Eliciting Expert Knowledge for Fuzzy Evaluation of Agricultural Production Systems

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Eliciting Expert Knowledge for Fuzzy Evaluation of Agricultural Production Systems

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Abstract

Public concern nowadays is an important frame of reference for the development of agricultural production systems. The development of such systems, therefore, involves both society level and production system level. Following Zadeh's *principle of incompatibility*, information obtained at production system level is interpreted at society level in linguistic terms. Fuzzy models promise to be a valuable tool as they link measurable information to linguistic interpretation using membership functions. The objective of this paper is to outline a procedure which deals with criticism regarding the inherent subjectivity in the construction of membership functions when using expert knowledge. The procedure guarantees the selection of appropriate expert knowledge, and provides a guideline supporting the selection of methods to elicit expert knowledge and construct membership functions. Also on the basis of the results in an illustrative example, it is concluded that the procedure outlined in this paper suitably deals with criticism regarding membership functions and, therefore, enables a practical implementation of fuzzy evaluation of agricultural production systems. Current research implements the procedure to build a fuzzy model which evaluates egg production systems in relation to public concern about the welfare of laying hens.

Keywords

Evaluation, fuzzy models, expert knowledge, knowledge elicitation, subjectivity.

1 Introduction

Public concern about, for example, food security and food safety, environmental degradation, and human and animal welfare nowadays is an important frame of reference for the development of agricultural production systems (e.g. [16], [25], [34], [35], [39], [40]). Such public concern emphasizes that agriculture is a human activity which takes its shape from being at the meeting point of natural systems and the rest of society [3, 29, 44]. The development of agricultural production systems, therefore, involves two system levels (cf. [53]). At society level, public concern is a perception of the impact of present agricultural production practices on society. At production system level, public concern finds a response in corrective measures to production practices (Fig. 1 (a)). For example, public concern for welfare of laying hens stimulated development of animal-friendly production practices like aviary and deep-litter production systems [14].

Public concern is a linguistic expression of a complex problem which generally can be characterized through multiple issues. Public concern regarding animal welfare, for example, comprises issues regarding animal behavior, physiology, health and production [14]. In an earlier paper [12], we proposed a four-phased framework which acknowledges that evaluating development of agricultural production systems involves both society level and production system level (Fig. 1 (b)). In Phase 1, the public concern is defined in its specific context and relevant stakeholders of the problem are identified. For example, welfare of laying hens is defined as a public concern in the Netherlands and farmers, consumers, veterinarians and scientists might be identified as relevant stakeholders. In Phase 2, context-dependent issues which characterize the public concern are determined by the stakeholders. For example, space allowance and the resultant possibility for hens to move is a relevant issue regarding welfare of laying hens. In Phase 3, issues are translated into measurable, context-dependent indicators. For example, the

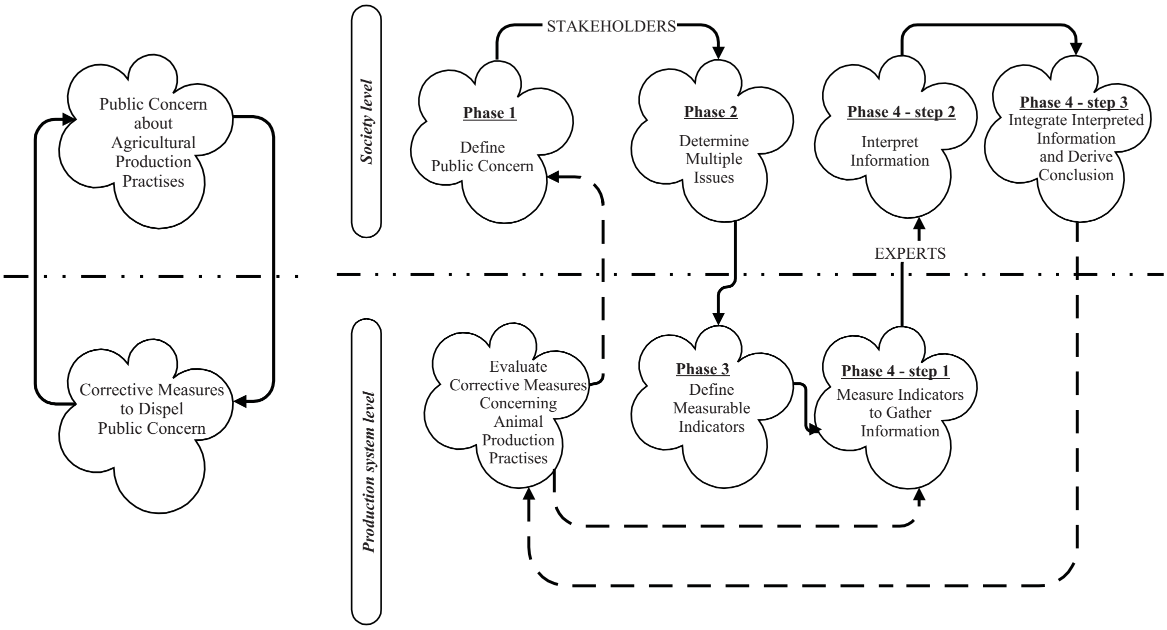

Figure 1: (a) Development of agricultural production systems builds on public concern about the impact of current agricultural activities on society. (b) Four-phased framework to evaluate the development of agricultural production systems.

issue “possibility to move” is translated into the indicator “stocking density” which at production system level is measured as the number of hens per m^2. Phase 4 of the framework consists of three steps. In Step 1, indicators are measured to gather information: e.g. stocking density is x hens per m^2. In Step 2, information gathered is interpreted: e.g. stocking density is *acceptable*. In Step 3, interpreted information is integrated to derive a conclusion: e.g. *if* stocking density is *acceptable*, *then* the possibility for hens to move is *good*.

Following Zadeh’s *principle of incompatibility* [50] — which is based on how humans understand and manage complexity — information obtained at production system level through measuring indicators (stocking density is x hens per m^2) typically is interpreted at society level in imprecise, linguistic terms (stocking density is *acceptable*). In other words, according to Zadeh’s *principle* there exists a trade-off between the complexity of a problem and the precision in formulating conclusions on the problem [38].

To make Phase 4 operational, we suggested the use of fuzzy models to link measurable information and its linguistic interpretation [12]. Membership functions (MFs) are at the core of fuzzy models, and proper use of such models, therefore, depends on proper construction of MFs

[24]. A number of elicitation methods are available to construct MFs using expert knowledge. Such MFs, however, are considered to be both the strongest and the weakest point of fuzzy models. They are the strongest, because MFs provide an understandable linguistic, context-dependent interpretation of information. They are the weakest, because MFs, paradoxically, are often regarded as too subjective with regard to their construction [31].

We propose that criticism regarding the inherent subjectivity in the construction of MFs mainly builds on two reasons. First, if expert knowledge is used to construct MFs, then *proper* selection of experts must ensure the use of *appropriate* expert knowledge. However, a justification for the selection of experts generally is absent in studies applying fuzzy models. Second, studies which apply expert knowledge to construct MFs either emphasize theoretical rather than practical aspects of elicitation methods (e.g. [4], [17], [32]), or do not discuss the construction of MFs at all (e.g. [1], [8], [47]). Therefore, as fuzzy models promise to be a valuable tool in evaluating development of agricultural production systems, a practical procedure to warrant proper selection of both experts and methods to elicit expert knowledge is needed.

The objective of this paper is to outline such a procedure and, thus, deal with criticism regarding the inherent subjectivity in the construction of MFs using expert knowledge. The procedure must constitute

(i) criteria which qualify a person as an expert, and

(ii) a selection of methods to elicit expert knowledge and construct MFs in a variety of practical situations.

