,1]$, where $\mu_{\tilde{A}}(x)$ describes the membership degree of element $x \in X$ to the fuzzy set $\tilde{A}$. An element $x$ cannot ($\mu_{\tilde{A}}(x) = 0$), can completely ($\mu_{\tilde{A}}(x) = 1$) or partly ($0 < \mu_{\tilde{A}}(x) < 1$) belong to the fuzzy set $\tilde{A}$. However, for crisp sets $\mu_A(x) \in \{0,1\}\ \forall x \in X$ applies to the membership degree. The approaches and concepts of FL became part of the standard repertoire of control engineering. In the future, they will have to be applied more and more in management sciences to meet the requirements of the VUCA world. This may lead to a better combination and coordination of human and artificial intelligence, since fuzzy calculations are common for human thinking.

People often think in terms of intervals, orders of magnitude and approximate figures rather than (seemingly) precise estimates (Albers 2000, Spengler/Vogt 2008, Vogt et al. 2001). These can be modeled (a) as so-called fuzzy numbers or fuzzy intervals or (b) in the form of so-called linguistic variables.

Ad (a): In fuzzy set theory, a fuzzy number $\tilde{Z}$ is defined as a (normalized, convex) fuzzy set whose membership function is continuous (at least piecewise) with only one (single) peak. Fuzzy intervals are characterized by several (and not just one) $x \in X$ with $\mu_{\tilde{A}}(x) = 1$. The graph of the membership function contains a plateau at the 1-level. For the practical handling of fuzzy numbers and intervals, their formulation and representation in *LR*-form is particularly useful, since they can be calculated easily. They are based on so-called left and right reference functions and are represented by the specification of three or four characteristic values. A *LR*-fuzzy number $\tilde{Z}$ is noted as $\tilde{Z} = (g, \underline{\alpha}, \overline{\alpha})_{LR}$ and a *LR*-fuzzy interval $\tilde{I}$ is noted as $\tilde{I} = (g_1, g_2, \underline{\alpha}, \overline{\alpha})_{LR}$, where for all elements $x = g$ and $x \in [g_1, g_2]$ the degree of membership equals 1. $\underline{\alpha}$ ($\overline{\alpha}$) symbolizes the left (right) spread around $g$ or $g_1$ respectively $g_2$ (see figure 2). In this context, a function $L: [0, \infty[\to [0,1]$ is called reference function of fuzzy numbers, if $L(0) = 1$ und $L$ is not rising in $[0, \infty[$. Often triangular fuzzy numbers and trapezoidal fuzzy intervals are used, where the left and right sides of the membership functions are linear. Thus, we receive reference functions of type $L\left(\frac{g-x}{\underline{\alpha}}\right) = max\left(0{,}1 - \frac{g-x}{\underline{\alpha}}\right)$ and $R\left(\frac{x-g}{\overline{\alpha}}\right) = max\left(0{,}1 - \frac{x-g}{\overline{\alpha}}\right)$ (see figure 2). For reference functions of *LR*-fuzzy intervals, analogous definitions apply. This results in the corresponding membership function $\mu_{\tilde{Z}}(x)$ for a *LR*-fuzzy number and $\mu_{\tilde{I}}(x)$ for a *LR*-fuzzy interval:

$$\mu_{\tilde{Z}}(x) := \begin{cases} L\left(\dfrac{g-x}{\underline{\alpha}}\right) & \text{if } x \leq g \\ R\left(\dfrac{x-g}{\overline{\alpha}}\right) & \text{if } x > g \end{cases} \quad \text{and} \quad \mu_{\tilde{I}}(x) := \begin{cases} L\left(\dfrac{g_1-x}{\underline{\alpha}}\right) & \text{if } x < g_1 \\ 1 & \text{if } g_1 \leq x \leq g_2 \\ R\left(\dfrac{x-g_2}{\overline{\alpha}}\right) & \text{if } x > g_2 \end{cases}$$

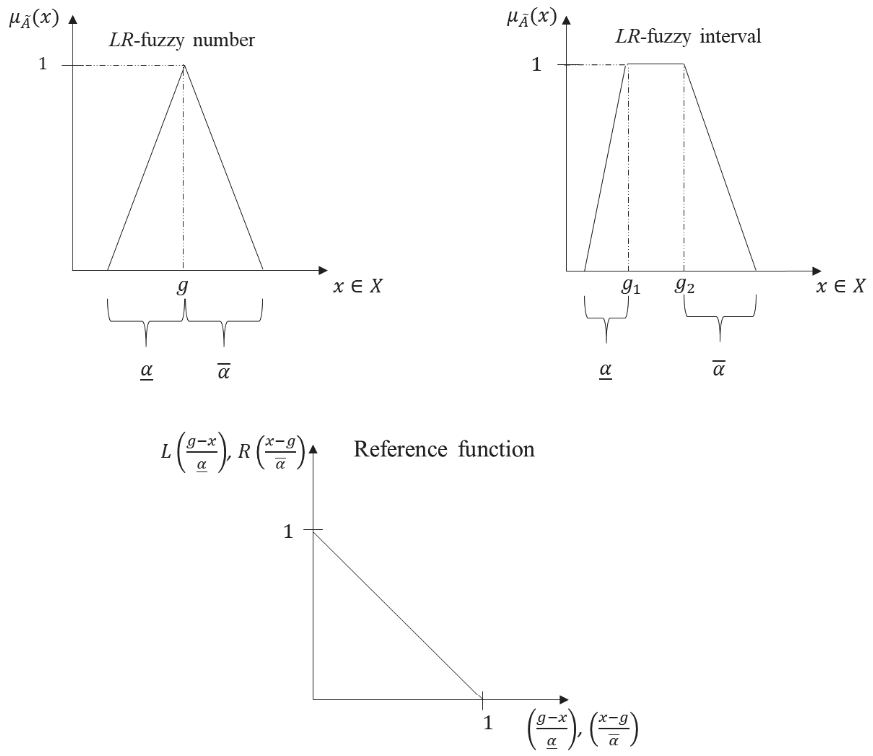


*Figure 2: LR-fuzzy number, LR-fuzzy interval and reference function*

Ad (b): Linguistic variables are quadruples, which include linguistic variables (e.g., productivity-enhancing roster, Wolbeck 2019), the corresponding underlying set (e.g., productivity values), the set of linguistic terms (e.g., «hardly», «halfway», «fairly», «very», «perfect»), and a semantic rule (which assigns a membership function to each linguistic term) (Zadeh 1988).

In addition to traditional fuzzy sets in the sense of Zadeh, the so-called intuitionistic fuzzy sets ($i$-fuzzy sets) proposed by Atanassov (1986) have expanded the fuzzy set theory in recent years and can be regarded as a promising further development. Intuitions are less about scientifically differentiated bases of estimations and justifications, but rather about afflatus or anticipated grasp (Metzger/Spengler 2019). While traditional fuzzy sets only use $\mu$ to assess the degree of membership of a set element, $i$-fuzzy sets also consider the difference $1-\mu$ in a more differentiated way. For each element of the underlying set ($x \in X$), in addition to the degree of membership $\mu(x)$, a degree of non-membership $\nu(x)$ and a degree of indeterminacy $\pi(x) = 1 - \mu(x) - \nu(x)$ are considered. The latter expresses to what extent one is unsure whether an element belongs to an $i$-fuzzy set or not. This creates considerably more possibilities for information differentiation than traditional fuzzy sets. These are particularly necessary in VUCA worlds, not least for uncertainty assessment. Therefore, $i$-fuzzy set theory, which is still in its relatively early stages of development, will also gain in importance in the future.

Methodologically, fuzzy mathematical optimization and, for reasons of practicability, fuzzy linear (FLP) or fuzzy mixed integer programming (FMIP) can be applied in HRM. In this regard, a wide range of solution methods exist (Ghanbari et al. 2020, Zimmermann 1978). FULPAL (fuzzy linear programming with aspiration levels) for single-objective and MOLPAL (multi-objective linear prgramming with aspiration levels) for multi-objective optimization, both designed by Rommelfanger (Rommelfanger 1989a, 1989b, 1990, 1996, Rommelfanger et al. 1989), are well suited for this purpose.

Here coefficients, right-hand sides and relations can be fuzzy. Let $x_j$ be the decision variable $j$, $\tilde{c}_j$ be the fuzzy objective function coefficient of the variable $j$, $\tilde{a}_{ij}$ be the fuzzy coefficient of the variable $j$ in constraint $i$, $\tilde{b}_i$ the fuzzy upper bound in the $i$-th constraint and $\tilde{\leq}$ the fuzzy smaller-equal-relation. Subsequently, the initial fuzzy model is e.g. formulated as follows:

$$\sum_j \tilde{c}_j \cdot x_j \rightarrow Max\ or\ Min! \tag{4}$$

subject to

$$\sum_j \tilde{a}_{ij} \cdot x_j \tilde{\leq} \tilde{b}_i \quad \forall i \tag{5}$$

$$x_j \geq 0 \quad \forall j \tag{6}$$

In this model, the values $\tilde{c}_j, \tilde{a}_{ij}$ and $\tilde{b}_i$ are fuzzy numbers or intervals of *LR*-type. Furthermore, the model is adaptable in several ways, e.g. by integration of crisp constraints and the use of (fuzzy) $\tilde{=}$- or $\tilde{\geq}$-relations. Moreover, it cannot be solved with the standard methods of linear optimization. Applying FULPAL, one has to formulate a compromise program. Additionally, suitable intermediate programs have to be solved, in which satisfaction with the overall solution is maximized and compliance with the constraints in the tolerance ranges is guaranteed. For reasons of space and simplification the algorithm is not shown in detail.

In addition to fuzzy optimization approaches, rule-based fuzzy expert systems (Arias-Aranda et al. 2010, Klir/Yuan 1995, Rajabi et al. 2019, Siler/Buckley 2005, Zadeh 1996) are also very well suited to solve (HRM) problems. Whereas in classical expert systems the conclusions and the input data represent crisp (monovalent, precise) values, in the fuzzy case at least the conclusions and possibly also the input data are fuzzy elements. The core of the system is formulated as follows: The system elements include at least two input variables and at least one output variable (in practical cases much more), which are formulated as linguistic variables. If the input variables are crisp, they have to be fuzzified first by determining the corresponding membership values.

Then they are processed in the inference component, which consists of the rule base, the inference mechanism and the linguistic output variables (including their membership functions). Only those rules whose if-component has a positive membership value contribute to the inference, so that the Degree of Fulfillment (DOF) is positive and thus the rule fires. Finally, the fuzzy output variables are defuzzified, if necessary, in order to obtain clear system results (e.g. recommendations for action). However, there are also cases in which the ambiguity of the inference result is deliberately retained and the defuzzification phase is omitted. For example, a fuzzy rule could be: IF the personnel demand is «medium» AND the productivity of the employees is «relatively low», THEN «quite a lot» employees should be provided. Depending on the case, the question of whether the recommendation to provide «quite a lot» employees should be defuzzified by the system or whether the interpretation should be left with the decision maker.

## 3. Selected Challenges and Methods of Fuzzy HRM

### *3.1. Fuzzy Scenario HRM*

In VUCA times, one is well advised to deal rationally with the economic environment also in HRM. For this purpose, an almost unmanageable number of methods have been developed in the last decades. In this context, the so-called scenario technique is not an isolated method but a toolbox consisting of a number of diverse instruments (Bradfield et al. 2005, Bishop et al. 2007, Chermack et al. 2001, Chermack, T.J./Lynham, S.A. (2002), Chermack/Swanson 2008, Clemons 1995, Dess et al. 2007, Godet 1987, 1995, 2001, Godet/Roubelat 1996, Grant 2008, Heijden 1996, 1997, 2000, Hill et al. 2016, Kluyver/Pearce II 2003, Lindgren/Bandhold 2003, Linnemann/Klein 1985, , McWhorter/Lynham 2014, Mietzner/Rieger 2005, Reibnitz 1995, Reibnitz/Hammond 1988, Roubelat 2000, Schoemaker/Heijden 1992, Spengler/Herzog 2023, Wack 1985a, 1985b, Wilson 1998). It is ultimately concerned with the creation of scenarios, where these are future development paths of data constellations relevant for decision-making (Georgantzas/ Acar 1995, Heijden 1997, 2000, Huss/Honton 1987, Kleiner 1999, Ringland 1998, Schoemaker 1993, 1995, Schwartz 1991, Simpson 1992). One usually follows these steps: First, one looks for the set of relevant impact factors for the field of investigation of interest (Reibnitz 1995). Since this set is usually very large, it is reduced to an operable set of descriptors by means of a so-called impact analysis (Gordon/Hayward 1968, Sarin 1978). These are then combined to so-called assumption bundles and analyzed for coherence by means of a consistency analysis (Kluyver/Pearce II 2003). In addition, the descriptors can be examined for cross impacts by probabilistic or possibilistic cross impact analyses (Helmer 1977, 1981, Weimer-Jehle 2006). Finally, cluster analyses are used to generate a set of scenarios comprising the worst case, the best case and one to three middle case scenarios.

In all areas univoke but also (which we recommend here) uncertain (De Kluyver/Moskowitz 1984) or fuzzy values (ambiguity in narrow sense and in broader sense) can be integrated. For example, so-called impact scores are determined in the course of the impact analysis. In the area of the labor market, these scores include wage conditions, labor supply, labor demand, personnel policy practices, but also gender, age, status or qualification structure. The impact score $b_{ij}$ then expresses how strongly factor $i$ influences factor $j$ (e.g., «1 = very low», «2 = low», «3 = medium», «4 = high» to «5 = very high»). Thus, $b_{ij} \in \{1,2,3,4,5\}$ applies. However, one could also use e.g. $b_{ij} \in [0,1]$. In FL, one would use a *LR*-fuzzy number, a *LR*-fuzzy interval, or a linguistic variable $\tilde{b}_{ij}$.

