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Assessment of Metaverse wearable technologies for smart livestock farming through a neuro quantum spherical fuzzy decision-making model

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ABSTRACT

Livestock wearable technologies are innovations designed to ensure livestock health management. However, the user aspect of these devices from farmers' perspective is still questionable. Additionally, livestock wearables are still in progress compared to the other wearables. Thus, this research aims to identify key design features regarding wearable smart collars (WSCs) and rank the alternative WSC prototypes within Metaverse, allowing farmers to select the best wearable device. To this end, an integrated neuro quantum spherical fuzzy multi-criteria decision-making (MCDM) framework is introduced via facial expressions to obtain the priority weights of WSC criteria with the improved decision-making trial and evaluation laboratory (DEMATEL) approach and to rank the WSC alternatives in Metaverse through the improved multi-objective optimization based on ratio analysis (MOORA) model. The novelties of this research are: (1) to build and introduce a novel decision support tool based on facial expressions, expert recommendations, and the quantum spherical fuzzy sets, (2) to guide industrial designers about the essential features of WSCs, whereas they are designing these devices, and (3) to help smallholder farmers to decide on the best WSC to enhance animal welfare and efficiency of animal production. Concerning the findings, "sound and stress analyzer" is the most significant feature, followed by "disease detection" and "price." Moreover, Prototype 3 is the best WSC for farmers to adopt for livestock health management. Some essential implications are further presented.

1. Introduction

On the one hand, technology has had a significant impact on social life since the beginning of humanity. With the internet entering our lives just before the millennium, technology has progressed at a dizzying pace (Zhao et al., 2023). The incredible changes in technological developments deeply affect people and societies and continue to improve living standards (Li et al., 2023). Especially in recent years, thanks to artificial intelligence (AI), the Internet of Things (IoT), big data, augmented/virtual reality, and cloud storage technologies, collecting and sharing data has become very easy. Thanks to the digital systems mentioned, interactions between connected objects can be recorded, monitored, and analyzed (Haseli et al., 2023). Thus, wearable technology products are becoming increasingly popular daily among products based on newly developing technology (Jan et al., 2023). On the other hand, the world population recently surpassed 8 billion, and based on United Nations (UN) projections, it will unsurprisingly reach 9.7 billion by 2050 (Mistry et al., 2023). Together with population growth, the global demand for animal products is expected to boost by 2050 as well as global demand for food (Yin et al., 2023). Accordingly, the need for more breeding animals to feed people, satisfy global demand for a variety of meat and ensure global food security (Davis and White, 2020) inevitably compels the livestock industry to grow globally (Tan et al., 2021). Notwithstanding, labor-intensive and low margins traditional animal production methods have still dominated the world (Smith et al., 2015). Besides, an increase in livestock losses due to infectious disease and quitting livestock farming due to economic reasons lead to trouble against the growth of the global livestock industry (Delabouglise et al., 2023; Nicolas, 2023). Additionally, the concerns about the adverse effects of livestock production on the environment and climate force the livestock industry to shift towards more sustainable and efficient production programs to meet the growing global demand for animal products (Pozo et al., 2021; Wang et al., 2021a).

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Nomenclature

AI	Artificial Intelligence
AR	Augmented Reality
AUs	Action Units
AV	Augmented Virtuality
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DLF	Digital Livestock Farming
DTs	Digital Twins
IoT	Internet of Things
MCDM	Multi-Criteria Decision Making
MOORA	Multi-Objective Optimization Based on Ratio Analysis
NPD	New Product Development
PLF	Precision Livestock Farming
SLF	Smart Livestock Farming
UN	United Nations
VR	Virtual Reality
WSC	Wearable Smart Collar
XR	Extended Reality

Once the concern of the scientific community and the intensive livestock industry over animal welfare and animal production efficiency is considered, the only direction for the livestock industry is to approach intensification and sustainability (Zhang et al., 2021). To increase operational efficacy, economic viability, and ecological sustainability in the intensive livestock industry, smart livestock farming (SLF) is one of the options to be adopted by contemporary farmers as successors to precision livestock farming (PLF) (Alshehri, 2023). In the face of the growing need for SLF, it is necessary to immediately leave traditional methods of animal production and management, which are outdated and non-comprehensive for addressing several livestock farming challenges (Kok et al., 2021). Driven by Agriculture 5.0, which employs technologies such as machine learning, IoT, AI, and sensor technologies to remotely monitor animals through digital platforms and gather and analyze data about their behavior and physical state in real-time, an ambiguity in decision-making on farm operations can be mitigated (Catala-Roman et al., 2024). Further, the other critical technologies of Agriculture 5.0 are digital twins and simulations (Holzinger et al., 2024).