To realize (i), a foundation which can be used to define selection criteria is needed (Section 2.1). In addition, it is meaningful to distinguish between the role of stakeholders and the role of experts in the evaluative framework (Section 2.2). To realize (ii), first the essence of fuzzy modeling is briefly discussed (Section 3.1) to provide the reader with an adequate background to consider a list of suitable elicitation methods (Section 3.2) which enables a comparison of these methods to support their practical application (Section 3.3). Next, the full procedure to elicit expert knowledge (Section 4) is demonstrated using an illustrative example on the welfare of laying hens (Section 5).

2 Criteria to select experts

2.1 Foundation to define selection criteria

Criteria to select experts guarantee elicitation of appropriate expert knowledge, i.e. they guarantee the quality of the expert knowledge required [36]. Three aspects are important.

1. How is expert knowledge obtained?
2. Which expert knowledge is available?
3. Which combination of expert knowledge is preferred?

An expert is a person whose knowledge in a specific domain (e.g. welfare of laying hens) is obtained gradually through a period of learning and experience [9, 45]. Learning and experience influence a person's cognitive, judgmental, social, creative, analytical, and procedural behavior [18]. According to Greenwell, especially a person's judgmental and analytical behavior provide tangible points of departure to define criteria identifying experts.

A person's judgmental behavior relates to making decisions, weighting evidence and assessing consequences; a person's analytical behavior relates to examining a complex problem through dealing with it in terms of mutually related parts [18]. Within the evaluation framework in Fig. 1 (b), an expert's judgmental and analytical experience typically is used at the boundary of both system levels. An expert, therefore, is familiar with an analysis of the public concern in terms of multiple issues (e.g. an analysis of the welfare of laying hens in terms of behavioral, physiological, health and production issues), and is able to judge measurements of indicators corresponding to these issues in linguistic terms (e.g. judge "stocking density" in terms of "acceptable" and "unacceptable"). A person's experience can be theoretical (e.g. experience obtained from scientific research), practical (e.g. experience obtained from farming practice) or a combination of both (e.g. experience obtained in the extension service or at experimental farms) [9, 42].

Expert knowledge is influenced by individual perspectives and goals [15]. Complete impartiality of expert knowledge, therefore, is difficult to achieve. An important consideration in the selection of experts is whether to use a heterogenous group of experts (e.g. both scientists and farmers) or a homogenous group of experts (e.g. only scientists). The effect of differences in personal experience on an expert's judgment is assumed to be smaller in a homogenous group compared to a heterogenous group. Scientists, therefore, might come to a different evaluation of production systems in terms of animal welfare than farmers [25]. Such differences, however, are not necessarily disadvantageous. A heterogenous group of experts can have an advantage over a homogenous group through considering all opinions and, thus, compensating for dissenting points of view by more liberal ones (cf. [37]).

In summary, criteria to identify experts are based on

(i) a person's period of learning and experience in a specific domain of knowledge, thus influencing his or her judgmental and analytical behavior, and

(ii) the specific circumstances in which experience is gained, e.g. in theoretical or practical circumstances.

Criteria based on (i) to identify experts regarding welfare of laying hens among a group of scientists, for example, can be the number of projects on welfare of laying hens a person has been working on, the number of scientific publications a person has published on the subject, a person's involvement in public debates on the subject, or the length of a person's period of learning and experience (cf. [36]). Criteria based on (ii) consider whether a heterogenous or a homogenous group of experts is preferred. Criteria can be assessed by both the person who is a candidate–expert, and by his or her peers. Although there exists no definite list of criteria, and even if criteria at best are formulated qualitatively, the important contribution is that the basis on which experts are to be selected is transparent and public.

2.2 Distinguishing between stakeholders and experts

Regarding the use of expert knowledge within the evaluation framework in Fig. 1 (b), it is important to distinguish between the role of *experts* in Phase 4 and the role of *stakeholders* in Phase 1 and Phase 2. That is, experts are not necessarily stakeholders and stakeholders are not necessarily experts. Stakeholders can be any group or individual who can affect or is affected by the behavior of the system [19, 30]. The role of stakeholders and experts in the evaluation framework is different, and so are the criteria for selection. Mitchell et al. [30], for example, present a comprehensive discussion of possible criteria to define stakeholders. The difference between experts and stakeholders can be demonstrated by considering the role of expert and non-expert witnesses in law [27]. An expert witness is allowed to give an opinion on the meaning of facts observed. Non-expert witnesses, however, only are allowed to affirm the facts observed but cannot give an opinion on the meaning of these facts. Experts, on the one hand, are allowed to give an opinion on the meaning of information gathered. Stakeholders, on the other hand, are allowed to formulate the relevant issues but cannot give an opinion on the meaning of information.

Thus, a person who qualifies as a stakeholder not necessarily qualifies as an expert, as stakeholders and experts are selected on the basis of different criteria. For example, although consumers are considered stakeholders regarding the welfare of laying hens in Dutch egg production systems [14], they are not necessarily experts qualified to judge whether specific stocking densities are acceptable with respect to a hen's possibility to move.

3 Elicitation of expert knowledge

3.1 Essence of fuzzy modeling

Fuzzy models are based on the theory of fuzzy sets [49] and, as discussed in [12], use MFs to operate "linguistic variables" and interpret indicator information using expert knowledge. In Fig. 2, a linguistic variable $\tilde{A}$ is characterized by [22, 51, 52]

(i) *name* of $\tilde{A}$,

(ii) *base variable* x of $\tilde{A}$,

(iii) *linguistic value* $\tilde{A}_i$ of $\tilde{A}$ ($i = 1 \ldots N$), and

(iv) *membership function* $\mu_{\tilde{A}_i}$ of $\tilde{A}_i$.

At society level, if "stocking density" is the *name* of $\tilde{A}$, then "acceptable" $(\tilde{A}_1)$ and "unacceptable" $(\tilde{A}_2)$ are *linguistic values* $\tilde{A}_i$ of $\tilde{A}$ $(N = 2)$. At production system level, indicator "stocking density" is measured as x hens per m^2 which is the *base variable* of $\tilde{A}$. A *membership function* $\mu_{\tilde{A}_i}$ defines linguistic value $\tilde{A}_i$ by determining the degree $\mu_{\tilde{A}_i}(x)$ to which stocking density x is "acceptable", $\mu_{\tilde{A}_1}(x)$, or "unacceptable", $\mu_{\tilde{A}_2}(x)$, by assigning to each x a value $\mu_{\tilde{A}_i}(x)$ between 0 and 1. In Fig. 2, the degree $\mu_{\tilde{A}_1}(x)$ to which stocking density x is "acceptable" decreases with increasing stocking density. Thus, if $\mu_{\tilde{A}_1}(x) = 1$, then linguistic statement "stocking density is acceptable" is true; if $\mu_{\tilde{A}_1}(x) = 0$, then linguistic statement

