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Agricultural assistance systems for decision support in livestock farming

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Assistance systems have the potential to improve farm management and administrative productivity while conserving resources significantly. Although a large number of assistance systems are already in use in agriculture, nevertheless, to our knowledge, there is no approach to modelling assistance systems that adequately represents the importance of the decision-making process and control. These two aspects are especially important to highlight in order to demonstrate the value of assistance systems in livestock farming and to drive forward future developments from an ethical perspective. An existing model for assistance systems is primarily technical, offering no insight into the area of decision-making processes. However, the decision-making processes are of particular importance from an ethical perspective, especially in the triangle of human animal-machine interaction. With the help of an exemplary depiction, the existing model is therefore extended and demonstrates the support for decision-making and the role of humans in the process.

Keywords
Digitalization, human-animal-machine interaction, sensors, decision-making, precision livestock farming

Assistance systems have already arrived in various forms in all areas of animal husbandry (Stachowicz and Umstätter 2020). All systems facilitate the planning, execution, and control of work processes. These features enable labor cost reduction and facilitate the documentation of a farm, for making external documentation requests easier to access (Lutz 2017). As a result, assistance systems can be a tool for implementing efficient production (Carillo and Abeni 2020; Neethirajan 2020). This circumstance affects all actors within the agricultural value chain (Gandorfer et al. 2017), as the digital network of actors, machines, and systems in agriculture is becoming increasingly dense.

Assistance systems have traditionally been used to automate mechanical processes, reducing the workload on humans and expanding their cognitive scope of action. Recent years have seen greater use of assistance systems due to advancements, for example, in the fields of hardware and software (Klocke et al. 2017). For instance, computer-aided documentation and the associated evaluations in herd management are being made available for livestock farming. Even with an increasing number of animals per farm, the development of computer aided documentation offers an opportunity to gather animal specific data (Carillo and Abeni 2020)

However, there are also ethical concerns about the digitization and use of assistance systems in agricultural animal husbandry. In addition to the possible reduction of human-animal interactions, there is also talk of the „objectification“ of animals (Neethirajan 2023). In many cases, the accuracy and reliability of the systems used must also be validated, so algorithms and targets must be carefully weighed. This must lead to trust between the farmer and the system so that decision support based

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on the data is possible (Jochemsen 2013, Neethirajan 2023). The greatest importance is attached to the influence of the digital technologies used on animal welfare, both in a negative and positive sense. With regard to the data generated, data security and data sovereignty are key ethical aspects and are also relevant for data management. Another important aspect is the environmental sustainability of animal husbandry. The use of assistance systems can have ecological and sustainable effects on livestock farming. For example, the use of resources can be optimized and waste production reduced to reduce the overall environmental impact of livestock production (Neethirajan 2023).

However, the topics and terms of digitalization have mostly not yet been prepared for the agricultural context. In addition to human-machine interaction, animal-machine interaction must also be considered in animal production. Because animals do not play a role in the production system in existing industry-based definitions, the various sources do not address machine-animal interaction. This interface occurs, for example, when a cow is milked by a robot. Animal-computer interactions (ACI) or animal-machine interactions have a long history and can be found in various areas where humans and other species interact (Mancini 2011). ACI aims at understanding the interaction between animals and (computer) technology. It is important to consider the context in which the interaction takes place, as contexts, activities, and relationships vary greatly between species. Examples include wild, domestic, working, farm, and laboratory animals. The interaction between animals, technology and other elements, such as humans, varies from case to case (Mancini 2011).

These variations in the interaction of influencing parameters also apply to assistance systems in agriculture. Therefore, an extended model for assistance systems in the context of agricultural animal husbandry was developed as part of the project ‚CattleHub'. The model is explained using a practical example. The study focuses primarily on supporting humans in the decision-making process. The study aims to examine the interaction between machines and animals, in addition to the traditional human-machine interaction. It takes into account the context, activities, and relationships that influence the interaction between animals, technology, and humans.