Metaverse, mimicking the real world through digital twins (DTs), IoT, AI, and Extended Reality (XR), has become an alternative platform for the livestock industry and several sectors (Neethirajan, 2023a; Deveci et al., 2023; Yaman et al., 2024). For instance, DTs in livestock farming are crucial in improving several animal farming processes, such as animal health and behavior monitoring (Neethirajan and Kemp, 2021a). In light of Agriculture 5.0, DTs can transform livestock production and management systems by ensuring real-time monitoring, simulation, and data analysis to promote sustainable farm management while enhancing animal welfare and productivity (Symeonaki et al., 2024). Accordingly, DTs allow farmers to make data-driven decisions and optimize overall farm efficiency, drawing upon different what-if scenarios (Kolekar et al., 2023). On the other hand, to effectively utilize the Metaverse technologies, farmers need to use wearable sensors for their animals to predict their behavior, monitor their physiological condition, and optimize their feeding and water usage (Neethirajan and Kemp, 2021b). Recently, the rapid development of advanced technologies has supported the rapid advancement in sensing technologies that enhance the effectiveness of animal production (Yin et al., 2023). To complement and enhance the effectiveness of sensing technologies, several devices, such as smart sensors, wearable technologies, or non-contact devices, have also been developed (Yin et al., 2023). Thus, livestock wearable technologies, which are directly attached to the farm animals in the forms of collars, ankle and tail bracelets, patchers, ear tags, and belly belts, serve as the eyes and ears of farmers (Neethirajan, 2020a). Consequently, through sensing technologies embedded in livestock wearable technologies, livestock farmers can conclusively gather information on their animals, including their movement behavior and biological state (Astill et al., 2020).

1.1. Motivation, novelty, and aim of the research

Most current research on wearable technologies concentrates on human applications, whereas some focus on pet applications (Zhang et al., 2021). Thus, though it has enormous importance in livestock health management, livestock wearable technologies are primarily in progress compared to human and pet wearables (Brophy et al., 2021). To contribute to the progress of these technologies, there are several review papers on livestock wearable technologies in the extant literature (i.e., Alipio and Villena, 2022; Džermeikaitė et al., 2023; Neethirajan, 2017; 2020; 2023a; Yin et al., 2023; Zhang et al., 2021). Moreover, there is a research on applying livestock wearables from the technology perspective (Neethirajan, 2023b). While the current literature on livestock wearables has been well-documented regarding technological aspects, the user aspect of livestock wearables from the farmer's perspective is limited to the studies that examine the factors influencing farmers' acceptance and adoption of wearables worn on their bodies. Based on the results of these studies, social influence (Yerebakan et al., 2022) and farmers' performance expectancy (Ronaghi and Forouharfar, 2020; Rübcke von Veltheim et al., 2021), technological interest (Yerebakan et al., 2022), and trust towards wearables (Abdollahzadeh et al., 2016) can influence their acceptance and adoption of these technologies, as well as compatibility, trialability (Yerebakan et al., 2022), perceived usefulness, and ease of use (Aubert et al., 2012). Moreover, socioeconomic factors, such as farmers' education and income level, support availability, and past experience in adopting any technologies can influence their adoption of these technologies (Das et al., 2019). Furthermore, animal-related factors such as body size, weight and shape, farm environments, and whether the wearables cause any inconvenience can be considered when adopting wearables (Neethirajan, 2020b). Though all these studies highlight the factors influencing farmers' adoption of wearables, the literature still lacks research that directly determines and prioritizes vital features essential for livestock wearables and selects the best alternative for livestock health management within a multi-criteria decision-making (MCDM) framework.