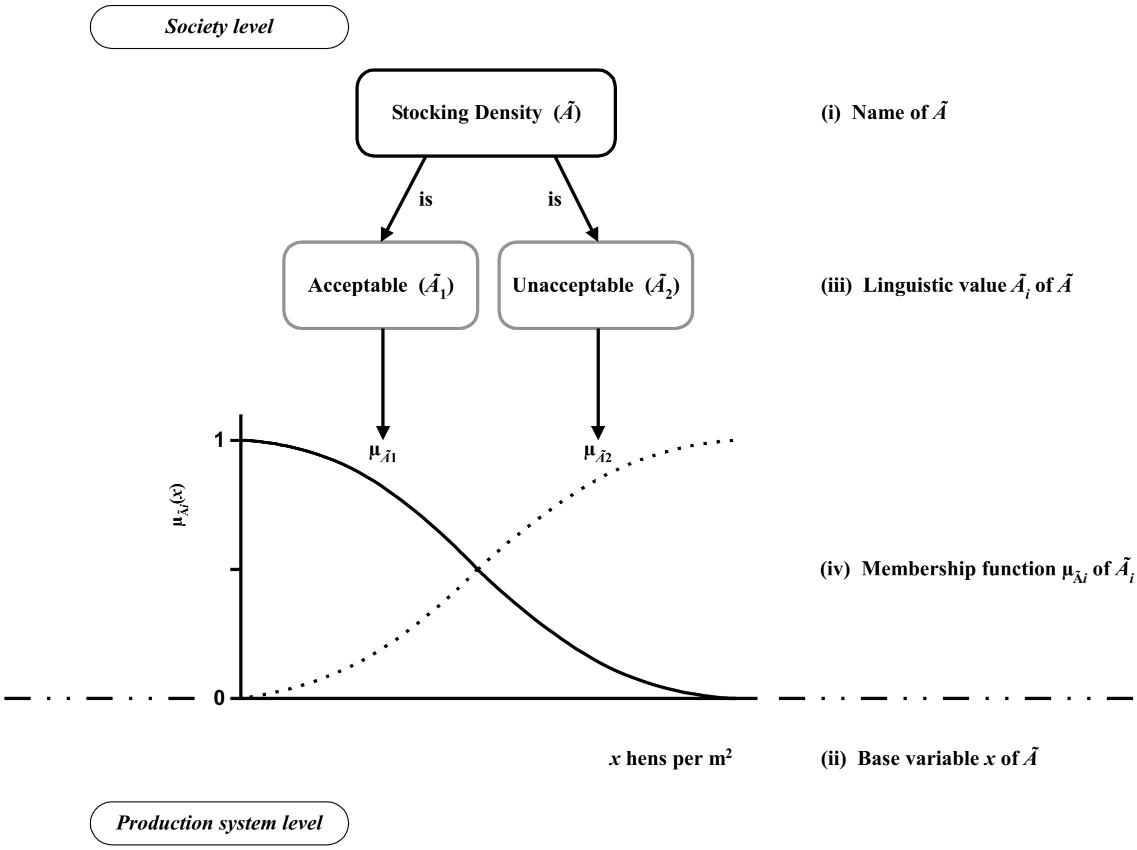

Figure 2: At society level, linguistic variable $\tilde{A}$ is characterized by (i) name of $\tilde{A}$, (iii) linguistic value $\tilde{A}_i$ of $\tilde{A}$, and (iv) membership function $\mu_{\tilde{A}_i}$ of $\tilde{A}_i$. At production system level, $\tilde{A}$ is characterized by (ii) base variable x of $\tilde{A}$ (based on [22, 51, 52]).

"stocking density is acceptable" is false; and if $0 < \mu_{\tilde{A}_1} < 1$, then $\mu_{\tilde{A}_1}(x)$ defines the degree to which linguistic statement "stocking density is acceptable" is true. In Fig. 2, $\tilde{A}_2$ is the standard fuzzy complement of $\tilde{A}_1$, so that $\mu_{\tilde{A}_2}(x) = 1 - \mu_{\tilde{A}_1}(x)$ [22].

Table 1 illustrates linguistic variables in three practical examples. The example "sustainable development" is based on [13]; the example "animal welfare" is based on the illustrative example used in this paper. The example "height of men" is a common illustration in the literature on fuzzy set theory [46]. The construction of $\mu_{\tilde{A}_i}$, i.e. the interpretation of base variable x in terms of linguistic value $\tilde{A}_i$, is realized by eliciting expert knowledge.

3.2 Elicitation methods

Different methods are available to elicit expert knowledge for the construction of membership functions. Different methods are based on different assumptions regarding the way an expert

Table 1: Characteristics (i) through (iv) of a linguistic variable illustrated using examples regarding "sustainable development", "animal welfare" and "height of men".

	Sustainable Development (de Boer and Cornelissen, 2001)	Animal Welfare (this paper)	Height of Men[a] (Türkşen, 1991)
issues $\in$ public concern[b]	**economic, ecological and societal issues** $\in$ *sustainable development* **secure farm continuity** $\in$ *sustainable development of egg production systems*	**behavioral, physiological, health and production issues** $\in$ *animal welfare* **possibility to move** $\in$ *welfare of laying hens*	**man** $\in$ *men*
context of *public concern*	**the Netherlands**	**the Netherlands**	**North America**
(i) linguistic variable $\tilde{A}$	**labor profit**	**stocking density**	**height**
(ii) base variable x of $\tilde{A}$ and its relevant range U	x NLG ($\times$ 1000) $U = [0, 100]$	x hens per m^2 $U = [0, 30]$	x meters $U = [0, 2.20]$
(iii) linguistic value $\tilde{A}_i$ of $\tilde{A}$, i.e. property $\tilde{A}_i$ of x	**high**	**acceptable**	**tall**
(iv) membership function $\mu_{\tilde{A}_i}$ of $\tilde{A}_i$	evaluation of labor profit of egg production systems by an expert who uses property **high** according to his/her understanding of the term within the context of labor profit of egg production systems in the Netherlands	evaluation of stocking density of laying hens by an expert who uses property **acceptable** according to his/her understanding of the term within the context of stocking density of laying hens in egg production systems in the Netherlands	evaluation of the height of a man by an expert who uses property **tall** according to his/her understanding of the term within the context of the height of a man in North America

[a]The example on "height of men" is an example often used in the literature to illustrate fuzzy set theory in general.
[b]The symbol $\in$ denotes that multiple issues are *an element of* a public concern, i.e. that a public concern comprises multiple issues.

determines the degree $\mu_{\tilde{A}_i}(x)$ to which x has property $\tilde{A}_i$ [17]. Four elicitation methods are presented. *Point estimation* (or polling), *interval estimation*, and *direct rating* originate from the literature [11, 20, 21, 24, 32, 46]; *transition interval estimation* is developed in this paper as an alternative to the other elicitation methods.

For each elicitation method, the expert evaluation mode (i.e. the way an expert evaluates the degree to which x has property $\tilde{A}_i$), the way an overall assessment of $\mu_{\tilde{A}_i}(x)$ is computed from individual expert assessments, the meaning of overall assessment $\mu_{\tilde{A}_i}(x)$, the number of experts needed to obtain a proper MF, and the characteristics of the MF constructed are discussed and illustrated. Further, advantages and disadvantages of elicitation methods are considered and, on this basis, elicitation methods are compared in Section 3.3 to support their practical application.

3.2.1 Point estimation

In point estimation (PE), an expert p ($p = 1 \ldots P$) determines unambiguously whether each x does or does not have property $\tilde{A}_i$, i.e. an expert's response is crisp. Expert p, therefore, assesses if $\mu_{\tilde{A}_i}(x)_p$ has value 1 or 0. An overall assessment $\mu_{\tilde{A}_i}(x)$ is computed as

$$\mu_{\tilde{A}_i}(x) = \frac{1}{P}\sum_{p=1}^{P} \mu_{\tilde{A}_i}(x)_p, \tag{1}$$

where $\mu_{\tilde{A}_i}(x) = 0.6$ means that 60% of P experts determine that x has property $\tilde{A}_i$. To obtain a proper MF, therefore, more than one expert is needed [22]. The MF constructed is characterized by data points $\mu_{\tilde{A}_i}(x)$.

Recall from Fig. 2 that stocking density is measured as x hens per m^2 and an expert evaluates stocking density in terms of "acceptable" $(\tilde{A}_1)$ and "unacceptable" $(\tilde{A}_2)$. In Fig. 3(a), expert p determines if stocking density x is "acceptable" $(\mu_{\tilde{A}1}(x)_p = 1)$ or if stocking density x is "unacceptable" $(\mu_{\tilde{A}1}(x)_p = 0)$. Expert p, therefore, determines an unambiguous distinction $x_{T_p} = 12$ hens per m^2 between acceptable stocking densities ($x \leq 12$ hens per m^2) and unacceptable stocking densities ($x > 12$ hens per m^2). An overall assessment $\mu_{\tilde{A}1}(x) = 0.6$ means that 60% of P experts determines that stocking density x is acceptable.