In the course of the consistency analysis, descriptors and the corresponding values must first be examined for consistency pairwise. For example, if three descriptors each have two values (e.g. «high», «low»; «strongly decreasing», «moderately increasing», etc.), six pairs of descriptors are obtained. These are then amalgamated into so-called acceptance bundles and also analyzed with regard to consistency. With fuzzy computing, the consistency values can be formulated as *LR*-fuzzy numbers or intervals (Dubois/Prade 1978, Spengler/Vogt 2008).

Modelling as linguistic variables is also possible, whereby the latter is particularly suitable for the construction of suitable fuzzy expert systems (Zadeh 1975, 1987).

### *3.2. Digitization as Future Technology for Fuzzy HRM*

3.2.1. Basics

We call things digital that are bit-coded, stored and distributed by computers (Vogelsang 2010). In this context, we can interpret the digitization at least as an action.

Under digitization we subsume all actions with the purpose to put things into a (partially) digital state. On the one hand, this can mean creating a digital version of something that already exists. On the other hand, it can also include the production of digital things without a non-digital counterpart. Both, (purely) digital technologies, such as big data applications or cloud computing (Armbrust et al. 2010), as well as semi-digital technologies, such as intelligent robotics or cyber-physical systems (Lee 2010; Anderl 2014), serve as tools in this context.

The digitization influences (a) HRM, (b) the implementation of FL in general and (c) its implementation in HRM in particular.

Ad (a): Due to the fact that many companies nowadays operate in a digital environment, decision fields in HRM (may) significantly change. On a political and legal basis, these changes refer to specific laws, ordinances, norms, etc., e.g. with regard to data protection, chronometry and chronology of working hours or the like.

The socio-cultural effects of digitization are reflected in possibly changing stakeholder needs and opportunities, such as the desire for digital customer service or teleworking. In addition, the needs or qualifications of (potential) workers in internal and external labor markets may vary and operational knowledge may be expanded by the development of digital technologies. For example, HR managers will (in the future) find themselves in situations in which teleworking through cloud solutions is technically feasible, legally permissible due to new legal situations, desired by employees and also economically reasonable through cost reductions with constant revenues.

Adjusted HRM goals and actions can therefore be derived from these changing conditions in a digital economic environment. Basically, the main purpose is still establishing and securing personnel availability and functionality by providing suitable actions of personnel planning and leadership. However, changes in personnel demands in quantitative, qualitative, local or temporal terms can result, for example, from the (partial) digitization of company service programs or the (positive) influence on productivity caused by the introduction of digital technologies. For example, the substitution of customer services by chatbots or increases in productivity through the complementary use of documentation software result in reductions of personnel demands. Digitization may also cause changing qualification profiles within the personnel and among workers in external labor markets. Regarding functionality goals, digitally supported behavior and the use of digital skills by workers can be increasingly expected. Due to the fact that in addition to such or similar changes in qualifications, behavioral demands on employees (can) also change, the actual use of digital technologies must be enforced and the use of digital skills must be encouraged within personnel management (keyword: digital leadership).

The current challenges of HRM therefore include the generation, evaluation and selection of suitable (digitally supported) personnel planning and leadership actions in order to deal economically rational with the above-described changes in decision fields.

Ad (b): Even if the implementation of fuzzy calculations does not generally require the support of digital technologies, their development has on the one hand contributed to the fact that these calculations can now be carried out with great complexity and often in a relatively short time. On the other hand, a.o. the generation, storage and evaluation of large amounts of data (in real time) enable an increased degree of precision regarding the detection of ambiguities within the company (environment).

Ad (c): The above-described potential changes in personnel demands, personnel and personnel assignment options as well as personnel behavioral demands are usually not unambiguously determinable, in terms of both their occurrence and their content. In this context, HRM decision problems under vagueness arise, for the solution of which fuzzy calculations are very well suited, due to their precise handling of ambiguities. In a sense, digitization creates a need for fuzzy calculations when solving HRM problems, but at the same time provides powerful tools for this purpose (see (b)). Accordingly, various fuzzy approaches for determining personnel demands, for estimating personnel movements, for formulating behavioral norms, for optimizing personnel assignments, etc. have been developed.

### 3.2.2. Data Mining in HRM

A phenomenon of advancing digitization is that during production processes, very large amounts of data are created intentionally or often even incidentally. In order to generate benefits from this usually disordered raw data, the so-called "data mining" has been developed, initiated by Agrawal et al. (1993). The term describes a number of methods that deal with the collection, clearing, processing and analysis of data as well as the derivation of meaningful findings from them (Aggarwal 2015). The term data mining is intended as metaphor to express that, similar to mining, one digs up “treasures” from a heterogeneous mass (here: unstructured data volume). Therefore, it is somehow about resolving or at least reducing the indeterminacy of the data.

In this context, data mining aims to derive relationships between the contained records (customers, employees, production processes, etc.) and their properties (or items, e.g. type and number of items purchased, qualifications, days off) from a data set. Essentially, the mining problem types Association Pattern Mining, Clustering, Classification and Outlier Detection have developed (see Aggarwal 2015).

Association Pattern Mining deals with the derivation of implications between individual properties or property bundles. First of all, the so-called support of property bundles has to be determined. The support provides information about the relative proportion of observations that contain the considered property bundle in the entire data set (Aggarwal 2015). Using the following symbols, we calculate the support of a property bundle as follows:

$D \coloneqq \left\{d \middle| d = 1, \dots, \overline{D}\right\} \coloneqq$ set of records

$I \coloneqq \left\{i \middle| i = 1, \dots, \overline{I}\right\} \quad \coloneqq$ set of items

$I^* \coloneqq \left\{i^* \middle| i^* = 1, \dots, \overline{I}^*\right\} \coloneqq$ set of item bundles

$I_{i^*} \coloneqq \{i|$ item $i$ belongs to item bundle $i^* \in I^*\}$

$k_{di} \coloneqq \begin{cases} 1, \text{ if record } d \text{ contains item } i \\ 0, \text{ else} \end{cases}$

$\sup(I_{i^*}) \coloneqq$ support of item bundle, with $\sup(I_{i^*}) \coloneqq \frac{|\{d | k_{di}=1 \ \forall \ i \in I_{i^*}\}|}{|D|} \quad \forall \ I_{i^*} \in \mathfrak{P}(I) \backslash \emptyset$

Example:

A supermarket studies the extent to which certain goods $i \in I \coloneqq \{i|i = 1, \dots, 10\}$ are purchased in combination by the supermarket's customers. For this purpose, different purchases $d \in D \coloneqq \{d|d = 1, \dots, 10\}$ are analyzed (see table 1):

| | $i = 1$ bread | $i = 2$ butter | $i = 3$ cheese | $i = 4$ sau-sage | $i = 5$ meat | $i = 6$ beer | $i = 7$ coke | $i = 8$ liquor | $i = 9$ potato chips | $i = 10$ eggs |
|---|---|---|---|---|---|---|---|---|---|---|
| $d = 1$ | × | × | × | × | | | × | × | × | × |
| $d = 2$ | × | × | × | × | × | × | × | × | × | × |
| $d = 3$ | × | | | × | × | × | × | × | × | × |
| $d = 4$ | × | × | × | | | × | × | × | × | × |
| $d = 5$ | × | × | | × | × | × | × | × | | |
| $d = 6$ | × | × | × | × | × | × | × | × | × | × |
| $d = 7$ | × | × | | × | × | × | × | | × | × |
| $d = 8$ | | × | × | × | × | | | | × | × |
| $d = 9$ | × | × | × | | | × | × | | × | × |
| $d = 10$ | × | × | × | × | × | × | × | × | × | × |

Legend: $\times :=$ purchase $d$ contains good $i$

*Table 1: Purchases and goods*

Specifically, the supermarket wants to examine the item bundle $i^* = 1$ and $i^* = 2$. The item bundle $i^* = 1$ contains alcoholic beverages and is composed as follows:

$$I_1 := \{i = 6, 8\}$$

The item bundle $i^* = 2$ consists of animal products and contains the following items

$$I_2 := \{i = 2, 3, 4, 5, 10\}$$

In order to determine the support of the two item bundles, the number of purchases containing all goods of the item bundle must be set in relation to the total number of purchases:

$$\sup(I_1) := \frac{|\{d | k_{di} = 1\ \forall\ i \in I_1\}|}{|D|}$$

The set $\{d | k_{di} = 1\ \forall\ i \in I_1\}$ consists of all purchases $d$ where $k_{d6} = k_{d8} = 1$. These are all purchases that contain at least the items beer ($i = 6$) **and** liquor ($i = 8$). Consequently:

$$\{d | k_{di} = 1\ \forall\ i \in I_1\} = \{d = 2, 3, 4, 5, 6, 10\}$$

$$\sup(I_1) := \frac{|\{d = 2, 3, 4, 5, 6, 10\}|}{|D|} = \frac{6}{10} = 0.6$$

$$\sup(I_2) := \frac{|\{d | k_{di} = 1\ \forall\ i \in I_2\}|}{|D|}$$

The set $\{d | k_{di} = 1\ \forall\ i \in I_2\}$ consists of all purchases $d$ where $k_{d2} = k_{d3} = k_{d4} = k_{d5} = k_{d10} = 1$. These are all purchases that contain at least the items butter ($i = 2$), cheese ($i = 3$), sausage ($i = 4$), meat ($i = 5$) **and** eggs ($i = 10$). Consequently:

$$\{d | k_{di} = 1\ \forall\ i \in I_2\} = \{d = 2, 6, 8, 10\}$$

$$\sup(I_2) := \frac{|\{d = 2, 6, 8, 10\}|}{|D|} = \frac{4}{10} = 0.4$$

The support results from the number of records that contain all items of the bundle $I_{i^*}$, divided by the total number of records in the data set (Aggarwal 2015). Thus, the support can be interpreted as the Bayesian a priori probability of the occurrence of the item bundle. The support is to be determined for all conceivable, non-empty item bundles (i.e. all elements of the power set of $I$ without the empty set).

By setting a minimum support $minsup$, we can determine the item bundles that appear sufficiently often in the data set. We refer to these as frequent patterns, frequent itemsets or large itemsets (Aggarwal 2015). The number of frequent itemsets $FI$ is defined as:

$$FI \coloneqq \{ I_{i^*} | \sup(I_{i^*}) \geq minsup\}$$

In order to derive association rules in form of implications from a data set, an additional measure called confidence is determined. Therefore, we consider two disjoint subsets $A$ and $B$ of any frequent itemset $I_{i^*} \in FI$ (with $A \cup B = I_{i^*}$ and $B = I_{i^*} \setminus A$) as well as the implication $A \Rightarrow B$. We designate the confidence $conf$ as the probability that if $A$ occurs, $B$ is also contained in an item bundle. Accordingly, the $conf$ of a rule $A \Rightarrow B$ is the conditional probability $conf(I_{i^*}|A)$, which can be calculated as follows (Aggarwal 2015):

$$conf(I_{i^*}|A) = \frac{\sup(I_{i^*})}{\sup(A)} = \frac{\sup(A \cup B)}{\sup(A)} \quad \forall\, I_{i^*} \in FI, A \subset I_{i^*} \text{ and } B = I_{i^*} \setminus A$$

Generally, we again formulate a bound $minconf$, in this case for the confidence. All implications $A \Rightarrow B$ with $\sup(I_{i^*}) \geq minsup$ and $conf(I_{i^*}|A) \geq minconf$ can then be determined as association rules.

We can formulate an algorithm for mining association rules in a very basic form, for example as follows:

1. $\sup(I_{i^*}) \coloneqq \frac{|\{d | k_{di}=1\ \forall\, i \in I_{i^*}\}|}{|D|} \quad \forall\, I_{i^*} \in \mathfrak{P}(I) \setminus \emptyset$

   [Determine the support $\sup(I_{i^*})$ for all logically possible item bundles $i^*$!]
2. $FI \coloneqq \{ I_{i^*} | \sup(I_{i^*}) \geq minsup\}$

   [Set a minimum support $minsup$ and determine the set of frequent itemsets $FI$!]
3. $conf(I_{i^*}|A) = \frac{\sup(I_{i^*})}{\sup(A)} = \frac{\sup(A \cup B)}{\sup(A)} \quad \forall\, I_{i^*} \in FI, A \subset I_{i^*}$ and $B = I_{i^*} \setminus A$

   [Calculate the confidence $conf(I_{i^*}|A)$ for all logically possible disjoint pairs of subsets $A$ and $B$ of all frequent itemsets $I_{i^*}$!]
4. $A \Rightarrow B \quad \forall\, I_{i^*} \in FI, A \subset I_{i^*}$ and $B = I_{i^*} \setminus A$, with $conf(I_{i^*}|A) \geq minconf$

[Set a minimum confidence $minconf$ and determine the implications $A \Rightarrow B$ for which $conf(I_{i^*}|A) \geq minconf$ holds!]

In the context of clustering problems, records are usually grouped regarding similar items via distance measures (clusters). Therefore, a.o. representative-based, hierarchical, probabilistic model-based, grid-based and graph-based algorithms have been developed (Aggarwal 2015). Classification approaches aim to assign individual records to previously defined groups with the help of decision trees, rule-based classifiers, probabilistic classifiers, neural networks, etc. (Aggarwal 2015). Outlier detection is used to identify abnormal records or items within a data set. This can be done, for example, with methods from the areas of extreme value analysis, probabilistic models, clustering for outlier detection, distance-based outlier detection or density-based methods (Aggarwal 2015).