Assistance systems in industrial production

In the context of industrial production, there is already much experience with assistance systems and hence definitions and terminology that can be used. Buchholz and Clausen (2009) defined the term of assistance system as a computer-based system that supports humans in making and executing decisions. The authors presented this as an integral part of human-machine interaction, which is characterized by the informational coupling and linking of machines and operators. Furthermore, they demonstrated that operators are not only provided with facts but also receive assistance in solving problems and making decisions.

Link and Hamann (2019) provided a comparable characterization of assistance systems. However, the two authors focused on how humans are supported in information recording (perception), information processing (decision-making), and work performance. According to the Chair of Database and Information Systems (2020) of the University of Rostock, assistance systems serve the user as support in certain situations or for specific actions. The authors argued that considering time is essential because the prerequisite for the support through an assistance system is an analysis of the current situation and, if necessary, a forecast of the future situation based on this. The authors also placed a strong emphasis on the human being since interactions must accommodate a human's innate need for action and should simplify output to prevent the user being overloaded. According to

Klocke et al. (2017), assistance systems that provide real time action also enable processes to be self optimized and regulated.

All of the above definitions emphasize the importance of assistance systems in supporting humans. The system and the generated data should support, simplify, and automate both the decision-making process and the subsequent action. According to Klocke et al. (2017), however, the aim is not to completely replace humans with assistance systems. Instead, they offer new options in the area of data- and model-driven learning and help with decision-making in complex processes within production systems.

Model framework for assistance systems in an agricultural context

The central aspect of industrial production is technology, whereas agriculture always refers to the biological system in which the respective assistance system is used. In livestock farming, there are also ethical aspects to be considered. This article primarily discusses the ethical aspects of (animal) welfare, sustainability, and the environmental impact of livestock farming (Jochemsen 2013). Therefore, we found that an extended model framework is needed to characterize and classify the different assistance systems and subsystems for livestock farming. As early as 2013, Rutten et al. undertook a classification of sensors and sensor systems for agricultural livestock farming based on a scheme with four levels. This framework was used to categorize 139 sensor systems for dairy farming. The four levels in the scheme showed the individual steps from the sensor to a final decision. Sensor systems on the market were assigned to the different levels and thus categorized. The model developed by Rutten et al. (2013) is ideal for this kind of technical categorization.

For future development, however, it is important to have a model in which not only the technology but also humans can be integrated into the process. This addition must happen because decisions and the processes that lead to them are critical in agricultural animal husbandry. Decisions and decision-making processes are crucial in agricultural animal husbandry due to the increasing negative views of consumers towards livestock farming. Criticisms of the production system in dairy farming and other animal husbandry branches have led to demands for changes in the interest of animal welfare and sustainability. Sensor technology can improve process efficiency and transparency (Neethirajan and Kemp, 2021). However, according to Dürnberger (2021), the effects of this increased transparency have not yet been fully determined and depend on various factors. We have, therefore, extended the model by Rutten et al. (2013) by two levels (Level IV and VI), emphasizing the steps of action and the feedback of information in the system. This modification enables a stronger focus on decision-making and subsequent action, as explained in the next section.

Boundary conditions and model approach for assistance systems in agricultural animal husbandry

The remarkable thing about assistance systems in agricultural livestock farming is the interaction between humans, animals, machines/robots, and buildings. Environment, physiology, or animal behavior all have an impact on the specific production system just as much as the chosen production methods, process control, and herd management. This aspect distinguishes between assistance systems in agriculture and those in industry, as the biological system plays a disproportionately large role in agriculture. The model shown in Figure 1 includes the aforementioned influencing factors and links them to the structure of humans, animals, assistance systems, and buildings.