The main advantage of PE is the simple processing of elicited expert knowledge. Also, PE can be applied to nominal, discrete and continuous base variables. The main disadvantage of PE is the contradiction between the crispness of the expert response mode (i.e. x does or does not have property $\tilde{A}_i$) and the fuzziness inherent in human interpretation of information (i.e.

x has property $\tilde{A}_i$ to a degree) [50]. Also, experts need to evaluate a number of individual x within the relevant range U of the base variable. Therefore, if a large number of x needs to be evaluated, then practical application of PE can be laborious and time-consuming for an expert, and influence the reliability of expert evaluations [11, 33].

3.2.2 Interval estimation

In interval estimation (IE), an expert p determines a sharply defined interval (over the relevant range U of the base variable) containing values of x for which property $\tilde{A}_i$ applies, i.e. an expert's response is crisp. Expert p, therefore, determines interval $\tilde{A}_{ip}$ on U for which $\mu_{\tilde{A}_i}(x)_p$ has value 1. An overall assessment $\mu_{\tilde{A}_i}(x)$ is computed using (1) where $\mu_{\tilde{A}_i}(x) = 0.6$ means that 60% of P experts determines that x is in the interval $\tilde{A}_i$. As in PE, more than one expert is needed to obtain a proper MF [22]. The MF constructed is characterized by data points $\mu_{\tilde{A}_i}(x)$.

In Fig. 3(b), expert p determines an interval $\tilde{A}_{1p}$ that contains all stocking densities x which the expert considers "acceptable". Expert p, thus, determines an unambiguous distinction $x_{T_p} = 12$ hens per m^2 between acceptable and unacceptable stocking densities as in PE. An overall assessment $\mu_{\tilde{A}1}(x) = 0.6$ means that 60% of P experts determines that stocking density x is acceptable.

The main advantage of IE is the simple processing of elicited knowledge. Also, by defining an interval over U practical application of IE is less laborious and time-consuming for an expert compared to evaluating individual x of U. As in PE, the main disadvantage of IE is the crispness of the response mode required from experts. Also, the range of application of IE is limited because the elicitation method cannot be applied to nominal base variables.

3.2.3 Direct rating

In direct rating (DR), an expert p directly determines the degree $\mu_{\tilde{A}_i}(x)$ to which each x has property $\tilde{A}_i$, i.e. fuzziness is allowed in an expert's response. Expert p, therefore, assigns to each x a value $\mu_{\tilde{A}_i}(x)_p$ from the interval $[0, 1]$. An overall assessment $\mu_{\tilde{A}_i}(x)$ is computed using (1) where $\mu_{\tilde{A}_i}(x) = 0.6$ means that on average x resembles a typical value x_t, which truly has property $\tilde{A}_i$ (i.e. $\mu_{\tilde{A}_i}(x_t) = 1$), to a degree of 0.6. One expert can be sufficient to obtain a proper MF [22]. The MF constructed is characterized by data points $\mu_{\tilde{A}_i}(x)$.

In Fig. 3(c), expert p determines the degree to which stocking densities are "acceptable" by

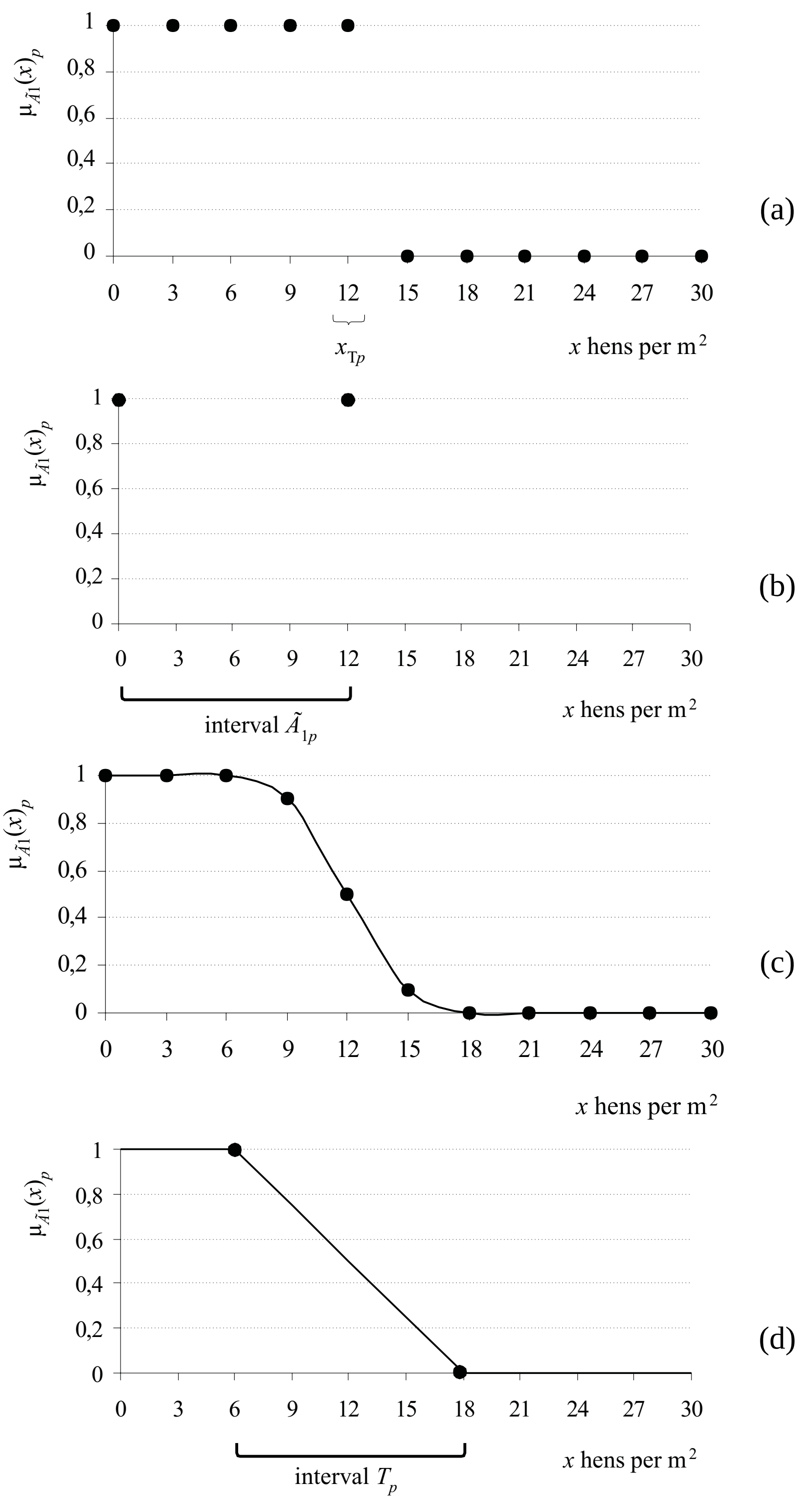

Figure 3: Four methods to elicit expert knowledge: (a) point estimation, (b) interval estimation, (c) direct rating, and (d) transition interval estimation. Expert p determines the degree $\mu_{\tilde{A}1}(x)$ to which base variable x (hens per m^2) is $\tilde{A}_1$ "Acceptable" (a) by determining x_{T_p}, (b) by determining interval $\tilde{A}_{1p}$, (c) by determining $\mu_{\tilde{A}1}(x)_p$, or (d) by determining interval T_p.