Accordingly, the lack of research that helps farmers decide on the optimum livestock wearables makes the task of smallholder farmers more challenging against these technologically complex products. Additionally, though it is an attention-grabbing topic for researchers and stakeholders, there is a tiny effort to design and produce livestock wearables in the marketplace. As a result, it may be beneficial to conceptually design livestock wearable prototypes with essential features to serve farmers within the context of SLF better. Besides its strategic role in SLF, Metaverse can be a cost-efficient and safe option for concept testing regarding livestock wearables through DTs and several products (Barrera and Shah, 2023). Driven by these motivations, this research aims to determine the critical design features regarding wearable smart collars (WSCs), a kind of livestock wearables, and choose the most promising WSC prototype developed in the Metaverse world, allowing farmers to select the best device for livestock health management. WSC is mainly employed since it is worn on animals' necks, allowing the farmers to gather real-time information on the physiological state of their animals at a remote distance to take timely action in the case of emergency (Saravanan and Saranya, 2017). Additionally, once the current marketplace is researched, there are only a few WSC examples that should be improved for livestock health management, allowing WSC to be conceptually designed and enhanced in Metaverse through their digital twins.

Drawing upon a research survey on wearable sensors for livestock health management and market research regarding animal wearables, eight key features are determined as selection criteria. These features include *metabolic activity tracker, movement and behavior analyzer, location tracker, antibiotic detection, disease detection, sound and stress analyzer, solar-powered battery,* and *price*. Afterward, five WSC prototypes are formed based on extant technological sensors to design livestock wearables. After experts' judgments regarding the evaluation criteria and alternatives are received, a novel integrated neuro quantum spherical fuzzy decision-making framework is developed through facial expressions, valuable communication tools that clearly reveal people's feelings, thoughts, and emotions and provide valuable information during decision-making (Kou et al., 2023), to decide the weight values of criteria with the improved decision-making trial and evaluation laboratory (DEMATEL) model, to rank the alternatives with the improved multi-objective optimization on the basis of ratio analysis (MOORA) approach. In sum, neuro quantum spherical fuzzy DEMATEL with golden cut and neuro quantum spherical fuzzy MOORA approaches are integrated for determining the most proper WSC. So, one of the foremost contributions of this research comes from its methodological approach. In the extant literature, DEMATEL has previously been utilized in several research on wearable technologies for humans (Büyüközkan and Güler, 2020; Kao et al., 2019; Liu and Han, 2020). Similarly, MOORA has also been adopted in previous research on wearables designed for humans (Ijaz et al., 2020). Different from the extant research, it is the first time that these MCDM methods are utilized in research on animal wearables within the framework based on facial expressions, expert recommendations, and the neuro quantum spherical fuzzy sets. The novelties of the proposed methodology include the innovations in decision-making with the integration of emotional intelligence by analyzing facial expressions, reducing uncertainties, and providing deeper insights into expert opinions. Also, quantum-based fuzzy sets and the application of the golden ratio enhance precision and minimize uncertainties in the evaluation process. The extended MOORA with quantum Spherical fuzzy sets promises another novelty with greater clarity and adaptability in alternative ranking, revolutionizing the decision-making landscape.

2. Research questions of the research

Regarding the discussion above, some research questions are arisen:

i) What are the critical WSC design features to be used for livestock health management?
ii) Which features should be mostly prioritized in the design of WSC?
iii) Which WSC prototype should be the best to be used in livestock health management?

To respond to these questions, therefore, a combined neuro quantum spherical fuzzy decision-making framework consisting of DEMATEL and MOORA is put forward. In this regard, firstly, the relative importance of WSC evaluation factors is extracted by Neuro Quantum Spherical fuzzy DEMATEL with the golden cut. Second, WSC alternatives in Metaverse are assessed with neuro quantum spherical fuzzy MOORA.