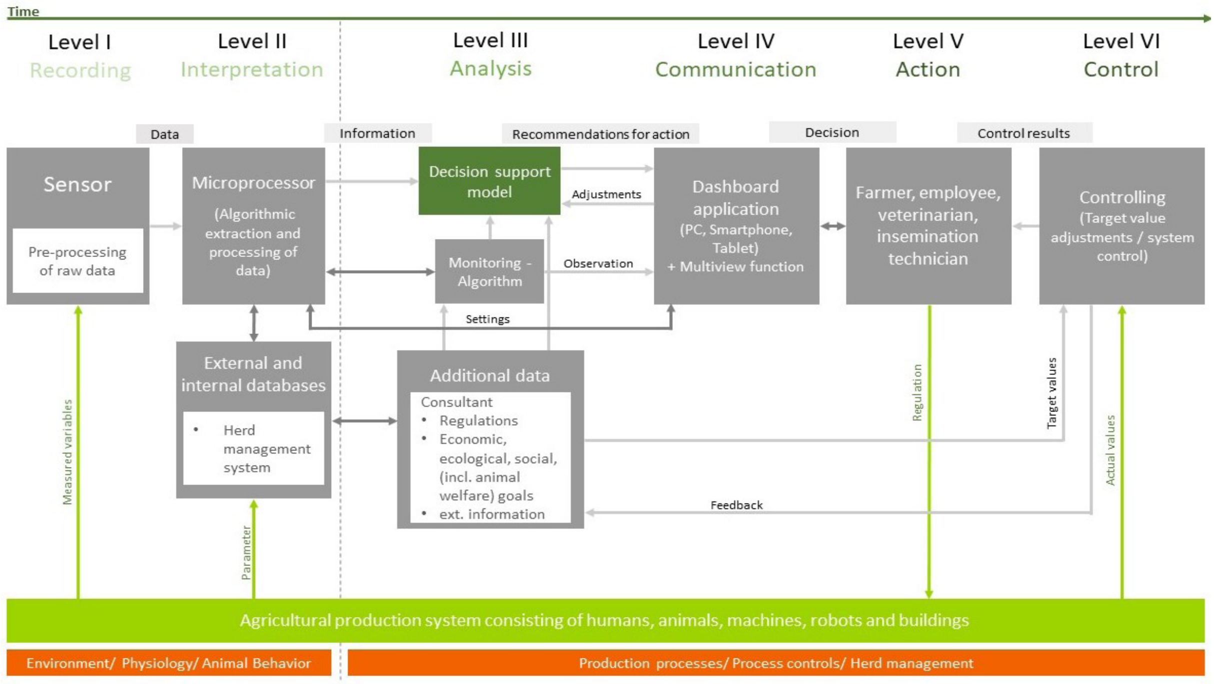

Figure 1: A model for the concept of assistance systems in agricultural animal husbandry.

In Level I, sensors, which often have integrated raw data pre-processing, record the measured variables. The resulting data remains as direct variables in Level I without a deeper meaning. In order to obtain information for decision support, the entire context must be established to derive the recommended action.

Level II is where the continuous aggregation of sensor data takes place, which can be done via microprocessors. Together with data from external and internal databases, algorithms extract and pre evaluate relevant animal or husbandry-related variables that are meaningful. It is possible to incorporate additional animal and sensor data produced by the agricultural production system into the internal and external databases. Since they cannot be recorded by sensors, information about animals, such as birthdates, ear tag numbers, or details about a cow's previous oestruses, can be added to databases manually.

Level III comprises the analysis in which the information generated in Level II on animal and environmental conditions contributes directly or via the monitoring algorithm to the Decision Support Model. In addition, further data from the databases from Level II can be used for decision-making, or external data can be merged. It is also possible to manually add information from the daily monitoring of the animals (e.g., observation of lameness). Information is also included on the objectives to be defined by the actors and the framework conditions to be observed by external services (e.g., test results of the milk delivered). In this way, knowledge – defined as verified information – is produced through networking and interpretation (Umstätter 2009, North 2020).