Table 2: Elicitation method originating from the literature categorized based on expert assessment and expert response.

	expert response[a]	
expert assessment[b]	crisp	fuzzy
individual x of U	PE[c]	DR
interval on U	IE	...

[a]Expert response can be unambiguous, i.e. crisp, or allow fuzziness.
[b]Expert assessment can be done by judging individual x of U, or by defining an interval on U.
[c]PE = point estimation, IE = interval estimation, DR = direct rating.

assigning a value from the interval $[0, 1]$ to stocking density x. For example, expert p evaluates $x = 9$ hens per m^2 as $\mu_{\tilde{A}1}(9)_p = 0.9$, i.e. expert p considers a stocking density of 9 hens per m^2 to be acceptable to a degree of 0.9. An overall assessment $\mu_{\tilde{A}1}(x) = 0.6$ means that, on average, P experts determine that stocking density x resembles a truly acceptable stocking density to a degree of 0.6.

The main advantage of DR is that it allows fuzziness in an expert's response mode, i.e. DR does not force experts to determine whether x does or does not have property $\tilde{A}_i$. Also, DR can be applied to nominal, discrete and continuous base variables. A disadvantage of DR, however, can be the low reproducibility of $\mu_{\tilde{A}_i}(x)_p$ due to the assignment of precise numerical grades and because small differences in numerical values for $\mu_{\tilde{A}_i}(x)_p$ may not seem to matter to an expert [26]. As in PE, if a large number of x needs to be evaluated, then practical application of DR can be laborious and time-consuming for an expert, and influence the reliability of expert evaluations [11, 33].

3.2.4 Transition interval estimation

Table 2 summarizes expert evaluation modes and expert response modes regarding PE, IE and DR. In the literature, no distinct elicitation method was found that allowed the expert evaluation mode to use intervals rather than judging individual x of U and, at the same time, allowing an expert's response mode to be fuzzy rather than crisp. Based on a crude concept described in [28], transition interval estimation (TIE) was developed to fill this gap.

In TIE, expert p determines an interval (over the relevant range U of the base variable) containing values of x for which expert p can make no unambiguous distinction whether property

$\tilde{A}_i$ does or does not apply, i.e. TIE allows a fuzzy response. Expert p, therefore, determines transition interval T_p on U bounded by $[x_{\min,p}, x_{\max,p}]$ for which $x_{\min,p} < x < x_{\max,p}$ and $0 < \mu_{\tilde{A}_i}(x)_p < 1$. The minimum value and maximum value in itself, however, are not meaningful: they can be characterized by the center point of and the range between both values. An overall assessment $\mu_{\tilde{A}_i}(x)$ in transition interval T, therefore, can be based on a linear transition characterized by center point x_{mp} and range d_p of T_p

$$x_m = \frac{1}{P}\sum_{p=1}^{P} x_{mp} \tag{2}$$

and

$$d = \frac{1}{P}\sum_{p=1}^{P} d_p, \qquad \text{and } d_p = x_{\max,p} - x_{\min,p}, \tag{3}$$

where x_m is the mean center point of T based on P assessments x_{mp} (see (2)), and d is the mean range of T based on P assessments d_p (see (3)). One expert, therefore, is sufficient to obtain a proper MF. Transition interval T is bounded by $[x_{\min}, x_{\max}]$ where $x_{\min}$ and $x_{\max}$ are defined as

$$x_{\min} = x_m - \frac{d}{2} \tag{4}$$

and

$$x_{\max} = x_m + \frac{d}{2}. \tag{5}$$

Next, $\mu_{\tilde{A}_i}(x)$ is computed as

$$\mu_{\tilde{A}_i}(x) = \begin{cases} 0 \text{ or } 1 & \text{when } x < x_{\min} \\ 0.5 \pm \frac{(x-x_m)}{d} & \text{when } x_{\min} \le x \le x_{\max} \\ 1 \text{ or } 0 & \text{when } x > x_{\max} \end{cases} \tag{6}$$

where $\mu_{\tilde{A}_i}(x) = 0$ for $x < x_{\min}$ and $\mu_{\tilde{A}_i}(x) = 1$ for $x > x_{\max}$ if the $\pm$–sign is positive, i.e. $\mu_{\tilde{A}_i}(x)$ is linearly increasing with increasing x. If the $\pm$–sign is negative, then the assessment of $\mu_{\tilde{A}_i}(x)$ in (6) for $x < x_{\min}$ and $x > x_{\max}$ is reversed, i.e. $\mu_{\tilde{A}_i}(x)$ is linearly decreasing with increasing x. As we consider this a first exploration in the possibilities of TIE, we have used the most elementary shape, i.e. a linear transition, to express the change in $\mu_{\tilde{A}_i}(x)$ over transition interval T. The transition of $\mu_{\tilde{A}_i}(x)$ over T, for example, also could be non-linear. The MF constructed is characterized by (6). Additionally, on condition that only linear transitions are used in (6), parameter d can be interpreted as a measure of fuzziness to express the uncertainty among experts regarding the change-over between x is $\tilde{A}_i$ and x is not–$\tilde{A}_i$.

In Fig. 3(d), expert p determines transition interval T_p bounded by $x_{\min,p} = 6$ hens per m^2 and $x_{\max,p} = 18$ hens per m^2. Thus, expert p considers stocking densities smaller than 6 hens per m^2 to be acceptable, stocking densities greater than 18 hens per m^2 to be unacceptable, and stocking densities between 6 and 18 hens per m^2 to be intermediate between completely acceptable and completely unacceptable. An overall assessment $\mu_{\tilde{A}1}(x) = 0.6$ means that, on average, P experts determine that x is in the interval T, i.e. P experts cannot determine unambiguously that x is either $\tilde{A}_1$ or not $\tilde{A}_1$.

The main advantage of TIE is that experts do not have to determine precise numerical assignments $\mu_{\tilde{A}_i}(x)$. Expert response mode can be fuzzy through defining an interval for which $0 < \mu_{\tilde{A}_i}(x) < 1$ without precisely having to specify $\mu_{\tilde{A}_i}(x)$. In addition, TIE is less laborious and time-consuming for an expert. A main disadvantage of TIE can be that the expert evaluation mode is less straightforward through the assignment of boundary values $x_{\min,p}$ and $x_{\max,p}$ of T_p compared to PE and IE. Also, the range of application of TIE is limited because the elicitation method cannot be applied to nominal base variables.

3.3 Comparison of elicitation methods

In Table 3, a qualitative comparison based on a practical application of elicitation methods is presented. The comparison considers

(i) the range of application,

(ii) the ease of the response mode for experts, and

(iii) the ease of constructing and interpreting MFs.

Regarding (i), both PE and DR can be applied to nominal, discrete and continuous base variables, whereas both IE and TIE cannot be applied in case the base variable is nominal. Regarding (i), PE and DR in Table 3 are the most appropriate elicitation methods.

Regarding (ii), the response mode of an expert in PE or IE is straightforward: the expert determines whether base variable x does or does not have property $\tilde{A}_i$. Both elicitation methods, however, do not allow fuzziness in the response mode of an expert and require a potentially difficult to define unambiguous threshold [43]. DR, in contrast, does allow fuzziness in an expert's response, but requires a potentially difficult way to define precise numerical value [26].

Table 3: Comparison of four methods to elicit expert knowledge to support their practical application.

criteria[b]	elicitation method[a] PE	IE	DR	TIE
(i) range of application:				
applicable to all types of base variables (nominal, discrete and continuous)	$+$	$-$	$+$	$-$
one expert is sufficient to obtain a proper MF	$-$	$-$	$+$	$+$
(ii) ease of response mode for experts:				
response mode is straightforward	$+$	$+$	$-$	$-$
response mode is consistent	$+$	$+$	$-$	$+$
response mode allows fuzziness	$-$	$-$	$+$	$+$
response mode is not time-consuming	$-$	$+$	$-$	$+$
(iii) ease of constructing and interpreting MFs:				
construction of MFs is uncomplicated	$+$	$+$	$+$	$+$
interpretation of MFs is straightforward	$-$	$-$	$-$	$+$

[a]Point estimation (PE), interval estimation (IE), direct rating (DR), and transition interval estimation (TIE).
[b]For $(+)$ the method fulfills the criterion; for $(-)$ the method does not fulfill the criterion.