2.1. Contributions of the research

Based on the arguments above, some critical practical contributions of the paper can be mentioned. First, drawing upon the scarcity of research on prioritization of the critical features required for livestock wearables in the form of WSC and ranking of WSC alternatives to select the best one among them, this research provides a deeper insight into key features of WSC. Thus, it helps animal caretakers to choose the best WSC based on specific features. Compared with the traditional livestock management practices performed by farmers themselves, the proposed WSCs incorporated several sensors to track and record the daily routines of animals (Groher et al., 2020a) and collect data about their current location, movement, grazing and drinking behaviors (Pandey et al., 2021), rumination and laying behaviors (Džermeikaitė et al., 2023), and metabolic indicators (Neethirajan, 2017). Accompanying smartphones through applications, WSCs enable farmers to store, visualize and analyze the collected data to take an immediate action (Bailey et al., 2021). Once the expensive laboratory testing for animals is considered (Neethirajan et al., 2017), the proposed WSCs with sensor technologies would provide several benefits to livestock management in terms of facilitating early detection of diseases in livestock animals and lowering economic losses due to their death. Hence, the research results will enhance livestock health management efficiency, mitigate animal death and loss, and promote sustainable development in livestock farming. Second, initiating from the lack of extant WSC alternatives in the marketplace, this research integrates concept testing for WSC with Metaverse technologies, in which the new product development (NPD) process is facilitated safely, ethically, and cost-efficiently. Finally, the research findings would be utilized by industrial engineers who invent and design livestock wearables and would guide livestock farm managers or farmers to decide on the best animal wearables in the form of WSC to enhance animal welfare and efficiency of animal production.

Regarding the theoretical contributions, recognizing that experts' facial expressions can reveal their emotional states could be a more holistic approach to decision-making that includes human factors. This contribution helps reduce uncertainties and leads to more realistic analysis results. Additionally, the incorporation of quantum mechanisms and spherical fuzzy sets introduces a unique method to handle different degrees in the evaluation process, ultimately improving the quality of decisions by using the extended methodologies of the DEMATEL and MOORA respectively.

2.2. Design of the research

Overall, the consecutive section contains an insight into smart farming and the Metaverse, followed by a thorough review of the literature on livestock wearables for livestock health management. The methodology section includes a precise explanation of the proposed methodological framework of the research, followed by the results of the methodology and stability. The further section discusses the findings within the context of their theoretical and practical implications. Finally, the last section concludes with limitations and future research suggestions.

3. Literature review

This section of the research is structured into two subsections. The first part focuses on smart livestock farming and Metaverse technologies. In the next section, wearable technology studies in livestock health management are examined.

3.1. Smart livestock farming (SLF) and Metaverse

Modern livestock farming is depicted by the adoption of advanced technologies that enhance the performance of the livestock industry (Liu et al., 2020). The adoption of precision livestock farming (PLF) and digital livestock farming (DLF) has led to a paradigm shift in the livestock industry, increasing the use of technologies for more sustainable livestock farming practices and improving livestock health and welfare (Jiang et al., 2023). In recent years, the adoption of SLF, a knowledge-based notion that utilizes information and communication technologies, helps farmers manage cyber-physical livestock farms within digital farming (Neethirajan, 2023c). Addressing several problems in livestock management, reducing labor, and increasing efficiency, SLF technologies have proven their effectiveness in enhancing livestock welfare (Jiang et al., 2023). On the other hand, there are still some concerns about livestock farming. First, as the world population is growing with increased food demand, animal farming requires more land, water, and other resources, including labor, to feed the increasing global population

(McClements, 2023). Second, the more animal production increases, the more animal waste leads to pollution and other environmental problems, such as climate change driven by carbon emissions (Rojas-Downing et al., 2017). To mitigate climate change and other complex issues regarding animal production, including the spread of disease in livestock farming, operational efficiency in farm management, and adoption of new technological advancements, virtual environments can be a promising option for practicing livestock farming (Neethirajan, 2023a). Drawing upon this insight, the Metaverse, allowing the creation of exact reproduction of the real world and tracking actions and behaviors of all living creatures through their avatars, has become a playground of the livestock industry, as well as of many sectors (Pamucar et al., 2023).