Obviously, data mining approaches have great application potential in HRM. In terms of personnel planning, this occurs, for example, in the determination of the relationships between specific personnel assignments and productivity or absenteeism of employees, while in leadership a.o. the determination of specific employee groups and their typical characteristics can be interesting (for a literature overview on data mining applications in HRM, see Strohmeier/Piazza 2013 for more in-depth information).

### 3.2.3. Simulations in HRM

For the computationally supported handling of vague decision-making situations, o.a. belief judgments with regard to the occurrence of future states as well as assessments about (fuzzy) characteristics of the influencing variables that determine these states are required. In addition to others, simulation models are particularly suitable for forecasting these variables. In this article, we understand simulations to be the most realistic imitation of the (future) developments of a system (e.g. Banks 1998). The goal is therefore to determine alternative scenarios of (here: HRM) relevant data (constellations) or decision variables and their relationships to one another. Methodologically, we can differentiate between simulations based on deterministic or stochastic data and according to whether they are static (i.e. single-period or time-independent) or dynamic (i.e. multi-period or time-dependent). The latter a.o. is additionally separated in discrete and continuous simulation models. Discrete simulations allow system changes only at certain times (e.g. beginning or end of a period) or at the occurrence of certain events. In continuous simulations, however, system elements or relationships can change at any time. In the following, we want to give a selected overview of simulation applications in HRM.

The static-stochastic simulations include so-called Monte Carlo simulations, in which possible scenarios are generated by random sample experiments. These are very well suited, for example, to deriving probability statements about the suitability of workers or about the existence of certain qualifications among workers in the context of employee selection decisions. Markov chain models, on the other hand, belong to the stochastic, dynamic and discrete simulations. They are based on the assumption that the state changes of system elements occur as stochastic processes with transition probabilities. They are often applied to forecast changes in personnel demands or personnel. In this regard, o.a. probabilities that a task type will have to be carried out in a different department in the future or that an employee will change the personnel type in the following period have to be determined. We can formulate a simple Markov chain model using the following symbols to estimate the development of the personnel differentiated by various structural characteristics (like qualifications, department, length of service, etc.):

$I \coloneqq \{i | i = 1, \ldots, \overline{I}\}$ := set of structural characteristic combinations

$T \coloneqq \{t | t = 1, \ldots, \overline{T}\}$ := set of periods

$g_i^t$ := Difference from hiring and firing workers with structural characteristic combinations $i$ in period $t$

$\mathbf{g_t}$ := Vector of recruitment and layoffs in period $t$

$prob_{ij}$ := Probability for the transition of employees with structural characteristic combination $i \in I$ into the group of employees with structural characteristic combination $j \in I$

**Prob** := matrix of the transition probabilities

$P_i^t$ := personnel with employees with structural characteristic combination $i$ in period $t \in T$

$\mathbf{P_t}$ := vector of the personnel in period $t \in T$

The basic equation of the Markov chain model relevant here is:

$$\mathbf{P_t} = \mathbf{P_{t-1}} \cdot \mathbf{Prob} + \mathbf{g_t}$$

$$\text{with } \mathbf{P_t} \coloneqq \left(P_1^t, P_2^t, \ldots, P_i^t, \ldots, P_{\overline{I}}^t\right), \mathbf{Prob} \coloneqq \begin{bmatrix} prob_{11} & \cdots & prob_{1j} & \cdots & prob_{1\overline{I}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ prob_{i1} & \cdots & prob_{ij} & \cdots & prob_{i\overline{I}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ prob_{\overline{I}j} & \cdots & prob_{\overline{I}j} & \cdots & prob_{\overline{I}\overline{I}} \end{bmatrix}$$

and $\mathbf{g_t} \coloneqq \left(g_1^t, g_2^t, \ldots, g_i^t, \ldots, g_{\overline{I}}^t\right)$

In each period $t$, the vector of the personnel results from the vector of the personnel of the previous period $t-1$ multiplied by the matrix of the transition probabilities plus the vector of the recruitment and layoffs in period $t$. In relation to the reference period $t = 0$, we can also formulate the equation more generally:

$$\mathbf{P_t} = \mathbf{P_0} \cdot \mathbf{Prob}^{t} + \sum_{\tau=1}^{t} \mathbf{g_\tau} \cdot \mathbf{Prob}^{t-\tau}$$

Other types of simulation that are often used in (inbound) call centers to forecast personnel demands are queuing models, which simulate the number of customers in the system, their waiting times, etc. on the basis of various probability distributions.

### *3.3. (Meta-)Heuristics for Solution of Personnel Assignment Problems*

In the context of solving decision problems, the question regularly arises, which types of methods can be used. In our opinion, it is always a matter of finding the optimal solution to a decision problem from an economic point of view.

However, situations are conceivable in which finding the optimal solution is either not possible, e.g. in the absence of a suitable procedure, or can only be realized with a very high effort.

Under such circumstances, it can be useful to use (meta-) heuristics (De Landtsheer et al. 2018, Wolbeck 2019).

Heuristic procedures represent a collection of rules or steps that should lead to a good solution for decision problems. This solution may or may not be the optimal solution (Laguna/Marti 2013). Usually a heuristically determined solution deviates from the optimal solution. In literature, different categories of heuristic methods are classified. There are, for example, procedures that serve to obtain randomly generated initial solutions, which should reduce the solution space, or procedures of the so-called local search (Silver 2004).

In the local search, one investigates the neighborhood of an initial solution with regard to possible improvements of an objective function value. In cases where a solution determined in this way represents an improvement, this result will be accept as a new solution and its neighborhood will be examined. This scheme will continue until no further improvement is possible (Silver 2004). By means of the local search, one can generate a local optimal solution, but it is unclear whether this is also a global optimal solution. This problem arises because a deterioration of objective function values is not allowed when using the local search and so the search for a global optimum is not continued. Metaheuristics, in particular, deal with the prevention of being stuck in such a local optimum (Silver 2004).

Metaheuristics provide a problem-independent framework with a set of guidelines for developing heuristic optimization algorithms and applying them to specific problems (Sörensen/Glover

2013). Modern metaheuristics include e.g. the methods of Tabu Search or Simulated Annealing (Ernst et al. 2004). The family of metaheuristics also includes evolutionary algorithms (Kruse et al. 2016).

The following steps generally characterize the Tabu Search:

First, an acceptable solution for a decision problem is identified, this can be done e.g. with the help of so-called opening procedures (e.g. northwest corner rule). After the identification of a first solution, one generates neighborhood solutions by implementation of elementary transformations. In contrast to the classical local search, a Tabu Search allows a deterioration of the objective function value when one select a neighborhood solution. By using a tabu list, one can prevent that already identified solutions come into consideration as solutions again. This prevents the procedure from remaining in a local optimum (Silver 2004).

The user of the Tabu Search has to decide which stop criterion is decisive. For example, a fixed number of iteration steps or the predefined achievement of a certain objective function value may be considered as criterions for the end of execution the Tabu Search.

In the context of HRM, heuristic methods can also be used e.g. for the allocation of labor forces to further different objects. For example, heuristics exist which assign the best worker to each object or assign each worker to the object for which they are best suited. Allocation objects can be e.g. workplaces. Under certain circumstances, evaluation criteria regarding the quality of the allocation (e.g. the required execution time of a worker for an activity) cannot be clearly determined. One instrument for dealing with such uncertainties is FL.

A connection between heuristic procedures and FL is drawn, for example, in the duty scheduling of aircraft crews. In particular, fuzzy sets or linguistic variables are implemented here in the use of a "day by day" heuristic in order to obtain, among other things, a satisfactory solution for a rotation problem of pilot assignments (Teodorović/Lučić 1998).

A further field of application in terms of personnel planning is the recruitment of personnel. Thus, it is possible to plan the preparation and execution of so-called assessment centers with the help of heuristic procedures. Among other things, this involves planning the starting times for various tasks to be performed by the participants and the assignment of participants and observers to the tasks (Zimmermann/Trautmann 2018).

### *3.4. Demography Sensitive Personnel Policy*

Demography is a description of a population by means of characteristic features such as income, religion, age or qualifications of people. First, we want to show how demographic developments can influence HRM.

Demographic changes can affect, among other things, the (a) company´s personnel, but also (b) recruitment potential of companies.

Ad (a): The development of the operational personnel is determined by company decisions (e.g. ordered further training with resulting changes in qualification) and demographic changes. In the context, companies must question how the current personnel and structure will develop in the future. In answering this question, aspects may arise that neither are certain nor determined. In addition to (partly) directly observable variables, such as qualification, age, origin and gender, there are also only indirectly observable characteristics for demographic developments. Thus, motivational aspects can be identified as characteristic features of a population or, in our context, a workforce. Basically, companies have to deal with the question how the motivation of their workforce will develop in the future. Due to the problem-inherent terminological fuzziness, e.g. «high motivation», and relational fuzziness, e.g. «employee A is more motivated than employee B», FL is a suitable instrument to deal with this vagueness. Accordingly, when considering current personnel and their future development, it is necessary to use suitable diagnostic and prognostic models that can handle uncertain and/or fuzzy aspects.

Ad (b): Demographic developments not only affect the company's internal workforce, but also the opportunities for recruiting employees. In principle, it makes sense to subdivide the overall labor market into sub-markets that are relevant for a company. Which sub-markets are relevant for a company depends, among other things, on the type of workers sought. Demographic aspects such as qualifications, age or the origin of the workforce can play a role here. Accordingly, demographic developments, e.g. changing fertility, mortality and migration rates, lead to changes in the sub-employment markets and consequently also in recruitment potential. Here, companies are usually also confronted with fuzzy conditions.

Under the aspect of changing personnel, it may be relevant to analyze them in terms of their structure and level. When looking at personnel, the question of segmentation arises. Various segmentation approaches have been developed for both personnel as well as for relevant external (sub-)labor markets. However, in addition to the basic segmentation, a decision must also be made regarding the assignment of employees to individual segments. As already mentioned, (e.g.) aspects such as qualification and motivation are usually characterized by a lack of clarity.

In principle, the segmentation of workers can only be done on the basis of a single criterion, e.g. the gender or age of individual workers. Thus, it may be conceivable to divide the entire workforce into the quantity of workers who are over 40 years old and the quantity of workers who are younger or equal to 40 years of age. In the case of segmentation that is subject to several, possibly fuzzy, criteria, it may be relevant to process these criteria in a rule-based system.

In the following, we want to illustrate the application of such a rule system with a simple example.

First, we define the following symbols:

$C \coloneqq \{c | c = 1, \dots, \overline{C}; c \text{ is a criterion}\}$

$SC^* \coloneqq \{sc | sc = 1, \dots, \overline{SC}; sc \text{ is a sub criterion}\}$

$L_{sc} \coloneqq \{l |\, l \text{ is linguistic term of sub criterion } sc \in SC^*\}$

$I \coloneqq \{i | i = 1, \dots, \overline{I}; i \text{ is a rule}\}$

$\mu_{sc}^{l}(x)$ := Degree of membership of an element $x$ to linguistic term $l$ of sub criterion $sc$

$X \coloneqq \{x | x \text{ is an element of the basic set}\}$

Experience or qualifications may be used as (possibly) relevant criteria for assigning a worker to a segment of the workforces. Under certain circumstances, the characteristics of individual criteria are determined by further sub-criteria, accordingly it can be advantageous to establish a criteria hierarchy.

For example, a criteria hierarchy for the mentioned problem can contain the two criteria "experience" ($c = 1$) and "qualification" ($c = 2$). As (possibly) relevant sub-criteria for a segmentation of the personnel age ($sc_1 = 1$) as well as seniority ($sc_1 = 2$) can be used. The qualification of employees can be determined, for example, by the criteria of the type of degree ($sc_2 = 1$, e.g. Bachelor's or Master's degree) or by considering the duration of the acquisition of a degree ($sc_2 = 2$).

We can formulate the following (exemplary) rule set for the criterion "experience" (see table 2). As an example, we define the set of linguistic terms for the sub-criteria $sc_1 = 1$ and $sc_1 = 2$ with $L_{sc_1=1} \coloneqq \{very\ young, young, old\}$ as well as $L_{sc_1=2} \coloneqq \{short, medium, long\}$.

| rule $i$ | IF… | AND… | THEN… |
|---|---|---|---|
| | age of the labor force | length of service of the labor force | experience of the labor force |
| 1 | very young | short | low |
| 2 | very young | medium | low |
| 3 | very young | long | medium |
| 4 | young | short | medium |
| 5 | young | medium | medium |
| 6 | young | long | medium |
| 7 | old | short | medium |
| 8 | old | medium | high |
| 9 | old | long | high |

*Table 2: Exemplary rule base for criterion „experience"*

The number of rules to be established in the exemplary presented rule set results from the combination of the set of sub-criteria $SC^*$ and the number of linguistic terms $|L_{sc}|$ to be considered for the respective criteria. Accordingly, $|I| = |L_{sc}|^{|SC^*|}$ gives the number of rules.