TIE provides a method that does allow fuzziness in expert response mode, and does not require a precise numerical evaluation as in DR. In contrast to PE and IE, however, the expert evaluation mode for TIE might be less straightforward. Regarding (ii), TIE in Table 3 is the most appropriate elicitation method.

Regarding (iii), all four elicitation methods use rather uncomplicated procedures to construct MFs, i.e. (1) through (6). MFs constructed from elicited knowledge applying PE, IE, and DR, however, are characterized only by data points $\mu_{\tilde{A}_i}(x)$, whereas the MF constructed from elicited knowledge applying TIE provides an additional uncertainty measure d which defines the degree of fuzziness in expert evaluation. A similar numerical measure is available for results from PE, IE or DR only after characterizing available data points using, for example, logistic functions (cf. [10]). Further, PE and IE need more than one expert to obtain a proper MF which can lead to problems if experts in a certain domain of knowledge are hard to find. Regarding (iii), TIE in Table 3 is the most appropriate elicitation method.

Table 3 can be used in practical situations to support decisions regarding the choice of elicitation method to apply.

4 Procedure to elicit expert knowledge

A six-step procedure to elicit expert knowledge is developed based on criteria to select experts, and on the choice of a method to elicit expert knowledge.

Step 1 Domain of Knowledge:

define the domain(s) of knowledge represented in the issues and corresponding indicators selected.

Step 2 Candidate-Experts:

identify candidate-experts within each domain of knowledge; candidate–experts can originate from various parts of society, e.g. universities, extension services, farming communities, or pressure groups.

Step 3 Selection Criteria:

criteria are based on

(i) *a person's period of learning and experience in a specific domain of knowledge, and*

(ii) *the specific circumstances in which experience is gained.*

Step 4 Selection of Experts:

criteria can be assessed by the person who is a candidate–expert, and by his or her peers.

Step 5 Elicitation Method:

determine the elicitation method(s) to be applied considering

(i) *the range of application,*

(ii) *the ease of the response mode for experts, and*

(iii) *the ease of constructing and interpreting MFs.*

Step 6 Knowledge Elicitation:

prepare written questionnaires or oral interviews to elicit expert knowledge.

A body of literature is available to properly prepare and apply Step 6 in the procedure (e.g. [48]). An in-depth study of Step 6, however, is beyond the objectives of this paper.

5 Illustrative example

5.1 Applying the six-step procedure

5.1.1 Selection of experts

An increasing number of Dutch consumers objects to battery housing systems that interfere with the natural behavior of laying hens [14]. Battery housing systems, for example, provide less possibilities for hens to move freely compared to animal-friendly housing systems like aviary systems or deep-litter systems. Providing a possibility for hens to move, therefore, is considered an important issue in relation to welfare [2, 5, 7]. Two animal welfare indicators which determine a hen's possibility to move have been selected in this illustrative example [6]: stocking density (AWI_1) and presence of perches (AWI_2). Table 4 defines characteristics of selected linguistic variables. The domain of knowledge, therefore, is the welfare of laying hens in Dutch egg production systems and, specifically, the influence of stocking density and presence of perches on a hen's possibility to move (Step 1).

Table 4: Two animal welfare indicators (AWI_1 and AWI_2) which influence a hen's possibility to move: selected linguistic variables and corresponding characteristics.

Indicator	Linguistic Variable	Linguistic Values ($\tilde{A}_i$)	Base Variable	Type of Base Variable	Relevant Range of Base Variable
AWI_1	stocking density	acceptable ($\tilde{A}_1$) unacceptable ($\tilde{A}_2$)	hens per m^2	continuous	$[0, 30]$
AWI_2	presence of perches	acceptable ($\tilde{A}_1$) unacceptable ($\tilde{A}_2$)	level 1: present level 2: not present	nominal	–

Eighteen candidate–experts were identified with the assistance of an ethologist of Wageningen University. The group of candidate-experts consisted of animal scientists, ethologists and researchers at experimental farms employed at Wageningen University and Research Center, and professionals from two societal institutions: the Dutch Society for the Protection of Animals and the Agricultural Extension Service (Step 2).

Selection criteria used were the number of projects a person was involved in regarding the domain of knowledge defined, a person's involvement in public debate, and the length of time of a person's experience in the domain of knowledge. Because of widely varying points of view within the domain of knowledge, a heterogenous group of experts was preferred (Step 3). After being approached to participate in this study, five candidate-experts declined participation because they were no longer working and, therefore, were no longer up-to-date in the domain of knowledge. Finally, 13 experts contributed to this study (Step 4).

5.1.2 Elicitation of expert knowledge

Regarding Step 5, transition interval estimation was applied for AWI_1, whose base variable is continuous. Results obtained from TIE are used to also illustrate PE and IE. To illustrate PE, center point x_{mp} in TIE is considered to be equal to x_{T_p} in PE (Fig. 3). To illustrate IE, the interval $[0, x_{mp}]$ on U is considered to be equal to the interval $\tilde{A}_{1p}$ on U in IE (Fig. 3).

Direct rating was applied for AWI_2, whose base variable is nominal. DR, however, was modified (DR_{mod}) to further align the expert response mode with TIE. Rather than defining a precise numerical assignment $\mu_{\tilde{A}_1}(x)$, experts in DR_{mod} defined an interval on $[0, 1]$, i.e. a μ–interval bounded by $[\mu_{\min,p}, \mu_{\max,p}]$ in which x has property $\tilde{A}_1$ to a degree $\mu_{\tilde{A}_1}(x)$ and $\mu_{\min,p} \leq \mu_{\tilde{A}_1}(x)_p \leq \mu_{\max,p}$. Next, $\mu_{\tilde{A}_1}(x)_p$ is defined as the center point of the μ–interval.

Experts contributed by way of written questionnaires which consisted of an introduction to this study, an example illustrating the evaluation mode and the response mode required, and the actual evaluation of AWI_1 and AWI_2 (Step 6).

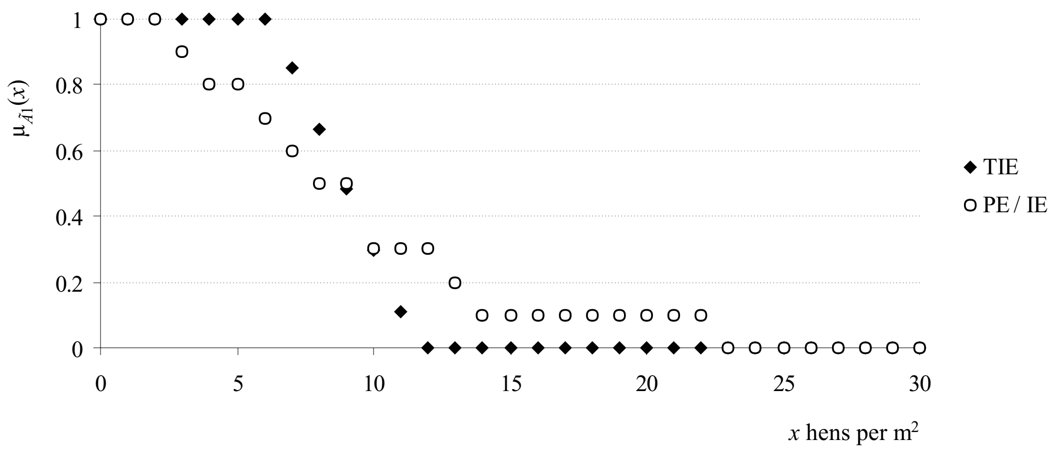

Figure 4: Membership function $\mu_{\tilde{A}1}(x)$ constructed for AWI$_1$ (Stocking Density) using transition interval estimation (TIE), and point estimation / interval estimation (PE/IE).