The main technological building blocks of the Metaverse, including AI, virtual reality (VR), augmented reality (AR), augmented virtuality (AV), DTs, and IoT, can provide an immersive experience for even smallholder farmers, as well as for everyone else in the virtual world (Kusuma and Supangkat, 2022). AI, enabling machines to think, learn, and act as individuals do, is an important technology to mirror actions of the virtual cosmos in the physical world (De Bruyn et al., 2020). VR technology, creating a simulated 3D environment utilizing computer-generated imagery and sensory experiences, such as sound, is the other building block of the Metaverse (Liagkou et al., 2019). Besides, whereas AR enriches the real-world atmosphere with digital content, AV lets real-world objects, systems, and processes achieve actions in a virtual universe (Lee et al., 2021). All these technologies can be used for building computer-based virtual environments in animal farming that mimic real-world farming systems and settings (Anastasiou et al., 2023). Hence, Metaverse has become a virtual universe that is used for enhancing animal welfare, improving sustainability and efficiency, and reducing costs, as well as addressing several concerns regarding animal production (Jukan et al., 2017).

The other Metaverse technology, DTs, are the digital replica of real-world objects, systems, and processes with high fidelity (Duan et al., 2021). DTs allow farmers to create digital representations of things, such as biological farm animals, and virtual copies of real-world systems, processes, and operations, such as farm feeding stations synchronized with physical systems, processes, and procedures using technologies like VR and AR (Neethirajan and Kemp, 2021b). Building three-dimensional virtual and visually interactive replica of physical or biological objects, systems, or process, DTs allow farmers to capture real-time data from the virtual field and enables analysis of the system through what-if scenarios to recognize potential problems before they emerge (Mulyani et al., 2023). The data gathered from DTs of farm animals, the digital copy of the physical livestock, can be integrated into virtual environments, virtual animal farms that imitate real-world farm matters or scenarios (Neethirajan, 2023d).

Blending several Metaverse technologies in livestock farming, researchers and livestock industry practitioners can reshape current methods used in the industry (Büyükakin and Soylu, 2023). The merge of these technologies can provide farmers and researchers new opportunities for livestock management through profoundly engaging and interactive experiences, allowing them to manipulate the virtual farm environments or DTs in controlled virtual settings for simulations, experimentations, and analyses (Jeong et al., 2023). Through the data gathered from the DTs of animals in virtual farms, farmers can assess and optimize several farming practices and anticipate potential challenges and issues with predictive modeling (Zhang et al., 2023). Accordingly, integrating DTs into virtual farms in Metaverse allows even smallholder farmers to improve sustainability and efficiency in farm management with more proactive and data-driven decision-making.

However, since information is communicated and transferred between real and virtual worlds through sensors embedded in smart devices, virtual environments necessitate the use of technologies to handle several aspects of animal farming (Wang et al., 2022). Farmers mostly use wearable technologies to establish a DT control system that assists them in comprehending livestock farming performance and increasing productivity (Mulyani et al., 2023). So, there are several wearables designed directly for the use of farmers (Caria et al., 2019). Nevertheless, in the face of the need for healthier animals, it is also essential to design and produce livestock wearable technologies with crucial features directly worn by livestock to collect and communicate real-time information on their movement and physiological state. Through DTs of real-world animals visualized in Metaverse, a safe and controlled experiment for determining the essential features of new livestock wearables can be made, new prototypes can be created, and the optimum livestock wearables for improving livestock health management can be selected. Overall, against the costly and time-consuming NPD process, Metaverse can also be an excellent environment to conceptually design and test prototypes of livestock wearables worn by farm animals through their DTs without causing any damage or stress for livestock.

3.2. *Wearable technologies for livestock health management*

As the future of livestock farming is more driven by intelligence and sustainability instead of old-fashioned traditional methods, SLF has become a critical way to attain intensive and sustainable development of livestock farming (Yin et al., 2023). To perform precise livestock production by maintaining livestock well-being, using advanced technologies, such as special feeding, behavior monitoring, or early disease detection, has rapidly become necessary for the livestock industry (Zhang et al., 2021). As per these intelligent technologies, sensing technology has become prominent to effectively track and record real-time information on movement, behavior, living environments, and physiological state of livestock animals instead of relying only upon traditional methods and farmers' senses (Astill et al., 2020). Thus, biosensors are crucial in livestock farming, from precise feeding to epidemic disease detection and movement and behavior analysis to sound and stress analysis (Neethirajan et al., 2017). However, to facilitate real-time monitoring and accurate recording, it is essential to integrate sensors with wearable technology (Cui et al., 2019).