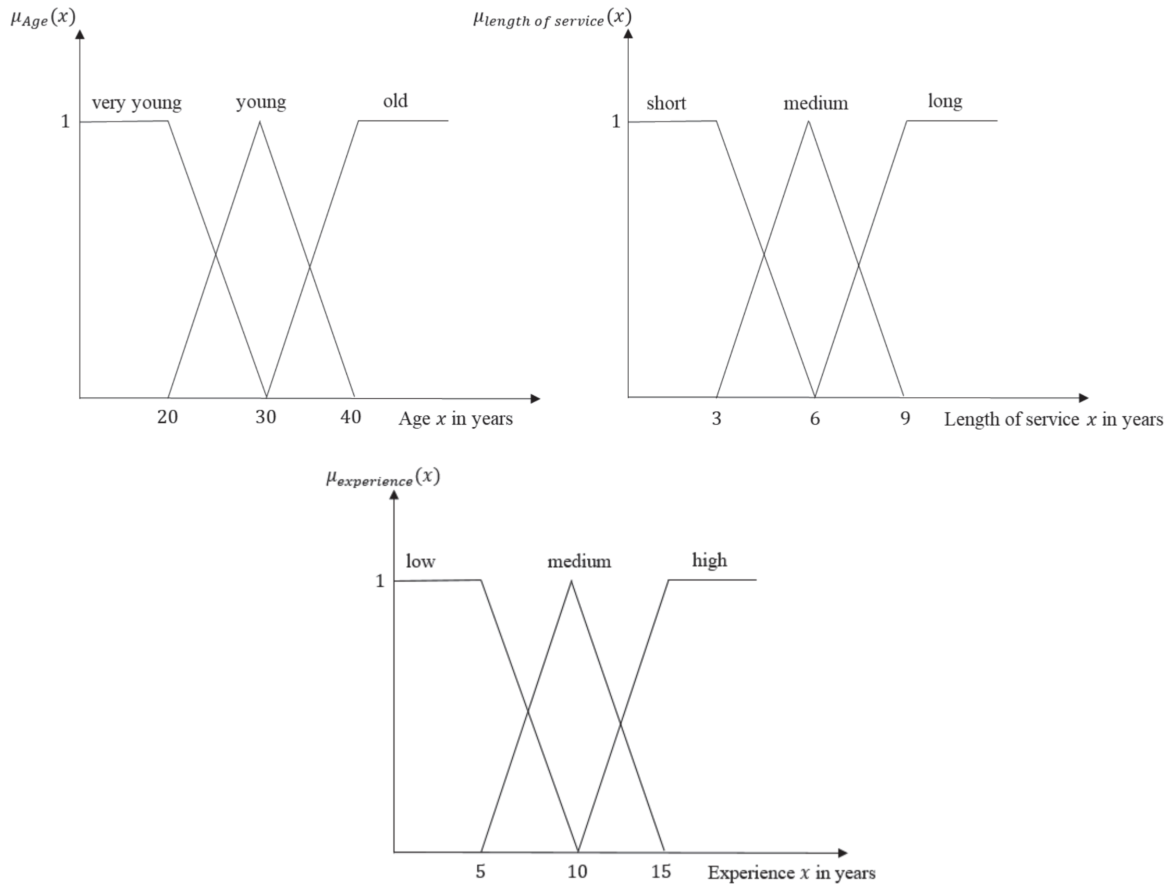


*Figure 3: Membership functions for selected criteria*

On the basis of a (e.g. crisp) input variable, membership values can be determined for the fuzzy sets of the linguistic variables "age" and "length of service". For this purpose, the decision maker defines membership functions in advance (see figure 3).

Based on this we can then fuzzify the input variables and determine the characteristics of the criterion "experience" on the basis of the so-called active rules in the rule set (see table 2).

For example, the input variable should assume a value of 26 years for age and 8 years for length of service. According to the linear membership functions shown in Figure 3, the following values result for the criteria age and length of service with the form $\mu_{sc} = (\mu_{sc}^{l})$:

$\mu_{Age} = (\mu_{Age}^{very\ young} = 0.4; \mu_{Age}^{young} = 0.6; \mu_{Age}^{old} = 0)$

$\mu_{length\ of\ service} = (\mu_{length\ of\ service}^{short} = 0; \mu_{length\ of\ service}^{medium} = 0.\overline{33}; \mu_{length\ of\ service}^{long} = 0.\overline{66})$

The so-called active rules can now be identified by looking at the determined degree of membership and the rule set. The result is that the rules $i = 2,3,5,6$ are active and have to be considered further.

By applying the (e.g.) minimum operator for linking fuzzy sets, the criteria "age" and "seniority" can be combined and thus the degree of fulfillment of an active rule ($DOF_i$) can be determined. The $DOF$ of inactive rules is always zero. Since several active rules lead to an identical expression of linguistic terms of the criterion "experience", the algebraic product can be used to determine the overall $DOF$ for just those rules:

$i = 2\text{:}\ \ DOF_2 = 0.\overline{33}$

$i = 3\text{:}\ \ DOF_3 = 0.4$

$i = 5\text{:}\ \ DOF_5 = 0.\overline{33}$

$i = 6\text{:}\ \ DOF_6 = 0.6$

$DOF_{total}(Low) = (1 - \left(1 - 0.\overline{33}\right)) = 0.\overline{33}$

$DOF_{total}(Medium) = (1 - (1 - 0.4) \cdot \left(1 - 0.\overline{33}\right) \cdot (1 - 0.6)) = 0.84$

$DOF_{total}(High) = 0$

We can thus state that, on the basis of the presented rule set, the defined membership functions and the exemplarily considered input values for age and length of service of a worker, the experience of that worker can be classified as «low» ($0.\overline{33}$) to a small degree and as «medium» (0.84) to a higher degree. This experience can then be processed in the hierarchy of criteria presented with the help of further rule sets in order to finally classify a worker in a segment of the personnel in order to serve further analyses.

In some cases, it might be desirable to derive a crisp result from the generated fuzzy output. Therefore, several defuzzification methods (e.g. Maxima or Distribution methods, Van Leekwijck/Kerre 1999) have been developed (See, inter alia, section 3.6.3 of the present paper and Spengler/Herzog 2023).

As already described above, demographic developments influence, among other things, personnel. In addition to structural and level changes, demographic aspects can also have an influence on absenteeism and/or fluctuation rates. It is also conceivable that personnel demands will change in the future. The personnel demands result from the three primary determinants working hours, company performance program and work productivity. In addition, secondary factors indirectly influence personnel demands via the primary determinants. These include, for example, supply and demand conditions on product and factor markets. Due to demographic developments, for example, it is possible that a currently high demand for various goods by consumers will dwindle in the future, resulting in a change in the company's product and service range (e.g. declining demand for DVD players).

### *3.5. Fuzzy Linear Personnel Allocation Planning*

In the following, we consider a decision-making situation in which fuzzy personnel demands differing in terms of type and time are to be covered by assigning sufficiently qualified employees who are not available yet in the company. Here, we concentrate on selected model components by only explicitly formulating the fuzzy constraints. We are searching for the minimum personnel costs (including optimal number of recruitments and layoffs) as well as optimal decisions about the personnel assignment. Employees are not always present (absenteeism) and the number of employees hired and fired is limited. Constraints are based on the explicit approach of personnel planning (Siegling et al. 2023a). The symbols are defined as follows:

<u>(Crisp) sets:</u>

$T \coloneqq \left\{t \middle| t = 1,2, \dots, \overline{T}; t \text{ is a period}\right\}$

$Q \coloneqq \left\{q \middle| q = 1,2, \dots, \overline{Q}; q \text{ is a job type}\right\}$

$R \coloneqq \left\{r \middle| r = 1,2, \dots, \overline{R}; t \text{ is a qualification type}\right\}$

$R_q \coloneqq \{r | \text{employees of type } r \text{ are capable of executing jobs of type } q \in Q\}$

$Q_r \coloneqq \{q | \text{jobs of type } q \text{ can be executed by employees of type } r \in R\}$

<u>(Fuzzy) data:</u>

$\widetilde{PD}_{qt} = (\underline{PD}_{qt}, \overline{PD}_{qt}, \underline{\alpha}_{qt}, \overline{\alpha}_{qt})_{LR} \coloneqq$ fuzzy personnel demand, $LR$-fuzzy interval with linear spreading (left and right)

$\widetilde{H}_{rt} = (H_{rt}, 0, \overline{\beta}_{rt})_{LR} \coloneqq$ fuzzy recruitment upper bound, $LR$-fuzzy number with linear right spreading

$\widetilde{F}_{rt} = (F_{rt}, 0, \overline{\delta}_{rt})_{LR} \coloneqq$ fuzzy layoff upper bound, $LR$-fuzzy number with linear right spreading

$\tilde{a}_{rt} = (\underline{a}_{rt}, \overline{a}_{rt}, \underline{\varepsilon}_{rt}, \overline{\varepsilon}_{rt})_{LR} \coloneqq$ fuzzy attendance rate, $LR$-fuzzy interval with linear spreading (left and right)

<u>Decision variables:</u>

$P_{rt} \coloneqq$ personnel of type $r \in R$ in period $t \in T$

$AP_{rqt} :=$ assigned personnel of type $r \in R$ for covering personnel demands of type $q \in Q_r$ in period $t \in T$

$h_{rt} :=$ number of employees of type $r \in R$ to be hired in period $t \in T$

$f_{rt} :=$ number of employees of type $r \in R$ to be fired in period $t \in T$

The objective function, which is not formulated here, aims to minimize the entire salary, recruitment and layoff costs. The set of constraints contains both fuzzy and crisp constraints. The latter are those for coordinating the assigned personnel and the personnel (second constraint of the explicit approach) and for periodically personnel updates as well as the non-negativity constraints for all variables. The fuzzy equation derived from the first constraint of the explicit approach for the coordination of personnel assignment and personnel demand, taking into account the fuzzy attendance rates, is formulated as follows:

$$\sum_{r \in R_q} \tilde{a}_{rt} \cdot AP_{rqt} = \widetilde{PD}_{qt} \; \forall \, q \in Q, t \in T \tag{7}$$

The following applies to the upper bound of recruitment and layoff:

$$h_{rt} \leq \widetilde{H}_{rt} \; \forall \, r \in R, t \in T \tag{8}$$

$$f_{rt} \leq \tilde{F}_{rt} \; \forall \, r \in R, t \in T \tag{9}$$

The constraints of type (7) have to be replaced by:

$$\sum_{r \in R_q} \tilde{a}_{rt} \cdot AP_{rqt} \gtrapprox \widetilde{PD}_{qt} \; \forall \, q \in Q, t \in T \tag{7a}$$

$$\sum_{r \in R_q} \tilde{a}_{rt} \cdot AP_{rqt} \lessapprox \widetilde{PD}_{qt} \; \forall \, q \in Q, t \in T \tag{7b}$$

This fuzzy model cannot be solved with the common methods of linear optimization. When using FULPAL (see 2.3 above), proceed as follows: If the bound $\underline{PD}_{qt}$ is undershot in constraint $(7a)$, this must be assessed. For this purpose, a further fuzzy set $\widetilde{N}_{qt}$ is introduced, whose membership function $\mu_{\widetilde{N}_{qt}}(\sum_{r \in R_q} \underline{a}_{rt} \cdot AP_{rqt})$ expresses the utility one gains when the quantity $\sum_{r \in R_q} \underline{a}_{rt} \cdot AP_{rqt}$ is used to cover $\widetilde{PD}_{qt}$. The utility value (membership value) equals zero if $\sum_{r \in R_q} \underline{a}_{rt} \cdot AP_{rqt} \leq \underline{PD}_{qt} - \underline{\alpha}_{qt}$ and it equals one if $\sum_{r \in R_q} \underline{a}_{rt} \cdot AP_{rqt} \geq \underline{PD}_{qt}$. In between it increases (e.g. linearly). Each constraint of type (7) is then substituted by a surrogate inequality of type $(10)$

$$\sum_{r \in R_q} (\underline{a}_{rt} - \underline{\varepsilon}_{rt}) \cdot AP_{rqt} \geq \underline{PD}_{qt} - \underline{\alpha}_{qt} \; \forall \, q \in Q, t \in T \tag{10}$$

as well as an objective function (11)

$$\mu_{\tilde{N}_{qt}}\left(\sum_{r\in R_q} \underline{a}_{rt} \cdot AP_{rqt}\right) \to Max! \tag{11}$$

With regard to (7b), (8) and (9) one proceeds analogously. Subsequently, this results in a multi-objective optimization program in which, subject to the above-mentioned constraints the original objective function and the objective functions for the constraints assessment are to be optimized. Ultimately, a model is constructed that is used to find the optimal compromise between satisfaction with constraints and minimization of personnel costs (see also Siegling et al. 2023a).

### *3.6. Fuzzy Leadership Style Choice*

3.6.1 Preliminary remarks

In personnel economics, the choice of a leadership style is about the question of how a supervisor should lead his or her employees in such a way that operational goals are achieved. In the present paper, we assume that such leadership decisions are made according to the situation. Thus, the optimal or at least a permissible leadership style has to be selected from a set of several possible leadership styles. For this choice a wide range of models has been developed in the scientific literature (see, inter alia, Blake/Mouton 1964, 1985, Blake et al. 1962, Hersey et al. 1996, Fiedler 1967, 1978 Reddin 1970) from which we want to pick out and focus on the so-called normative decision model by Vroom & Yetton (Jago/Ettling/Vroom 1985, Vroom/Yetton 1973). While the original model is based on univocal rules, in this paper we consider a fuzzy rule system (Siegling et al. 2023b).

3.6.2 Vroom & Yetton's normative decision model as a system of crisp rules[2]

The participation rate is the degree to which employees are involved in the decision-making process. Vroom & Yetton consider five leadership styles differentiated according to the participation rate ($I_1, I_2, \ldots, I_5$):

$I_1$:= The supervisor makes the factual decision alone, based on his current level of information.