The Decision Support Model provides recommendations for action, which are then displayed on a medium (e.g., PC, smartphone, etc.) and thus communicated (Level IV). Alarm lists, which can be presented to the farmer in a variety of graphical formats, are typically the basis for the recommended course of action. Due to the particular importance of the medium as an interface between humans and the assistance system, on which the recommendations for action (e.g., for adjusting feeding) are visualized, communication is to be regarded as an independent level. Farmers can also use the medium to adjust settings regarding the evaluation in Level II. One example of this is the specification of threshold values. At the same time, the media serve as a platform for the interpretation (Level II) of the data collected in Level I.

After the recommended action is communicated through a medium, either humans or an automated system can make a decision (Level V) and transform it into an action. Assistance systems are intended to relieve farmers in their daily work, contribute to increasing animal welfare, and improve animal health. The actions that are recommended thus support the farmer to make decisions. In some systems, decision-making can take place without humans if this is ethically justifiable. Here, for instance, the decision-making process involves the use of artificial intelligence (AI) for analysis (Level III). Examples include autonomous feeding systems that use a sensor to determine the amount of feed in the trough and thus independently determine the time for the next feeding.

With Level V, the farmer or the automated system intervenes in the production system in such a way that the target values are achieved as far as possible (regulation). The target values are the result of both the farmer's planning (e.g. planned lifetime yield of a dairy cow of 40,000 kg of milk) and legal requirements (e.g. cell or germ count content of the milk). These can be different target values such as milk yield per cow, reduction of ammonia emissions, improvement of labor, or optimization of the barn climate.

Level VI is used for monitoring. The decisions made with the help of the assistance system are controlled by comparing actual values with the previously defined target values. The control is done in order to continuously optimize the production system and ensure the quality of the data collected by the assistance system. This control can refer to an automatic system that constantly calibrates itself or adjusts in accordance with the farmer‘s decisions based on the assistance system‘s recommended actions.

The actual variable values come from the agricultural production system, including the entire production process, process control, or herd management. The control results from Level VI (e.g. a difference of 10,000 kg milk between target and actual lifetime performance) are then linked back to Level III in order to make any necessary adjustments in the Decision Support Model (e.g. a correction of the target value for lifetime performance).

Case study CowManager

In the following section, the extended model approach will be put into practice by using the assistance system CowManager (CowManager B.V., Netherlands) (Figure 2). The system consists of software, a router, and an ear tag with an integrated sensor that records the animal-related variables temperature and acceleration. Each ear tag of the CowManager is provided with a QR code, which is used to link the herd management system and the animal-specific ear tag. This allows both indirect variables (activity, rumination, and feeding behavior) as well as the direct variable (ear temperature) to be recorded. Based on this data and the variables generated from it in conjunction with other data and algorithms, the CowManager should be able to make statements about animal health, feeding, and fertility.