Recently, small biosensors can be embedded into several wearable devices utilizing IoT and wireless communication technology (Zhang et al., 2019). Though most of the wearable sensor technologies are designed to serve for improving human health and disease diagnosis, based on the merits of IoT technology, wearables have started to be adopted in livestock farming to collect large amounts of data on farm animals at any time and any places leading to ease in analysis and evaluation of their conditions (Zhang et al., 2021). Animals can directly wear wearables equipped with sensor technologies to collect and communicate data on their sweat contents, body temperature, behavior and movement, stress level, sound, and pH level, as well as to detect viruses and pathogens and prevent illness (Neethirajan et al., 2017). Accordingly, livestock wearable technologies enable farmers to detect disease early, either for timely diagnosis and remedy or to prevent the spread of disease in whole livestock herds (Džermeikaitė et al., 2023). Besides, multi-functional livestock wearables allow livestock caretakers to do more in less time (Neethirajan, 2017). Thus, as practicable and effective technology in the livestock industry, they have become inseparable from intensive livestock production systems to monitor livestock health and behavior.

However, while implementing WSC in different farming scales, from smallholder farms to large commercial operations, it is crucial to consider their scalability and cost-effectiveness. Given the conditions, wearable technologies for livestock animals may not always be feasible in some aspects. First, farmers have to lower input costs per animal, such as veterinary care and the cost of labor, to keep their profitability. Nevertheless, since wearables are not reusable and have a high per-unit cost, WSCs can be expensive for farmers if they need to monitor many livestock animals (Groher et al., 2020a; 2020b). Accordingly, depending on the herd size, implementing WSCs in livestock health management may be difficult for small-size farms because they cannot spread out the cost over time per livestock animal (Pandey et al., 2021). Therefore, adopting WSCs in animal health management may not make sense for small farmers unless WSCs are designed to be highly durable and reusable for multiple animals. Second, depending on the size of the farms, financial barriers such as wearable technology adoption and training costs can increase for farmers (Jerhamre et al., 2022). As a result, overall investment in money and time required to implement and learn wearable technologies may just become a burden on the shoulders of small-size farms. Finally, financial stress caused by ambiguous return on investment of wearables may make it difficult for smallholder farmers to adopt these technologies because they do not tend to see the long-run payoff of these investments (Makinde et al., 2022).

In addition, while implementing WSCs in livestock management, it is essential to consider any potential stress or discomfort caused by the wearables. On the one hand, manual data collection and recording in traditional livestock management mainly cause stress response and animal discomfort, which lead to low animal efficiency compared with data collection and recording performed by wearables in SLF (Zhang et al., 2021). On the other hand, if wearables in WSCs are large and heavy for many livestock animals, the possible behavioral differences caused by the additional weight and discomfort must be examined discreetly (Mao et al., 2023). The anatomic nature of livestock animals in terms of body size, shape, and weight mostly obstructs the design of wearables that can be used for long periods (Pandey et al., 2021). Sometimes, wearables worn on animals for traceability or identification can lead to potential damage to the animals (Schillings et al., 2021). Despite their benefits for livestock health monitoring, wearables may influence animals' behaviors, cause stress and discomfort, and lower their efficiency since livestock animals may not consent to be tracked and monitored like humans (Neethirajan, 2024).

The other consideration related to wearables is the technical challenges and limitations associated with developing and deploying these technologies, including selecting biocompatible materials, sensor technologies, wireless data transmission, and tracking different analyses simultaneously (Salim and Lim, 2019). As per these challenges, sensor technologies for livestock health management still have some limitations compared with human wearables. First, though biosensors can provide high detection accuracy and specificity, continuity of detection can be poor, and sensitive parts can quickly fail because of damage from dirt, sunlight, dust, fur, and environmental factors (Neethirajan, 2020b). Since WSCs are easy to fall and are mostly influenced by external environmental conditions, they can have low monitoring and data accuracy (Zhang et al., 2020). Second, livestock animals' metabolic activities, such as temperature and heart rate (Kim et al., 2019) and behaviors (Iqbal et al., 2021) may vary depending on their environment, thus influencing the data collected by sensors. Therefore, while sensors efficiently provide continuous data to farmers, data accuracy can sometimes be low because of measurement errors regarding heart rate or blood pressure, requiring further examination (Alipio and Villena, 2023). Third, since a single sensor can misconstrue the well-being of livestock animals, wearables are equipped with multi-sensor data fusion for accurate evaluation (Pandey et al., 2021). However, in the case of multi-sensor data fusion, the data accuracy can also be lost, requiring more data collection (Zhang et al., 2021).