$I_2$:= The supervisor makes the decision on the matter alone after obtaining information from the employees.

[2] We refer here to the basic model of Vroom & Yetton, for such situations, in which several coworkers are subordinate to the supervisor (Vroom/Yetton 1973)

$I_3$ := The supervisor makes the factual decision alone, after discussing the factual decision problem in individual meetings with the employees.
$I_4$:= The supervisor makes the factual decision alone, after discussing the factual decision problem with the group of employees.
$I_5$:= The supervisor presents the factual decision problem to the group of employees, everyone develops and evaluates alternative courses of action as a group and the group make a joint factual decision. The supervisor is an equal member of the group.

Provided that one accepts the participation rate as a differentiation criterion for leadership styles - and there is nothing seriously wrong with that - this leadership style list is quite reasonable. However, one misses the complete delegation to the body (without co-decision by the superior) and the possibility of obtaining information from other persons (than one's own employees).

The leadership situation is analyzed according to a total of seven criteria in question form, whereby these are recorded dichotomously in each case and are to be answered with "yes" or "no" ($J_1, J_2, \dots, J_7$):

$J_1$ := Is the quality of the decision important? (Note: Here we are asking about quality, not whether the decision itself is important).
$J_2$:= Does the supervisor feel sufficiently informed to make a quality factual decision?
$J_3$:= Does the supervisor think the factual problem is sufficiently structured?
$J_4$:= Is the acceptance of the factual decision on the part of the employees important for its implementation?
$J_5$:= Does the supervisor assume that a factual decision made in an authoritarian manner will be accepted?
$J_6$:= Will employees align their solution contributions with the organizational goal?
$J_7$ := Is it to be expected that employees will argue about the evaluation of the alternative actions?

The list of situation determinants can be accepted as reasonable, although the level of information of the employees, as provided for another model version by Vroom & Yetton (Vroom/Yetton 1973), but also the forecast qualification of employees and supervisors could be taken into account. Also, leadership costs and revenues are at best implicitly considered in both leadership styles and leadership situations. Moreover, the dichotomization of situation determinants is based on a simplifying and complexity-reducing assumption, which is removed in later work (Vroom/Jago 1988). With seven questions, each with two possible answers, there are a total of ($2^7 =$) 128 possibilities (leadership situations) for combining the answers (variations with repetition).[3]

For the purpose of leadership style selection, decision rules are to be applied. Vroom & Yetton propose the following seven decision rules ($DR_1, DR_2, \dots, DR_7$) in the version presented here, where ¬ symbolizes negation, ∧ logical and (both ... and) and → implication:

<u>$DR_1$ (Information rule):</u>[4] $J_1 \wedge \neg J_2 \rightarrow \neg I_1$

Note: This rule is undoubtedly plausible, because if decision quality is important but the supervisor is not sufficiently informed for a good factual decision, it makes no sense for him to decide based on his current level of information.

<u>$DR_2$ (Trust rule):</u> $J_1 \wedge \neg J_6 \rightarrow \neg I_5$

Note: This rule is also plausible to a certain extent, because if the quality of the decision is important but conflicts are to be expected among the employees about the factual decision to be made, they should not be allowed to participate in the decision if it is assumed that conflict resolution is not possible or at least not possible with reasonable effort. In principle, however, they can then be used in upstream stages of the decision-making process. The fact that conflicts can also have a negative impact in this process (e.g., through strategic information and consultation behavior) is apparently not considered relevant by Vroom & Yetton and therefore only $I_5$ is excluded here.

<u>$DR_3$ (Structure rule):</u> $J_1 \wedge \neg J_2 \wedge \neg J_3 \rightarrow \neg(I_1, I_2, I_3)$

Note: If the decision quality is important, but the supervisor is not sufficiently informed for a good factual decision and he considers the factual decision problem as unstructured, the supervisor should not decide authoritatively. This is plausible as far as it goes. Nor, according to Vroom & Yetton, should he or she seek advice in one-on-one meetings. That - as assumed by Vroom (1976) – $I_2$ and $I_3$ are always too cumbersome, ineffective and inefficient here is questionable and whether group discussions can make up for the deficits is at least worth discussing.

<u>$DR_4$ (Acceptance rule):</u> $J_4 \wedge \neg J_5 \rightarrow \neg(I_1, I_2)$

Note: If the acceptance of the factual decision on the part of the employees is important but it can be assumed that an authoritarian decision will not be accepted by them, then it is logical that neither of the two authoritarian leadership styles is chosen here.

---

[3] Siegling et al. (2023b) list all 128 possible combinations.

[4] Read: If question $J_1$ is answered yes and question $J_2$ is answered no, then do not choose leadership style $I_1$.

$DR_5$ (Conflict rule): $J_4 \wedge \neg J_5 \wedge J_7 \rightarrow \neg(I_1, I_2, I_3)$:

Note: If it is important that the employees accept the factual decision, but an authoritarian factual decision is not likely to be accepted by them and conflicts over the order of preference are to be expected, then there is a case for not selecting $I_1$, $I_2$ and $I_3$. Whether, in this case, $I_4$ is actually better than $I_3$ is at least debatable.

$DR_6$ (Fairness rule): $J_4 \wedge \neg J_5 \wedge \neg J_1 \rightarrow \neg(I_1, I_2, I_3, I_4)$

Note: Vroom & Yetton consider it fair if the employees in the group (co-)decide, if the acceptance of the decision is important, an authoritarian decision is probably not accepted but the quality of the decision is irrelevant. It remains to be seen whether every employee actually considers it fair when he or she is called upon to make qualitatively irrelevant decisions.

$DR_7$ (Acceptance prioritization rule): $J_4 \wedge \neg J_5 \wedge J_6 \rightarrow \neg(I_1, I_2, I_3, I_4)$

Note: Here, Vroom & Yetton apparently assume that only a group decision can eliminate the presumed conflicting goals. However, this assumption is also debatable.

It goes without saying that leadership style selection can be made on the basis of these seven rules - the first three of which relate to decision quality and the other four to decision acceptance - by analyzing the current leadership situation and then applying the corresponding rule(s).

### 3.6.3 The normative decision model of Vroom & Yetton as a fuzzy rule-based system

The initial model of Vroom & Yetton is based on Boolean (two-valued or binary) logic, which knows only two states, namely true or false, yes or no or 0 or 1. Thus an element $x$ belongs either completely (or completely not) to a set. For the membership value of such a crisp set $A$ holds $\mu_A(x) \in \{0,1\}$. In the context of the so-called fuzzy logic (Buckley/Eslami 2002, Gottwald 1993, Pedrycz 1993, Piegat 2001, Zadeh 1983, Zimmermann 1987, 1996) membership values can also be graduated, such that for the membership of an element $x$ to a fuzzy set $\tilde{A}$ $\mu_{\tilde{A}}(x) \in [0,1]$ holds (Bellmann/Zadeh 1970, Dubois et al. 2000, Dubois/Prade 1980, Pedrycz 1993, Piegat 2001, Wang/Chang 2000, Zimmermann 1996).[5] Since $\{0,1\} \subset [0,1]$ unambiguity is always a special case of fuzziness.

Crisp rule systems usually use the modus (ponendo) ponens as an inference rule (Dubois/Prade 1991, Mamdani 1981, Zimmermann 1987): it consists of (at least) two premises and one conclusion:

[5] See section 2.3 of this paper.

Premise 1: If $A$ then $C$

Premise 2: $A$ is present

Conclusion: It follows $C$

This inference mechanism is also used in fuzzy control systems:

Premise 1: If $\tilde{A}$ then $\tilde{C}$

Premise 2: $\tilde{A}$ is present

Conclusion: It follows $\tilde{C}$

In the context of fuzzy control (Driankov et al. 1993), linguistic variables (for $\tilde{A}$ and $\tilde{C}$) are often used. These represent quadruples (Dubois/Prade 1978, Spengler/Herzog 2023, Zadeh 1975, 1987). They consist of the name of the linguistic variable, of the set of linguistic terms, of the base set on which the linguistic variable is defined, and of a semantic rule that assigns a membership function to each linguistic term. The design of an expert system based on fuzzy rules (Hall/Kandel 1991, Zimmermann 1996) is basically carried out in three steps:

1. Step: Fuzzification of the rule input by constructing membership functions for the input variables.
2. Step: Fuzzy inference (Bouchon-Meunier 1991, Dubois/Prade 1991, Piegat 2001, Schneider/Kandel 1991, Yager 1991, Zadeh 1983) by formulating the rule base, applying the inference mechanism, and deriving the linguistic output variables (including construction of corresponding membership functions).
3. Step: Defuzzification of the fuzzy output

In the original model of Vroom & Yetton (1973), the leadership styles $I_1, I_2, I_3, I_4$ and $I_5$ are discretely differentiated. Such a differentiation can also be implemented in the context of a fuzzy rule system by taking the effectiveness expressions $\tilde{E}$ of the different leadership styles as fuzzy conclusion variables of the rules in the form of singletons.[6] In the present work, however, the aim is not to make a discrete but a continuous differentiation of leadership styles on the basis of a bipolar continuum of the participation rate ($x_{PR}$). At the poles of this continuum, $x_{PR} = 0$ (completely authoritarian leadership) and $x_{PR} = 1$ (complete delegation of factual decision-making) apply. The participation rate is used here as a linguistic variable with the linguistic terms *low*, *medium* and *high*.

[6] Singletons represent a special case of the FL: These are one-element fuzzy sets for whose membership value $0 < \mu_{\tilde{A}}(x^*) \leq 1$ holds (Piegat 2001).

In the original model (see chapter 3.6.2), the leadership situation is analyzed according to a total of seven determinants ($J_1, J_2, \ldots, J_7$) in the form of questions, each of which is recorded dichotomously and must be answered with "yes" or "no". $J_1$ is about the importance of the (factual) decision quality ($DQ$), $J_2$ about the adequacy of the superior's level of information ($ILL$), $J_3$ about the structuredness of the factual problem ($PS$), $J_4$ about the importance of the acceptance of an authoritative decision ($IAAD$), $J_5$ about the possibility of acceptance of an authoritatively made decision ($PAAD$), $J_6$ about the goal orientation of the employees ($GO$) and $J_7$ about the expectation of evaluation conflicts among the employees ($CE$). In the fuzzy rule model to be formulated here, the evaluation of the corresponding questions or, more precisely, their truthfulness or degree of truth $x_d \in [0,1]$ is not dichotomous, but in bipolar continua $x_{DQ}, x_{ILL}, x_{PS}, x_{IAAD}, x_{PAAD}, x_{GO}$ and $x_{CE}$.

We also model these as membership functions for the linguistic terms $l$ for criterion $d$ as follows (figure 4):

$$\mu_d^{low}(x_d) = \begin{cases} 1 \;\; for\ 0 \le x_d \le 0.25 \\ \frac{0.4-x_d}{0.15} \;\; for\ 0.25 < x_d \le 0.4 \\ 0 \;\; otherwise \end{cases} \tag{12}$$

$$\mu_d^{medium}(x_d) = \begin{cases} \frac{x_d-0.25}{0.25} \;\; for\ 0.25 \le x_d \le 0.5 \\ \frac{0.75-x_d}{0.25} \;\; for\ 0.5 < x_d \le 0.75 \\ 0 \;\; otherwise \end{cases} \tag{13}$$

$$\mu_d^{high}(x_d) = \begin{cases} \frac{x_d-0.6}{0.15} \;\; for\ 0.6 \le x_d \le 0.75 \\ 1 \;\; for\ 0.75 < x_d \le 1 \\ 0 \;\; otherwise \end{cases} \tag{14}$$

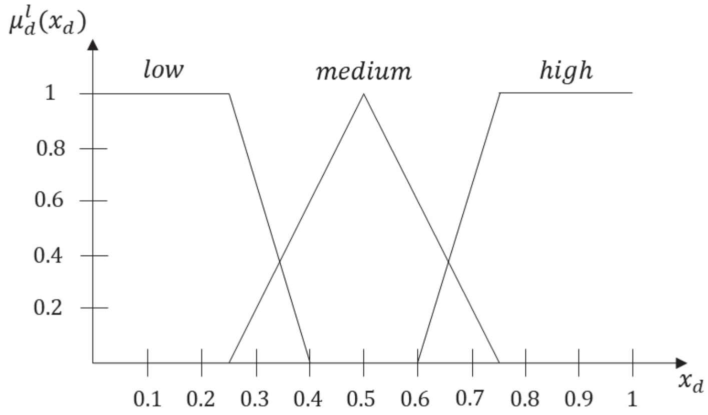


*Figure 4: Graphs of the membership functions*

We assume such shapes of the membership functions, although we can also model other (e.g., piecewise continuous, bell-shaped, and trapezoidal) ones.