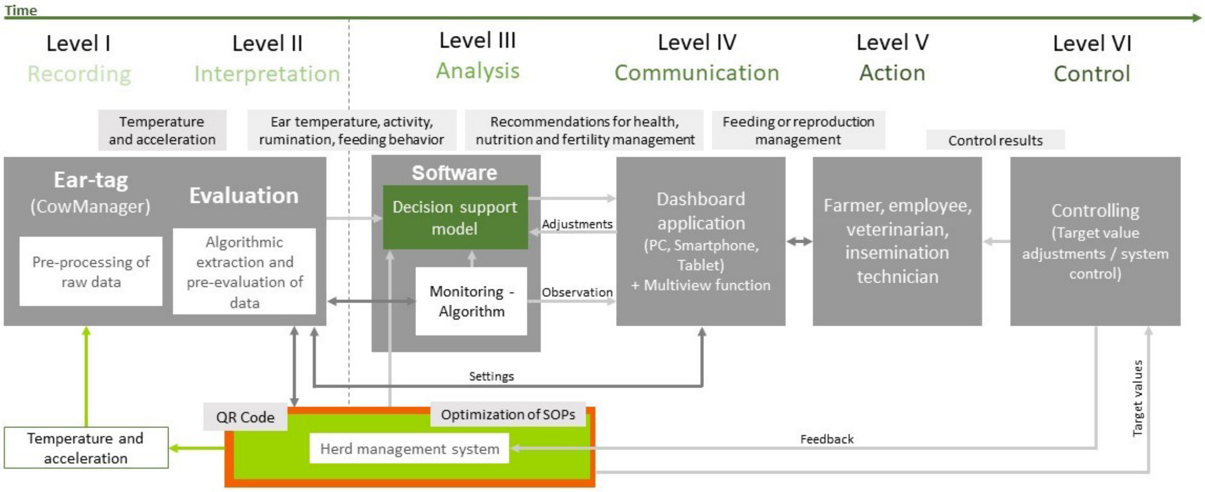

Figure 2: Presentation of the model approach using the CowManager as a practical example. (SOP: Standard Operating Procedure)

The raw data recorded by the ear tag is pre-processed (Level I). By linking the sensor with the animal`s number, additional information is added to the algorithmic extraction and pre-evaluation of the data (Level II). The additional information includes, for example, animal specific data on calving, insemination, and husbandry groups. This data is used as a basis for interpretation and the creation of additional indirect parameters. Afterwards, the information generated from this is integrated into the Decision Support Model software (Level III). In addition, the farmer can enter external information into the system, e.g. from observations of the animal or the weather forecast. The Decision Support Model takes the input parameters into account when calculating and evaluating the output variables with regard to activity, rumination, feeding behavior, and ear temperature and generates animal-specific alarm values or work lists for the farmer.

The CowManager system communicates and shows the suggested actions produced by algorithms through a dashboard application that may be accessed as an app on a mobile device or a PC. In addition, push-up messages can be generated on the mobile device (Level IV). A multi-view function of the CowManager system also allows external but authorized persons, such as the vet or insemination technician, to view the recommendations for action. Based on the alarm lists, the vet could, for example, directly adjust necessary examinations or treatments (Level V). In this way, actions can be taken with regard to health, nutrition, or fertility, which then can affect milk yield or the calving interval. Level VI (target value comparison) shows whether any adjustments need to be made to the standard operating procedure (SOP) in the agricultural production system. A uniform working method for all employees should be the aim (Buschsieweke et al. 2016). Feedback on the farm's objectives is provided to the herd management system by the operator or by automated technology. If necessary, the target values must be adjusted by the responsible person.

Discussion

Decision support is crucial in assistance systems, especially in agricultural animal husbandry. Emphasizing the role of humans in dealing with biological systems is essential for effective decision making. In order to place greater emphasis on the subsequent actions of humans or automated technology, we have extended the model by Rutten et al. (2013) to include the area of decision-making. In Rutten et al. (2013), the four levels are used to classify the technical status of a system. In this paper, we wanted to use the model to establish the sub-steps in decision support in order to highlight the benefits of assistance systems for farmers and to drive forward the development of assistance systems. These considerations are particularly important in the context of the ethical questions that agriculture faces in the course of advancing digitalization in animal husbandry. This fragment discusses animal welfare, sustainability, and appropriate data handling. Mancini (2011) raises questions about the evaluation of new technologies and determining the interaction between humans, technologies, other elements, and contextual factors. By expanding human-machine interaction to include the animal component, it is particularly important to analyze decision-making at a higher level of detail. The presented model approach contributes to the use of sensor technology in various areas of animal husbandry, not limited to dairy farming (Stachowicz and Umstätter 2020). It can be applied to all animal species and the sensor technology used there. The model demonstrates that an assistance system can provide support in dealing with ethical aspects by obtaining additional data, but cannot anticipate the answer. Obtaining additional data generates information that farmers can actively use for support.