Another challenge is the durability of wearables (Neethirajan, 2023b). When livestock animals are uncomfortable with wearables, they are prone to remove them, leading to poor livestock health monitoring (Arshad et al., 2023). Durability is also important when applied to multiple livestock animals. Herein, if wearables are designed as reusable wearables used for many animals instantly through software for monitoring the herd or via external sensors for tracking multiple livestock animals, their durability for farmers will be enhanced (Makinde et al., 2022). Finally, battery life is another limitation of wearables. For constant livestock health monitoring, sensors need continuous power, but the short life of batteries and their time-consuming replacement can create challenges for farmers (Neethirajan, 2017). Besides, once the environmentally unfriendly nature of batteries, which necessitates recycling, is considered, farmers' demand for self-powered biosensors is expected to increase. On the other hand, since the sustainable power supply technology is not improved enough for wearables, the density of self-powered energy for wearables used in SLF can still be low, and their endurance can still be weak (Zhang et al., 2021).

Despite all limitations and challenges, wearable IoTs have been increasingly integrated with existing farm management systems and data analytics tools in recent years since traditional farming equipment leads to more stress to animals, requires recoding data manually, and has high power consumption (Zhang et al., 2021). Compared with the conventional monitoring methods, such as taking notes, keeping a farm diary, or employing simple equipment without data sharing capacity, collecting data about livestock animal health through biosensors integrated with smartphones or handheld tools can be more reliable and effortless (Neethirajan, 2017). Multi-sensor data fusion technology driven by big data analysis has come into use by farmers to collect more information about the health, behavior, and genetics of livestock animals for better precision and intelligent farming without experienced herdsmen (Astill et al., 2020). Through biosensor technologies embedded in wearable devices, data about livestock animals' movement, living conditions, physiology, and behavior are efficiently tracked and recorded in real-time (Neethirajan et al., 2017). Through solar-powered receivers mounted on livestock animals, the obtained data is conveyed to a central server, leading to ease in viewing the final data on an office computer or a custom dashboard (Neethirajan, 2017). Additionally, by integrating farmers' smartphones with biosensors through information and communication technologies, farmers can perform real-time tracking, precise recording, and data collection at any time, place, and environmental conditions and help them analyze and assess the status of the animals monitored (Neethirajan and Kemp, 2021a). The traditional input-intensive farming approach has turned into an information-based farm management approach by making all animal care processes automated, controlled, and continually monitored (Neethirajan, 2023b). With the effective management of big data and record-keeping in real time, livestock animals' behaviors can be modeled, illnesses can be detected, and immediate actions can be taken (Basnet and Bang, 2018). So, the timely feedback about the state of every livestock animal sent to the farmers via applications for health monitoring makes them make decisions in time.

On the other hand, integrating wearable sensor technologies in farm management requires considering the ethical and privacy implications of using WSCs, especially in data collection and storage. Through sensors embedded in wearable IoTs, big data about livestock animals' health, genetics, and behavior can be collected, recorded, and stored in "clouds" (Neethirajan, 2017). Yet, farmers are reluctant to use these technologies and share their information with third parties against cyber-attacks, theft, or fraud (Wiseman et al., 2019). Since big data can be used to conclude themselves, their operations, and livestock animals, farmers also need to know that their information will be secure before sharing it to protect the privacy and safety of their farms and animals (Neethirajan, 2023). Similarly, sensor and wearable IoT manufacturers are reluctant to share information with farmers and third parties. Additionally, the lack of technical standards, the use of different metrics, protocols, and frequencies to collect data, and unique algorithms employed by wearable IoT manufacturers obstruct comparing data from various sensors manufactured by other manufacturers (Neethirajan and Kemp, 2021a). Thus, how vast amounts of data are collected, stored, and used and who has access to use it can lead to many problems regarding data privacy, security, and ownership (Morrone et al., 2022). However, by using secure data storage, data transfer protocols, and data anonymization, big data protection and security could be enhanced for farmers and sensor manufacturers (Neethirajan, 2017). Besides, ethically, the use of wearables can negatively influence farmers' duty of care and the human-animal relationship, influencing animal welfare and productivity (Schillings et al., 2021). Though endless health monitoring

Table 1
The extant research on livestock wearable technologies.