5.2 Results

Table 5 and Fig. 4 show results of applying TIE for AWI$_1$. The resulting MFs $\mu_{\tilde{A}1}$ and $\mu_{\tilde{A}2}$ which define linguistic values "Acceptable" $(\tilde{A}_1)$ and "Unacceptable" $(\tilde{A}_2)$ are

$$\begin{array}{ccc} \mu_{\tilde{A}1} & \mu_{\tilde{A}2} & \\ \left\{\begin{array}{c} 1 \\ 0.5 - \frac{(x-8.9)}{5.4} \\ 0 \end{array}\right. & \left\{\begin{array}{c} 0 \\ 0.5 + \frac{(x-8.9)}{5.4} \\ 1 \end{array}\right. & \begin{array}{c} x < 6.2 \\ 6.2 \leq x \leq 11.6 \\ x > 11.6 \end{array} \end{array} \tag{7}$$

where $\tilde{A}_2$ is the standard fuzzy complement of $\tilde{A}_1$ [22]. Experts, therefore, consider stocking densities to change from acceptable to unacceptable at approximately 9 hens per m^2 regarding a hen's possibility to move.

Table 6 shows practical results when implementing Step 2 of Phase 4 in the evaluation framework of Fig. 1. Based on MF $\mu_{\tilde{A}1}$ (7), minimum standards — according to European Union legislation — concerning stocking densities in different egg production systems are examined for their degree of truth $\mu_{\tilde{A}1}(x)_{\text{TIE}}$ regarding the linguistic statement "Stocking Density is Acceptable". Experts consider biological egg production systems to provide the most acceptable stocking densities in relation to a hen's possibility to move $(\mu_{\tilde{A}1}(x)_{\text{TIE}} = 0.9)$, they are inconclusive where the acceptability of stocking densities for deep–litter and aviary systems is concerned $(\mu_{\tilde{A}1}(x)_{\text{TIE}} = 0.5)$, but they consider stocking densities in systems with enriched cages and battery cages as completely unacceptable $(\mu_{\tilde{A}1}(x)_{\text{TIE}} = 0)$.

Table 5: Results of applying transition interval estimation for AWI$_1$ (Stocking Density).

	transition interval T_p[a]			
expert p	$x_{\min,p}$	$x_{\max,p}$	x_{mp}[b]	d_p[b]
1	3	8	5.5	5
2	7	17	12	10
3	1	4	2.5	3
4	2	8	5	6
5	6	12	9	6
6	6	12	9	6
7	2	4	3	2
8	5	8	6.5	3
9	6	9	7.5	3
10	10	14	12	4
11	7	10	8.5	3
12	6	20	13	14
13	20	25	22.5	5
			$x_m = 8.9$	$d = 5.4$
			(sd[c] 5.3)	(sd[c] 3.3)

[a]Expert p $(p = 1 \dots P, P = 13)$ determines transition interval T_p bounded by $x_{\min,p}$ and $x_{\max,p}$ between acceptable and unacceptable stocking densities over a relevant range of $[0, 30]$ hens per m^2.

[b]mean centre point x_m and mean range d to construct MF are computed on basis of P assessments x_{mp} and d_p.

[c]sd = standard deviation

Table 6: Minimum standards for stocking densities in different egg production systems according to European Union legislation, and expert evaluation of their acceptability $\tilde{A}_1$ applying transition interval estimation $(\mu_{\tilde{A}1}(x)_{\mathrm{TIE}})$.

egg production system	stocking density (x hens per m^2)	$\mu_{\tilde{A}1}(x)_{\mathrm{TIE}}$
biological	6	0.9
deep–litter	9	0.5
aviary	9	0.5
enriched cage	13	0
battery cage	18	0

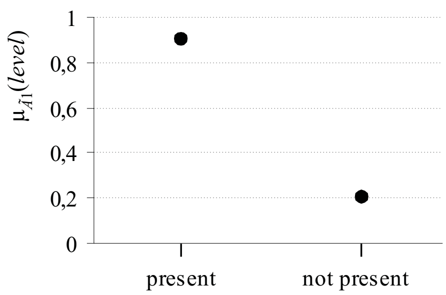

Figure 5: Membership function $\mu_{\tilde{A}1}$ constructed for AWI$_2$ (Presence of Perches) using modified direct rating.

Table 7 and Fig. 4 show results for both PE and IE, based on the set of data in Table 5 obtained from applying TIE. In Fig. 4, the MF from TIE shows a smaller degree of fuzziness compared to the MF from PE/IE, because of lower sensitivity of TIE to outliers (i.e. the response of expert 13 in Table 5). Considering that both MFs are based on the same set of data, the difference seems to be systematic (cf. [41]).

Table 8 and Fig. 5 show the results of applying DR$_{\mathrm{mod}}$ for AWI$_2$. One expert did not respond, and one expert did not correctly respond to the questionnaire regarding AWI$_2$, so $P = 11$. The degree $\mu_{\tilde{A}1}(x)$ to which level 1 (perches present) is “Acceptable” is 0.9; the degree $\mu_{\tilde{A}1}(x)$ to which level 2 (perches not present) is “Acceptable” is 0.2. Experts, therefore, consider the presence of perches an important contribution to a hen’s possibility to move.

Table 7: Results of both point estimation and interval estimation for AWI_1 (Stocking Density) over a relevant range of $[0, 30]$ hens per m^2.

x	$\sum(\mu_{\tilde{A}1}(x)_p = 1)$	$\mu_{\tilde{A}1}(x)$
0	13	1
1	13	1
2	13	1
3	12	0.9
4	11	0.8
5	11	0.8
6	9	0.7
7	8	0.6
8	7	0.5
9	6	0.5
10	4	0.3
11	4	0.3
12	4	0.3
13	2	0.2
$14 \ldots 22$	1	0.1
$23 \ldots 30$	0	0

Note: results are derived from applying transition interval estimation assuming $x_{mp} = x_{T_p}$ for point estimation, and assuming interval $[0, x_{T_p}] =$ interval $\tilde{A}_{1p}$ for interval estimation.

Table 8: Results of applying modified direct rating for AWI$_2$ (Presence of Perches) which has two levels: perches present (level 1) and perches not present (level 2).

	μ_p–interval for level 1 (perches present)[a]			
expert p	$\mu_{\min,p}$	$\mu_{\max,p}$	range	$\mu_{\tilde{A}1}(\text{level 1})_p$
1	0.8	1	0.2	0.9
2	0.5	0.8	0.3	0.7
3	1	1	0	1
4	0.8	1	0.2	0.9
5	0.6	0.9	0.3	0.8
6	1	1	0	1
7	0.9	1	0.1	1
8	0.8	1	0.2	0.9
9	0.7	0.9	0.2	0.8
10	0.75	1	0.25	0.9
11	1	1	0	1
		mean range	0.2(sd[b] 0.1)	
		$\mu_{\tilde{A}1}$(level 1)		0.9(sd[b] 0.1)
	μ_p–interval for level 2 (perches not present)[a]			
expert p	$\mu_{\min,p}$	$\mu_{\max,p}$	range	$\mu_{\tilde{A}1}(\text{level 2})_p$
1	0	0.2	0.2	0.1
2	0.1	0.4	0.3	0.25
3	0	0	0	0
4	0	0.2	0.2	0.1
5	0.1	0.6	0.5	0.35
6	0.5	1	0.5	0.75
7	0	0.1	0.1	0.05
8	0.2	0.4	0.2	0.3
9	0.1	0.3	0.2	0.2
10	0.25	0.5	0.25	0.38
11	0	0.5	0.5	0.25
		mean range	0.3(sd[b] 0.2)	
		$\mu_{\tilde{A}1}$(level 2)		0.2(sd[b] 0.2)

[a]Expert p $(p = 1 \ldots P, P = 11)$ determines the μ_p–interval bounded by $\mu_{\min,p}$ and $\mu_{\max,p}$ on a scale of 0 to 1 which determines the degree to which levels of AWI$_2$ are acceptable $(\tilde{A}_1)$.