For the purpose of leadership style selection, Vroom & Yetton bring a total of seven decision rules ($DR_1$, $DR_2$, …, $DR_7$) into play in the version presented in section 3.6.2. However, in the fuzzy rule system to be formulated here, these are not constructed as singular rules, but as rule blocks $DR_k$ $(k = 1, 2, \ldots, 7)$, each composed of several rules differentiated (according to the combinations of linguistic terms).[7] In the following, we use these symbols:

$\overline{K} \coloneqq \{k | k = 1, \ldots, K; k \text{ is a rule block}\}$

$\overline{M}_k \coloneqq \{m = M_{k-1} + 1, M_{k-1} + 2, \ldots, M_k \lceil m \in \overline{M}; m \text{ is a decision rule in block } k \in \overline{K}; M_0 = 0\}$

$\overline{M} \coloneqq \bigcup_{k \epsilon \overline{K}} \overline{M}_k$ (Set of all decision rules)

$\widetilde{PR}_k \coloneqq$ fuzzy participation rate of decision rule block $k$

$\widetilde{PR}_m^k \coloneqq$ fuzzy participation rate of decision rule $m \in \overline{M}_k$ in decision rule block $k \in \overline{K}$

$\widetilde{PR}_{total} \coloneqq$ total participation rate

$DOF_m \coloneqq$ Degree of fulfillment of decision rule $m \epsilon \overline{M}_k$ $(k \in \overline{K})$

$DOF_{total}^{l,k} \coloneqq$ Total degree of fulfillment of linguistic term $l$ in decision rule block $k \in \overline{K}$

**Decision rule block $k = 1$:**

The decision rule block $k = 1$ corresponds to the crisp information rule $DR_1$ from the basic model. This requires $J_1 \wedge \neg J_2 \rightarrow \neg I_1$. The fuzzy rule block $k = 1$ now demands:

$\widetilde{DQ} \wedge \widetilde{ILL} \rightarrow \widetilde{PR}_1$

**Decision rule block $k = 2$:**

The decision rule block $k = 2$ corresponds to the crisp confidence rule $DR_2$ from the basic model. This requires $J_1 \wedge \neg J_6 \rightarrow \neg I_5$. The fuzzy rule block $k = 2$, on the other hand, now requires:

$\widetilde{DQ} \wedge \widetilde{GO} \rightarrow \widetilde{PR}_2$

[7] The rule system formulated by Siegling et al. (2023b) comprises a total of 135 rules, which we cannot list individually here for reasons of limited space.

**Decision rule block $k = 3$:**

The decision rule block $k = 3$ corresponds to the crisp structure rule $DR_3$ from the basic model. This requires $J_1 \wedge \neg J_2 \wedge \neg J_3 \rightarrow \neg(I_1, I_2, I_3)$. The fuzzy rule block $k = 3$, on the other hand, now requires:

$\widetilde{DQ} \wedge \widetilde{ILL} \wedge \widetilde{PS} \rightarrow \widetilde{PR}_3$

**Decision rule block $k = 4$:**

The decision rule block $k = 4$ corresponds with the acceptance rule $DR_4$ from the basic model. This requires $J_4 \wedge \neg J_5 \rightarrow \neg(I_1, I_2)$. The fuzzy rule block $k = 4$, on the other hand, requires now:

$\widetilde{IAAD} \wedge \widetilde{PAAD} \rightarrow \widetilde{PR}_4$

**Decision rule block $k = 5$:**

The decision rule block $k = 5$ corresponds with the conflict rule $DR_5$ from the basic model. This requires $J_4 \wedge \neg J_5 \wedge J_7 \rightarrow \neg(I_1, I_2, I_3)$. The fuzzy rule block $k = 5$, on the other hand, requires now:

$\widetilde{IAAD} \wedge \widetilde{PAAD} \wedge \widetilde{CE} \rightarrow \widetilde{PR}_5$

**Decision rule block $k = 6$:**

The decision rule block $k = 6$ corresponds with the fairness rule $DR_6$ from the basic model. This requires $J_4 \wedge \neg J_5 \wedge \neg J_1 \rightarrow \neg(I_1, I_2, I_3, I_4)$. The fuzzy rule block $k = 6$, on the other hand, requires now:

$\widetilde{IAAD} \wedge \widetilde{PAAD} \wedge \widetilde{DQ} \rightarrow \widetilde{PR}_6$

**Decision rule block $k = 7$:**

The decision rule block $k = 7$ corresponds with the acceptance prioritization rule $DR_7$ from the basic model. This requires $J_4 \wedge \neg J_5 \wedge J_6 \rightarrow \neg(I_1, I_2, I_3, I_4)$. The fuzzy rule block $k = 7$, on the other hand, requires now:

$\widetilde{IAAD} \wedge \widetilde{PAAD} \wedge \widetilde{GO} \rightarrow \widetilde{PR}_7$

For the purpose of explanation and in order not to go beyond the scope, we show an example rule set from block $k = 1$ below:

Given two linguistic input variables and three linguistic terms each, there are a total of 9 rules $m \in \overline{M}_1$. These are, for example (see table 3):

| rule $m \in \bar{M}_1$ | $\widetilde{DQ}$ | $\widetilde{ILL}$ | $\widetilde{PR}_m^1$ |
|---|---|---|---|
| 1 | low | low | medium |
| 2 | medium | low | medium |
| 3 | high | low | high |
| 4 | low | medium | medium |
| 5 | medium | medium | medium |
| 6 | high | medium | high |
| 7 | low | high | medium |
| 8 | medium | high | medium |
| 9 | high | high | low |

*Table 3: Rule block 1*

For example, if $x_{DQ} = 0.7$ and $x_{ILL} = 0.3$, inserting in (12), (13) as well as (14) or from the graphs of the membership functions $\mu^l_{\widetilde{DQ}}$ and $\mu^l_{\widetilde{ILL}}$, it follows that rules 2, 3, 5 and 6 are active ($DOF > 0$) and the others are inactive ($DOF = 0$) (see figure 5).

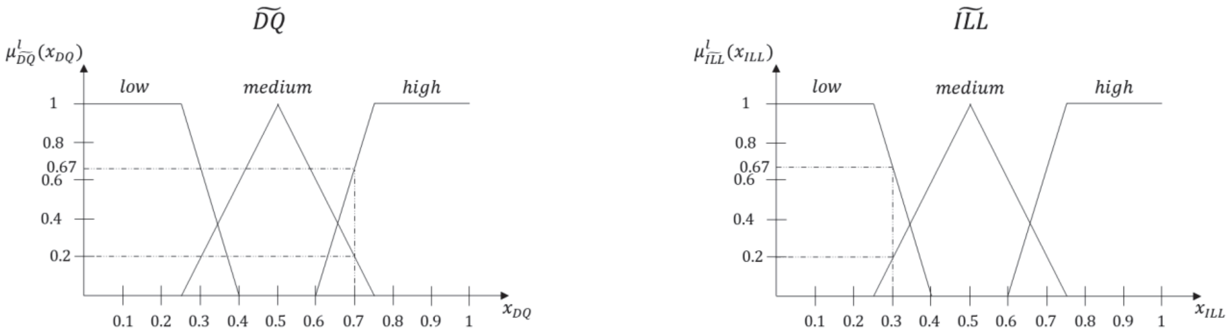


*Figure 5: Membership function of $\widetilde{DQ}$ and $\widetilde{ILL}$ of decision rule block $k = 1$*

After processing all (seven) rule blocks, the total output and the membership function of the total participation rate can be derived. In the example of Siegling et al. (2023b), the fuzzy output set is given by (see figure 6):

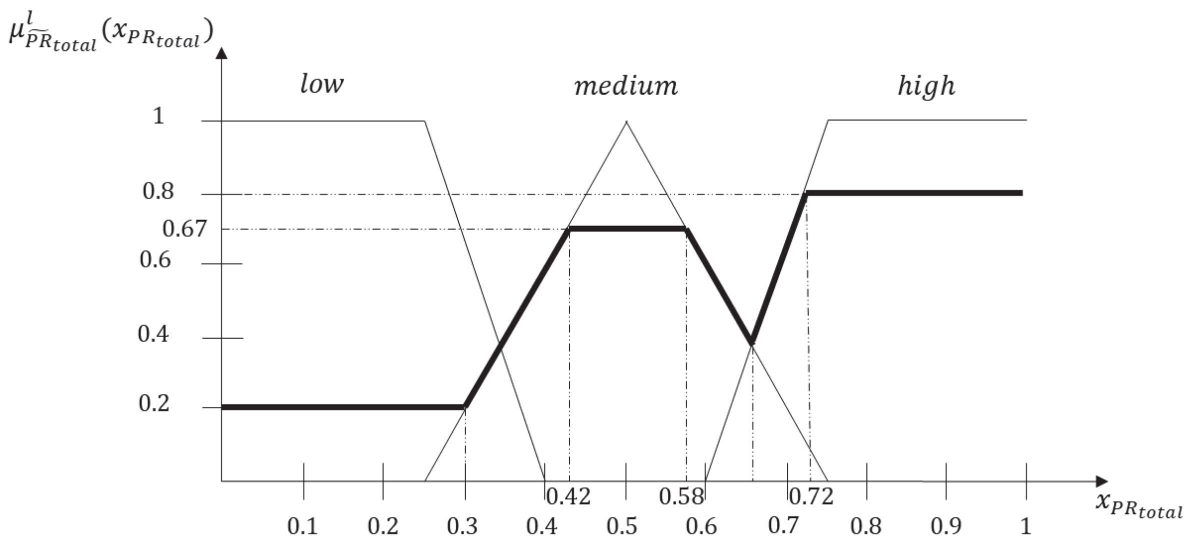


*Figure 6: Membership function of $\mu^l_{\widetilde{PR}_{total}}(x_{PR_{total}})$*

To obtain a precise conclusion, it may be useful to defuzzify the fuzzy total participation rate $\widetilde{PR}_{total}$. For this purpose – if one follows the Time Investment Model (Vroom/Yetton 1973) – various maximum methods can be considered (Piegat 2001, Spengler/Herzog 2023). If the first-of-maxima-method (respectively last-of-maxima-method) is chosen, for example, $x_{PR_{total}} = 0.72$ (respectively 1) see figure 27. On the other hand, if one follows the Time Efficient Model (Vroom/Yetton 1973), one would choose a minimum method: With the first-of-minimum method, $x_{PR_{total}}$ would be 0 in the above example and 0.3 with last-of-minimum-method.

However, in fuzzy control, the center-of-gravity-method is also frequently used. The center of gravity (*COG*) of an area can be understood as its center point. The *COG* of a membership function is the center of mass of the membership values. In order to compute centroids, one must determine first of all the contents of the area. As is well known, integral calculus is used for this purpose, especially for (at least partially) curved function graphs. For the exact procedure in detail, see e.g. Spengler/Herzog (2023). The *COG* of the cited example is shown in figure 7:

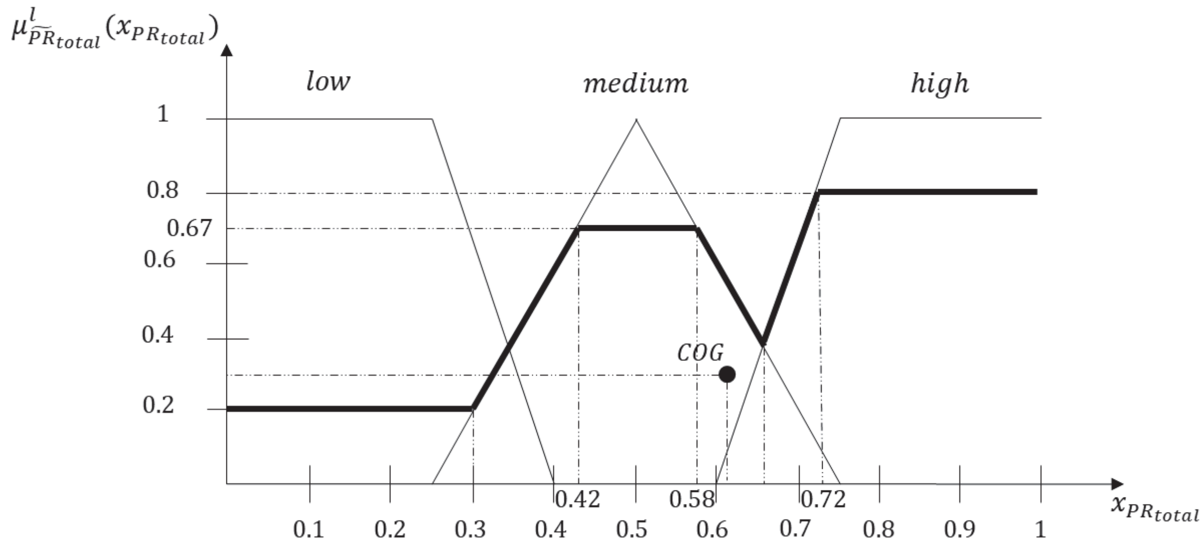


*Figure 7: Representation of the fuzzy output set and corresponding center of gravity*

$x_{cog} = 0.62$ can then be interpreted as the mean participation rate in the example.

## 4. Conclusions

If processing large amounts of data or considering particularly complex, dynamic and contingent environmental scenarios, if highly complex and complicated decision problems have to be solved and one has to search for hidden data, methods of AI and FL are necessary and have to be linked skillfully, effectively and efficiently with one another in HRM (An et al. 2007, Beynon 2009, Hüllermeier 2011, Kruse et al. 2000, Molina et al. 2019).

This connection is done via approaches, which have made amazing progress in recent years. However, as the corresponding problem pressure will increase immensely in the future due to a world that is constantly getting more global, more turbulent and is in some cases confronted with ever-increasing disruptions, the corresponding methods will have to be applied and further developed to an even greater extent.

## References

**Aggarwal, C.C. (2015):** Data mining: the textbook, Springer: New York et al.

**Agrawal, R./Imieliński, T./Swami, A. (1993):** Mining association rules between sets of items in large databases, in: Proceedings of the 1993 ACM SIGMOD international conference on Management of data, pp. 207-216.