Although the definitions of assistance systems from industrial production partly cover assistance systems from agriculture, these definitions focus only on humans and not animals. Humans are of particular importance due to the duty of care in livestock farming. Nevertheless, the aspect of ethics in relation to animals takes on an even greater significance due to the responsibility that humans have towards their fellow creatures (Cesarani and Pulina 2021). For this reason, our focus in Figure 1 is mainly on the levels "Communication - Action - Control" at Levels IV to VI. According to Dürnberger (2021), the effects of evolving digitalization on animals must be considered in an ethical context with reference to animal welfare and animal health. A "rebound effect," in which individual animal observation is minimized, and relies only on statistics, needs to be avoided. However, the primary factor in acquiring a sensor system is the reduction of working hours for farmers (Hostiou et al. 2017). It is crucial to balance technological advancements with direct animal observation. Although sensor systems can decrease the amount of time farmers spend on direct animal contact, it is essential to avoid extreme cases. The implementation of assistance systems is not intended to replace humans in the production process, but rather to aid them. Additionally, the implementation of an assistance system introduces new work tasks, such as proper data and alarm list management (Hostiou et al., 2017), and a shift in responsibilities. The time required for routine tasks, such as heat detection, is reduced, allowing for more time to be allocated to other tasks. The effective and efficient utilization of labor on farms is a significant motivator for implementing assistance systems. The literature often emphasizes the benefits of using individual farm data for production and production management. Additionally, demonstrating an extended model approach can facilitate the development of assistance systems in this area. This can include showcasing networking options and optimizing standard operating procedures (SOPs) (Schick 2018). Well-developed standard operating procedures (SOPs) result in clearly defined and understandable tasks and responsibilities, as well as standardized work processes. This can save time, improve work quality, and increase work efficiency (Buschsieweke et al., 2016). It is important to note that the model described above provides decision support and reduces the time required for animal observation if the data and alarm lists are handled appropriately. However, this approach does not comprehensively take over the decision-making process and the work involved.

According to Wolf and Strohschen (2018), the value of information increases with its quantity and, in particular, with the degree of networking that creates added value. When it comes to networking, a distinction can be made between a human-machine interface and a machine-machine interface (Klocke et al. 2017). In the context of livestock farming, however, the animal-machine interface is also worth mentioning. As animals do not play a role within the existing industry-related definitions, the various sources do not address animal-machine interaction or human animal-machine interaction. Bendel (2015) describes human-machine interaction as a well-established area of research, whereas animal-machine interaction has received little attention to date. In his opinion, there is a lack of fundamental considerations and systematization. To comprehend the interaction between animals and computer technology, it is essential to consider the context in which the interaction occurs. The interaction between animals, technology, and other elements such as humans varies based on these factors (Mancini 2011). In this context, it is important to take appropriate account of the animal in the adapted model as well. The model approach allows for context assignment, incorporating animal related data as measured variables in raw data processing to provide animal-specific information. As a result, the model also demonstrates the interaction between the machine and the animal. Both the animal machine interaction and the human-animal interaction are of great relevance when using assistance systems, which is why the term of human-animal-machine interaction should be used in this context.

Conclusion

The social debate and the demands placed on livestock farming have changed considerably in recent years. Agriculture finds itself in a field of tension between different interests. In principle, assistance systems can provide support in this area of conflict and help to simplify the transparency of documentation and communication. Assistance systems can aid in addressing ethical concerns by providing additional data, but they cannot replace human judgment. The focus should be on obtaining data that farmers can actively use to make informed decisions. To achieve this, it is necessary to integrate the animal component into the human-machine interaction and conduct a more detailed analysis of decision-making. Understanding these interactions requires consideration of the specific species, contexts, activities, and relationships involved. The proper consideration of animals in the modeling approach, along with the actors and technical components, enables a comprehensive understanding of human-animal-machine interaction. The presented modeling approach emphasizes the importance of decision support, ethical considerations, and the integration of humans, animals, and technology in the development and application of assistance systems in agriculture.

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