[b]sd = standard deviation

6 Discussion

Fuzzy models promise to be a valuable tool in evaluating the development of agricultural production systems, as such development nowadays is directed by public concern about the impact of current agricultural practices. Membership functions (MFs) are at the core of such fuzzy models. The objective of this study was to outline a procedure which dealt with criticism regarding the inherent subjectivity in the construction of MFs when using expert knowledge. We suggested that such a procedure should consider

(i) selection of appropriate expert knowledge, and

(ii) selection of methods to elicit expert knowledge and construct MFs.

6.1 Selection of expert knowledge

The criteria defined in this study to determine whether a person qualifies as an expert are expressed in qualitative terms. Qualitative criteria increase the transparency in selecting experts and, at least, prevent ad hoc choices. It is, however, possible to quantify such criteria [36] using rating scales as described by Nunnally [33]. The procedure to elicit expert knowledge, however, already is a time-consuming activity. To fully quantify Steps 3 and 4 in order to establish a person's degree of expert knowledge will occupy more of an expert's time and might well diminish an expert's willingness to participate [48]. If, however, a quantitative degree of expert knowledge for experts is determined, then (1), (2) and (3) can be further adapted to include weighting of the contribution of individual experts based on their degree of expert knowledge.

Considering public recognition of final evaluation results, credibility can play an important role in selecting experts. Experts reflect trustworthiness because they act both in the public interest and with regard to actual technical standards and practice [23]. In Fig. 1(b), experts typically have to empathize with situations at both society and production system level. Although farmers have considerable practical experience regarding the daily care of their animals, it remains to be seen whether farmers are qualified to actually judge the welfare of their animals. Credibility of evaluation in the eyes of the public or the authorities, however, may well increase when farmers are included as experts [23]. Nevertheless, farmers if not included as experts can still play an important role as a stakeholder in the evaluation framework presented in this paper.

6.2 Selection of elicitation methods

Qualitative comparison regarding practical application of four elicitation methods showed that the appropriateness of an elicitation method and, therefore, the choice of an elicitation method depends on the starting point for comparison:

1. the range of application,

2. the ease of the response mode for experts, or

3. the ease of constructing and interpreting MFs.

Regarding 1, using PE and DR are appropriate methods. Regarding 2 and 3, TIE is an appropriate method. The actual choice, therefore, can depend on practical aspects like the type of base variables providing the input for the fuzzy model. Also, the choice to use just one elicitation method can be a rational one, thus requiring only a single response mode from the experts for all base variables involved. According to [33] a single response mode can increase the reliability of expert assessments. The choice for applying just one elicitation method can also be preferred considering that different elicitation methods result in different MFs for the same base variable, an effect that can be systematic [41].

Results of the illustrative example show that experts are able to assess a measurable indicator in linguistic terms, which information can be used to construct MFs as shown in Fig. 4 and Fig. 5. The procedure could be further improved by using the supplementary information provided by standard deviations in Table 5, and mean ranges and standard deviations in Table 8, to allow an expression of the uncertainty regarding the reliability of a particular MF. This uncertainty can be expressed through computing type–2 fuzzy sets [22]. However, these authors also state that computational demands in defining type–2 fuzzy sets generally outweigh the advantage of including the supplementary information.

6.3 Application of membership functions in fuzzy models

Cornelissen et al. [12] developed two fuzzy models to evaluate development of agricultural production systems. In Fig. 6, the results of Step 2 in Phase 4, i.e. the emphasis of the study in this paper, are integrated in Step 3 using fuzzy aggregation or approximate reasoning to derive a conclusion about the problem at hand.

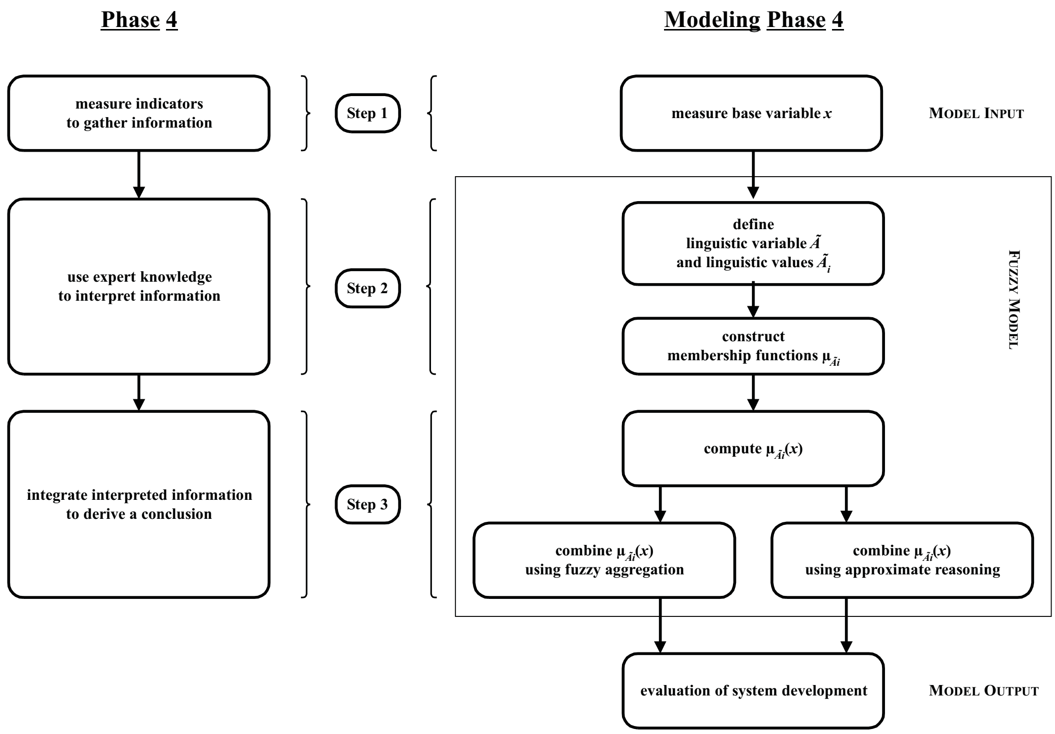

Figure 6: Operationalization of Steps 1 through 3 of Phase 4 in a fuzzy model[12]

Integrating of all interpreted information provided by different indicators will enable a more accurate conclusion. In Table 6, for example, experts were inconclusive where the acceptability of stocking density in relation to a hen's possibility to move in deep–litter and aviary systems was concerned. Integrating the results on stocking density with additional results about the contribution of the presence of perches to a hen's possibility to move will provide a more complete understanding.

7 Conclusion

Public concern nowadays is an important frame of reference for the development of agricultural production systems. Fuzzy models promise to be a valuable tool in evaluating such development, if a suitable response to criticism regarding the inherent subjectivity in the construction of membership functions is outlined. Also on the basis of the results in the illustrative example, the procedure outlined in this study suitably deals with such inherent subjectivity and enables practical implementation of a fuzzy evaluation of agricultural production systems. Current research implements the procedure to build a fuzzy model which evaluates egg production systems in relation to public concern about the welfare of laying hens.

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