**Albers, W. (2000):** The Theory of Prominence as a Tool to Model Boundedly Rational Numerical Decision Processing, in: Gigerenzer, G./Hammerstein, P./Selten, R. (Eds.): Bounded rationality: The Adaptive Toolbox Box, Dahlem Workshop Reports.

**An, A./Stefanowski, J./Ramanna, S./Butz, C.J./Pedrycz, W./Wang, G. (2007):** Rough Sets, Fuzzy Sets, Data Mining and Granular Computing, Springer: Berlin/Heidelberg.

**Anderl, R. (2014):** Industrie 4.0 - Advanced Engineering of Smart Products and Smart Production, in: Technological Innovations in the Product Development, 19th International Seminar on High Technology, Conference paper, Piracicaba: Brazil.

**Arias-Aranda, D./Castro, J.L./Navarro, M./Sánchez, J.M./Zurita, J.M. (2010):** A fuzzy expert system for business management, in: Expert Systems with Applications, Vol. 37, No. 12, pp. 7570–7580.

**Armbrust, M./Fox, A./Griffith, R./Joseph, A.D./Katz, R./Konwinski, A./Lee, G./Patterson, D./Rabkin, A./Stoica, I./Zaharia, M. (2010):** A view of cloud computing, in: Communications of the ACM, Vol. 53, No. 4, pp. 50-58.

**Atanassov, K.T. (1986):** Intuitionistic Fuzzy Sets, in: Fuzzy Sets and Systems, Vol. 20 No. 1, pp. 87-96.

**Banks, J. (1998):** Principles of Simulation, in Banks, J. (Ed.): Handbook of simulation: principles, methodology, advances, applications, and practice, pp. 3-30, John Wiley & Sons: Danvers.

**Bellmann R.E./Zadeh, L.A. (1970):** Decision-Making in a Fuzzy Environment, in: Management Science, Vol. 17, No. 4, pp. 141-164.

**Bendor, J./Glazer, A./Hammond, T. (2001):** Theories of Delegation, in: Annual Review of Political Science, Vol. 4, pp. 235-269.

**Bennett, N./Lemoine, G.J. (2014):** What a difference a word makes: Understanding threats to performance in a VUCA world, in: Business Horizons, Vol. 57, No. 3, pp. 311—317.

**Beynon, M.J. (2009):** Using Dempster-Shafer Theory in Data Mining, in Wang, J. (Ed.): Encyclopaedia of Data Warehousing and Mining, pp. 2011-2018, Information Science Reference: Hershey.

**Bishop, P./Hines, A./Collins, T. (2007):** The current state of scenario development: an overview of techniques, in: Foresight, Vol. 9, No. 1, pp. 5-25.

**Blake, R.R./Mouton, J.S. (1964):** The managerial grid, Gulf Publishing: Houston.

**Blake, R.R./Mouton, J.S. (1985):** The managerial grid III, 3rd edition, Gulf Publishing: Houston.

**Blake, R.R./Mouton, J.S./Bidwell, A.C. (1962)**: Managerial grid, in: Advanced Management-Office Executive, Vol. 1, No. 9, pp. 12-15.

**Bouchon-Meunier, B. (1991)**: Inferences With Imprecisions and Uncertainities in Expert Systems, in: Kandel, A. (Ed.): Fuzzy Expert Systems, pp. 43-54, CRC Press: London et al.

**Bradfield, R./Wright, G/Burt, G./Cairns, G./Van Der Heijden, K. (2005):** The origins and evolution of scenario techniques, in: Futures, Vol. 37, No. 8, pp. 795–812.

**Buckley, J.J./Eslami, E. (2002)**: An Introduction to Fuzzy Logic and Fuzzy Sets, Springer: Heidelberg/New York.

**Camerer, C./Weber, M. (1992):** Recent Developments in Modeling Preferences: Uncertainty and Ambiguity, in: Journal of Risk and Uncertainty, Vol. 5, No. 4, pp. 325-370.

**Chermack, T.J./Lynham, S.A. (2002):** Definitions and Outcome Variables of Scenario Planning, in: Human Resource Development Review, Vol. 1, No. 3, pp. 366-383.

**Chermack, T.J./Lynham, S.A./Ruona, W.E.A. (2001):** A Review of of Scenario Planning Literature, in: Futures Research Quarterly, Vol 17, No.2, pp. 7-32.

**Chermack, T.J./Swanson, R.A. (2008):** Scenario Planning: Human Resource Development's Strategic Learning Tool, in: Advances in Developing Human Resources*,* Vol. 10, No. 2, pp. 129-146.

**Choquet, G. (1954):** Theory of Capacities, in: Annales de l'institut Fourier, Vol. 5, pp. 131-295.

**Clark, P.B./Wilson, J.Q. (1961):** Incentive Systems: A Theory of Organizations, in: Administrative Science Quarterly, Vol. 6, No. 2, pp. 129-166.

**Clemons, E.K. (1995):** Using Scenario Analysis to Manage the Strategic Risks of Reengineering, in: Sloan Management Review, Vol. 36, No. 4, pp. 61-71.

**Curley, S.P./Yates, J.F./Abrams, R.A. (1986):** Psychological Sources of Ambiguity Avoidance, in: Organizational Behavior and Human Decision Processes, Vol. 38, No. 2, pp. 30-256.

**De Kluyver, C.A./Moskowitz, H. (1984):** Assessing scenario probabilities via interactive goal programming, in: Management Science, Vol. 30**,** No. 3, pp. 273-278.

**De Landtsheer, R./Delannay, G./Ponsard, C. (2018):** Dealing with Perceived Fairness when Planning Doctor Shifts in Hospitals, in: ICORES, pp. 320-326.

**Dess, G.G./Lumpkin, G.T./Eisner, A.B. (2007):** Strategic Management – creating competitive advantages, McGraw-Hill/Irwin: New York.

**Driankov, D./Hellendoorn, H./Reinfrank, M. (1993):** An Introduction to Fuzzy Control, Springer: Berlin/Heidelberg.

**Dubois, D./Ostasiewicz, W./Prade, H. (2000)**: Fuzzy Sets: History and Basic Notions, in: Dubois, D./Prade, H. (Eds.): Fundamentals of Fuzzy Sets, pp. 21-124, Springer: Boston et al.

**Dubois, D./Prade, H. (1978):** Operations on Fuzzy Numbers, in: International Journal of Systems and Science, Vol. 9, No. 6, pp. 613-626.

**Dubois, D./Prade, H. (1980)**: Fuzzy Sets and Systems: Theory and Applications, Academic Press: New York et al.

**Dubois, D./Prade, H. (1991):** Fuzzy sets in approximate reasoning, Part 1: Inference with possibility distributions, in: Fuzzy Sets and Systems, Vol. 40, pp. 143-202.

**Einhorn, H.J./Hogarth, R.M. (1986):** Decision Making under Ambiguity, in: Journal of Business, Vol. 59, No. 4, pp. 225–250.

**Ellsberg, D. (1961):** Risk, Ambiguity, and the Savage Axioms, in: The Quarterly Journal of Economics, Vol. 75, No. 4, pp. 643 - 669.

**Ernst, A.T./Jiang, H./Krishnamoorthy, M./Sier, D. (2004):** Staff scheduling and rostering: A review of applications, methods and models, in: European Journal of Operations Research, Vol. 153, No. 1, pp. 3-27.

**Farmer, R.N./Richmann, B.M. (1970):** Comparative Management and Economic Progress, 2nd ed., Bloomington (Ind.).

**Fiedler, F.E. (1967).** A theory of Leadership effectiveness, Mc. Graw-Hill Series in Management.

**Fiedler, F.E. (1978):** The contingency model and the dynamics of the leadership process, in: Advances in experimental social psychology, Vol. 11, pp. 59-112.

**Fox, C.R./Tversky, A. (1995):** Ambiguity Aversion and Comparative Ignorance, in: The Quarterly Journal of Economics, Vol. 110, No. 3, pp. 585-603.

**Franke, G. (1978):** Expected Utility with Ambiguous Probabilities and 'irrational' Parameters, in: Theory and Decision, Vol. 9, No. 3, pp. 267–283.

**Frisch, D./Baron, J. (1988):** Ambiguity and Rationality, in: Journal of Behavioral Decision Making, Vol. 1, No. 3, pp. 149-157.

**Georgantzas, N.C./Acar, W. (1995):** Scenario-Driven Planning: Learning to Manage Strategic Uncertainty, Quorum: Westport.

**Ghanbari, R./Ghorbani-Moghadam, K./Mahdavi-Amiri, N./De Baets, B. (2020):** Fuzzy linear programming problems: models and solutions, in: Soft Computing, Vol. 24, pp. 10043-10073.

**Ghirardato, P./Maccheroni, F./Marinacci, M. (2004):** Differentiating ambiguity and ambiguity attitude, in: Journal of Economic Theory, Vol. 118, No. 2, pp. 133-173.

**Gilboa, I./Marinacci, M. (2016):** Ambiguity and the Bayesian Paradigm, in Arló-Costa, H./Hendricks, V.F./Van Benthem, J. (Eds.): Readings in Formal Epistemology, pp. 385–439, Springer International: Cham.

**Gilboa, I./Schmeidler. D. (1989):** Maxmin expected utility with a non-unique prior, in: Journal of Mathematical Economics, Vol. 18, No. 2, pp. 141–153.

**Godet, M. (1987):** Scenarios and Strategic Management, Butterworths: London.

**Godet, M. (1995):** Global Scenarios: Morphological and Probability Analysis, in: European-Commission Institute for Prospective Technological Studies (Ed.): Scenario Building: Convergences and Differences, pp. 17-31, Sevilla.

**Godet, M. (2001):** Creating Futures: Scenario Planning as a Strategic Management Tool, Eco nomica-Brookings: London.

**Godet, M./Roubelat, F. (1996):** Creating the Future: The Use and Misuse of Scenarios, in: Long Range Planning, Vol. 29, No. 2, pp. 164-171.

**Gordon, T.J./Hayward, H. (1968):** Initial Experiments With the Cross Impact Matrix Method of Forecasting, in: Futures, Vol. 1, pp. 100-116.

**Gottwald, S. (1993)**: Fuzzy Sets and Fuzzy Logic. Foundations of Application from a Mathematical Point of View, Springer: Wiesbaden.

**Grant, R.M. (2008):** Contemporary Strategy Analysis – Text and Cases, 8. Edition, Wiley: West Sussex.

**Hall, L. O./Kandel, A. (1991)**: The Evolution From Expert Systems to Fuzzy Expert Systems, in: Kandel, A. (Ed.): Fuzzy Expert Systems, pp. 3-21, CRC Press: London et al.

**Heijden, K. v. d. (1996):** Scenarios: The Art of Strategic Conversation, John Wiley & Sons: Chichester.

**Heijden, K. v. d. (1997):** Scenarios, Strategies and the Strategy Process, Nijenrode University: Netherlands.

**Heijden, K. v. d. (2000):** Scenarios and Forecasting: Two Perspectives, in: Technological Forcasting and Social Change, Vol. 65, pp. 31-36.

**Helmer, O. (1977):** Problems in futures research: Delphi and causal cross-impact analysis, in: Futures, Vol. 9, No. 1, pp. 17-31.

**Helmer, O. (1981):** Reassessment of cross-impact analysis, in: Futures, Vol. 13, No. 5, pp. 389-400.

**Hersey, P./Blanchard, K.H./Johnson, D.E. (1996):** Management of Organizational Behavior, 7th edition, Prentice Hall: USA.

**Hill, C.W.L./Schilling, M.A./Jones, G.R. (2016):** Strategic Management – Theory, Cengage Learning: Boston.

**Hüllermeier, E. (2011):** Fuzzy Sets in machine learning and data mining, in: Applied Soft Computing, Vol. 12, No. 2, pp. 1493-1505.

**Hurwicz, L. (1951):** Optimality criteria for decision making under ignorance, Cowles Commission Discussion Paper: Statistics, No. 370.

**Huss, W.R./Honton, E.J. (1987):** Scenario Planning: What Style Should You Use?, in: Long Range Planning, Vol. 20, No. 4, pp. 21-29.

**Jago, A.G./Ettling, J.T./Vroom, V.H. (1985):** Validating a Revision to the Vroom/Yetton Model: First Evidence, in: Academy of Management Proceedings, pp. 220-223.

**Kahn, B.E./Sarin, R.K. (1988):** Modeling Ambiguity in Decisions under Uncertainty, in: Journal of Consumer Research, Vol. 15, No. 2, pp. 265–272.

**Kleiner, A. (1999):** Scenario Practice, in: Whole Earth Quarterly, Vol. 11, No. 3, pp. 167-191.

**Klir, G.J./Yuan, B. (1995):** Fuzzy sets and fuzzy logic: theory and applications. Prentice Hall.

**Kluyver, C.A.d./Pearce II, J.A. (2003):** Strategy – A View from the Top, Pearson Education: New Jersey.

**Knight, F.H. (1921):** Risk, uncertainty, and profit, Houghton-Mifflin: Boston.

**Kofler, E. (2001):** Linear partial informations with applications, in: Fuzzy Sets and Systems, Vol. 118, No. 1, pp. 167-177.

**Kofler, E./Kmietowicz, Z./Pearman, A. (1984):** Decision Making with Linear Partial Information (L.P.I.), in: Journal of the Operational Research Society, Vol. 35, No. 12, pp. 1079–1090.

**Kruse, R./Borgelt, C./Nauck, D. (2000):** Problems and Prospects in Fuzzy Data Analysis, in: Azvine, B./Nauck, D./Azarmi, N. (Eds.): Intelligent Systems and Soft Computing. Lecture Notes in Computer Science, Springer: Berlin/Heidelberg.

**Kruse, R./Borgelt, C./Braune, C./Mostaghim, S./Steinbrecher, M. (2016):** Computational Intelligence – A Methodological Introduction, 2nd ed., Springer: London.

**Kunreuther, H./Meszaros, J./Hogarth, R.M./Spranca, M. (1995):** Ambiguity and underwriter decision processes, in: Journal of Economic Behavior & Organization, Vol. 26, No. 3, pp. 337-352.

**Laguna, M./Martí, R. (2013):** Heuristics, in Gass, S.I./Fu, M.C. (Eds.): Encyclopedia of Operations Research and Management Science, Springer: Boston.

**Lee, E.A. (2010):** CPS foundations, in: Design Automation Conference (DAC), 2010 47th ACM/IEEE.

**Liao, S.-H. (2005):** Expert system methodologies and applications – a decade review from 1995 to 2004, in: Expert Systems with Applications, Vol. 28, No. 1, pp. 93-103.

**Lindgren, M./Bandhold, H. (2003):** Scenario Planning: The Link Between Future and Strategy, Palgrave Macmillan: New York.

**Linneman, R.E./Klein, H.E. (1985):** Using Scenarios in Strategic Decision Making, in: Business Horizons, Vol. 28, No. 1, pp. 63-74.

**Mack, O./Khare, A. (2016):** Perspectives on a VUCA World, in Mack, O./Khare, A./Krämer, A./Burgart, T. (Eds.), Managing in a VUCA World, pp. 3-19, Springer International: Switzerland.

**Mamdani, E.H. (1981):** Advances in the Linguistic Synthesis of Fuzzy Controllers, in: Mamdani, E.H./Gaines, B.R. (Eds.): Fuzzy Reasoning and its Applications, pp. 311-323, Academic Press: London.

**McWhorter, R.R./Lynham, S.A. (2014):** An Initial Conceptualization of Virtual Scenario Planning, in: Advances in Developing Human Resources, Vol. 16, No. 3, pp. 335–355.

**Metzger, O./Spengler, T**. (2019): Modeling rational decisions in ambiguous situations: a multi-valued logic approach, in: Business Research, Vol. 12, No. 1, pp. 271-290.

**Mietzner, D./Reger, G. (2005):** Advantages and disadvantages of scenario approaches for strategic foresight, in: International Journal of Technology Intelligence and Planning, Vol. 1, No. 2, pp. 220-239.

**Molina, C./Ruiz, M.D./Serrano, J.M. (2019):** Representation by levels: An alternative to fuzzy sets for fuzzy mining, in: Fuzzy Sets and Systems, Vol. 401, pp. 113-132.

**Pedrycz, W. (1993)**: Fuzzy Control and Fuzzy System, 2. Edition, Wiley: New York et al.

**Piegat, A. (2001)**: Fuzzy Modeling and Control, Physica: Heidelberg/New York.

**Rajabi, M./Hossani, S./Dehghani, F. (2019):** A literature review on current approaches and applications of fuzzy expert systems, A Preprint, September 20, 2019.

**Reddin, W.J. (1970)**: Managerial effectiveness, ERIC Institute of Educational Science: New York.

**Reibnitz, U.v. (1995):** Scenario Techniques: How to Make the Best of Future Challenges in a Rapidly Changing Global Environment, in: European Commission Institute for Prospective Technologocial Studies (Ed.): Scenario Building Convergences and Differences, pp. 47-51, Sevilla.

**Reibnitz, U.v./Hammond, P. (1988)**: Scenario Techniques, Germany, McGraw-Hill: Hamburg

**Ringland, G. (1998):** Scenario Planning: Managing for the Future, John Wiley: New York.

**Rommelfanger, H. (1989a):** Inequality relations in fuzzy constraints and its use in linear fuzzy optimization, in: Verdegay, J.L./Delgado, M. (Eds.): The interface between artificial intelligence and operations research in fuzzy environment, pp. 195-211, TÜV: Rheinland,

**Rommelfanger, H. (1989b):** Interactive decision making in fuzzy linear optimization problems, in: European Journal of Operational Research, Vol 41, pp. 210-217.

**Rommelfanger, H. (1990):** FULPAL – An interactive method for solving (multiobjective) fuzzy linear programming problems, in: Slowinski, R./Teghem, J. (Eds.): Stochastic versus fuzzy approaches to multiobjective mathematical programming under uncertainty, pp. 279-299, Springer: London et al.

**Rommelfanger, H. (1996):** Fuzzy linear programming and applications, in: European Journal of Operational Research, Vol. 92, No. 3, pp. 512-527.

**Rommelfanger, H./Hanuscheck, R./Wolf, J (1989):** Linear programming with fuzzy objectives, in: Fuzzy sets and systems, Vol. 29, No. 1, pp. 31-48.

**Roos, G./Fernström, L./Pike, S. (2004):** Human resource management and business performance measurement, in: Measuring Business Excellence, Vol. 8, No. 1, pp. 28-37.

**Roubelat, F. (2000):** Scenario Planning as a Networking Process, in: Technological Forecasting and Social Change, Vol. 65, pp. 99-112.

**Sarin, R.K. (1978):** A Sequential Approach to Cross-Impact Analysis, in: Futures, Vol. 10, pp. 53-62.

**Schneider, M./Kandel, A. (1991)**: General Purpose Fuzzy Expert Systems, in: Kandel, A. (Ed.) Fuzzy Expert Systems, pp. 23-41, CRC Press: London et al.

**Schoemaker, P. (1993):** Multiple Scenario Development: Its Conceptual and Behavioral Foundation, in: Strategic Management Journal, Vol. 14, pp. 193-213.

**Schoemaker, P. (1995):** Scenario Planning: A Tool for Strategic Thinking, in: Sloan Management Review, Vol. 37, No. 2, pp. 25-40.

**Schoemaker, P./Heijden, K.v.d. (1992):** Integrating Scenarios into Strategic Planning at Royal Dutch/Shell, in: Strategy and Leadership, Vol. 20, No. 3, pp. 41-46.

**Schmeidler, D. (1989):** Subjective probability and expected utility without additivity, in: Econometrica, Vol. 57, No. 3, pp. 571–587.

**Schwartz, P. (1991):** The Art of the Long View, Doubleday: New York.

**Siegling, K.M./Spengler, T./Herzog, S. (2023a):** Personnel planning and leadership as central personnel economic instruments, in: FEMM Working Paper Series, University of Magdeburg, No. 9/2023.

**Siegling, K.M./Spengler, T./Herzog, S. (2023b):** Rule-based systems for leadership style selection, in: FEMM Working Paper Series, Working Paper No. 07/2023, Magdeburg.

**Siler, W./Buckley, J.J. (2005):** Fuzzy expert systems and fuzzy reasoning, Wiley: Hoboken, NJ.

**Silver, E. (2004):** An overview of heuristic solution methods, in: Journal of the Operational Research Society, Vol. 55, No. 9, pp. 936-956.

**Simpson, D.G. (1992):** Key lessons for Adopting Scenario Planning in Diversified Companies, in: Planning Review, Vol. 20, No. 3, pp. 11-18.

**Slovic, P./Tversky, A. (1974):** Who accepts Savage's axiom?, in: Behavioral Science, Vol. 19, No. 6, pp. 368–373.

**Sörensen, K./Glover, F.W. (2013):** Metaheuristics, in: Gass, S.I. / Fu M.C. (Eds.), in: Encyclopedia of Operations Research and Management Science, Springer: Boston.

**Spengler, T./Herzog, S. (2023):** Defuzzification in Scenario Management – A theoretical and practical Guide, in: FEMM Working Paper Series, Working Paper No. 05/2023, Magdeburg.

**Spengler, T./Vogt, B. (2008):** Analyzing numerical responses - A model and its application to examples from personnel and organizational management, in: Journal of Neuroscience, Psychology and Economics, Vol. 1, No. 1, pp. 17-32.

**Strohmeier, S./Piazza, F. (2013):** Domain driven data mining in human resource management: A review of current research, in: Expert Systems with Applications, Vol. 40, No. 7, pp. 2410-2420.

**Sugeno, M. (1974):** Theory of fuzzy integrals and its applications, Doct. Thesis, Tokyo Institute of technology.

**Tan, H. (2017):** A brief history and technical review of the expert system research, in: IOP Conf. Series: Materials Science and Engineering, Vol. 242, No. 1, 012111.

**Tan, C.F./Wahidin, L.S./Khalil, S.N./Tamaldin, N./Hu, J./Rauterberg, G.W.M. (2016):** The Application of Expert System: A Review of Research and Applications, in: ARPN Journal of Engineering and Applied Sciences, Vol. 11, No. 4, pp. 2448-2453.

**Teodorović, D./Lučić, P. (1998):** A fuzzy set approach to the aircrew rostering problem, in: Fuzzy Sets and Systems, Vol. 95, No. 3, pp. 261-271.

**Van Leekwijck, W./Kerre, E. (1999):** Defuzzification: criteria and classification, in: Fuzzy Sets and Systems, Vol. 108, No. 2, pp.159-178.

**Vogelsang, M. (2010):** Digitalization in open economies: Theory and policy implications, Springer: Berlin/Heidelberg.

**Vogt, B./Uphaus, A./Albers, W. (2001):** Numerical Decision Processing causing stock price clustering?, in: Homo Oeconomicus, Vol. 18, No. 2, pp. 229-240.

**Vroom, V.H./Jago, A.G. (1988):** Managing participation: A critical dimension of leadership, in: Journal of Management Development, Vol. 7, No. 5, pp. 32-42.

**Vroom, V.H./Yetton, P.W. (1973):** Leadership and decision-making, University of Pittsburgh Press: USA.

**Wack, P. (1985a):** Scenarios: Shooting the Rapids, in: Harvard Business Review, Vol. 63, No. 6, pp. 139-150.

**Wack, P. (1985b):** Scenarios: Uncharted Waters Ahead, in: Harvard Business Review, Vol. 63, No. 5, pp. 73-89.

**Wald, A. (1949):** Statistical decision functions, in: The Annals of Mathematical statistics, Vol. 20, No. 2, pp. 165-205.

**Wang, H.-F./Chang, W.-Y. (2000)**: Fuzzy Scenario Analysis in Strategic Planning, in: Int. J. General Systems, Vol. 30, No. 2, pp. 193-207.

**Weimer-Jehle, W. (2006):** Cross-impact balances: A system-theoretical approach to cross-impact analysis, in: Technological Forecasting & Social Change, Vol. 73, No. 4, pp. 334–361.

**Wilson, I. (1998):** Mental Maps of the Future: An Intuitive Logics Approach to Scenarios, and: The Effective Implementation of Scenario Planning: Changing the Corporate Culture, both in: Fahey, L./Randall, R.M. (Eds.): Learning from the Future: Competitive Foresight Scenarios, pp. 81-108 and pp. 352-368, John Wiley & Sons: New York.

**Wolbeck, L. (2019):** Fairness Aspects in Personnel Scheduling, in: Diskussionsbeiträge Fachbereich Wirtschaftswissenschaft Freie Universität Berlin, No. 16.

**Yager, R.R. (1991)**: On the Representation of Relational Production Rules in Expert Systems, in: Kandel, A. (Ed.) Fuzzy Expert Systems, pp. 55-67, CRC Press: London et al.

**Zadeh, L.A. (1965):** Fuzzy Sets, in: Information and Control, Vol. 8, No. 3, pp. 338-353.

**Zadeh, L.A. (1975):** The Concept of a Linguistic Variable and its Application to Approximate Reasoning – Part I, in: Information Sciences, Vol. 8, pp. 199-249.

**Zadeh, L.A. (1983)**: The role of fuzzy logic in the management of uncertainty in expert systems, in: Fuzzy sets and systems, Vol. 11, No. 1-3, pp. 199-227.

**Zadeh, L.A. (1987):** The Concept of a Linguistic Variable and its Application to Approximate Reasoning – Part II, in: Yager, R.R./ Ovchinnikov, S./ Ton, R.M./ Nguyen, H.T. (Eds.): Fuzzy Sets and Applications: Selected Papers by L. A. Zadeh, pp. 271-327, Wiley: New York et al.

**Zadeh, L.A. (1988):** Fuzzy logic, in: Computer, Vol. 21, No. 4, pp. 83-93.

**Zadeh, L.A. (1996):** Fuzzy Logic = Computing with Words, in: IEEE Transactions on Fuzzy Systems, Vol. 4, No. 2, pp. 103-111.

**Zimmermann, H.-J. (1978):** Fuzzy programming and linear programming with several objective functions, in: Fuzzy sets and systems, Vol. 1, No. 1, pp. 45-55.

**Zimmermann, H.-J. (1987):** Fuzzy Sets, Decision Making, and Expert Systems, Kluwer Academic: Boston et al.

**Zimmermann, H.-J. (1996)**: Fuzzy Set Theory – and Its Applications, Third Printing, Kluwer-Nijhoff: Boston et al.

**Zimmermann, A./Trautmann, N. (2018):** A list-scheduling heuristic for the short-term planning of assessment centers, in: Journal of Scheduling, Vol. 21, No. 2, pp. 131-142.

**Otto von Guericke University Magdeburg**
Faculty of Economics and Management
P.O. Box 4120 | 39016 Magdeburg | Germany

Tel.: +49 (0) 3 91 / 67-1 85 84
Fax: +49 (0) 3 91 / 67-1 21 20

**www.fww.ovgu.de/femm**

ISSN 1615-4274