Author(s)	Aim	Applied Objects	Type of Research
Neethirajan et al. (2017)	To review emerging technological developments used in monitoring livestock health.	Livestock	R.R.
Neethirajan (2017)	To explore various wearable technologies and nano biosensors for detecting several infectious diseases of cattle.	Cattle	R.R.
Pons et al. (2017)	To present wearable tracking systems for discovering behaviors and body posture of animals.	Animals	R.R.
Benjamin and Yik (2019)	To review the literature on relevant wearable sensors and sensor network systems used for pig welfare.	Pig	R.R.
Waterhouse et al. (2019)	To explore the use of wearable and fixed PLF technologies in extensive farming.	Livestock	R.R.
Cui et al. (2019)	To implement a wearable stress monitoring system to identify more pressure information on sheep during transportation.	Sheep	R.R.
Eckelkamp (2019)	To highlight the role of wearable precision dairy technologies in detecting illnesses.	Dairy cows	R.R.
Pratama et al. (2019).	To present a smart collar recording information on body temperature, heart rate, and movement of cattle.	Cattle	A.R.
Muminov et al. (2019)	To develop a smart collar for monitoring goat behavior, decreasing GPS error.	Goat	A.R.
Astill et al. (2020)	To review the recent smart sensor technologies influencing poultry operations and their relation to big data analytics and IoT systems.	Poultry	R.R.
Nootyaskool and Ounsrimung (2020)	To present the smart cow collar for monitoring cow health.	Cow	A.R.
Hendriks et al. (2020)	To review studies on the lying behavior of dairy cows derived from wearable accelerometers.	Dairy cows	R.R.
Griesche and Baeumner (2020)	To review recent developments in wearable biosensors used in the livestock industry to improve food safety.	Livestock	R.R.
Karthick et al. (2020)	To review the current developments in domestic, farm, and wild animal healthcare.	Domestic, farm, and wild animals	R.R.
Nie et al. (2020)	To understand the possibility of continuous heart rate wearable sensors for livestock used for long-term monitoring.	Livestock	R.R.
Chung et al. (2020)	To determine the efficiency of utilizing implantable biosensors and wireless communication technology to track the heat-stress levels of dairy cows in real time.	Dairy cow	A.R.
Zhang et al. (2020)	To design a wearable multi-sensor system and facilitate its test experiment for sheep during transportation.	Mutton sheep	A.R.
Zhang et al. (2021)	To present technical features, applications, benefits, and challenges of wearable Internet of Things (W-IoT) devices used in farm animals.	Livestock	R.R.
Lee and Seo (2021)	To review wearable wireless sensor systems for cattle.	Cattle	R.R.
Nunes et al. (2021)	To develop a computational device using wearable sensing and deep learning to differentiate chew and bite events in horses.	Horse	A.R.
Neethirajan and Kemp. (2021c)	To review the significance of digital phenotyping concerning farm animals.	Livestock	R.R.
Irshad et al. (2021)	To review various types of wireless wearable sensors for cattle and pet animals used for tracking and monitoring and categorize them into different classes for their types, domains, and functionalities.	Cattle and et animals	R.R.
Pandey et al. (2021)	To introduce a remote monitoring ear tag sensor for analyzing the health and welfare of pigs.	Pig	A.R.
González-Sánchez et al. (2021)	To present a low-cost neck-mounted wearable device for monitoring cow data.	Cow	A.R.
Wang et al. (2021b)	To create a wearable multi-sensor-enabled decision support system for mutton sheep farming to provide safety and quality of mutton sheep.	Mutton sheep	A.R.
Casas et al. (2021)	To design a smart wearable for extensive livestock monitoring in these fields.	Livestock	A.R.
Go et al. (2022)	To promote a classification scheme of the most advanced level intelligent wearable devices and biosensors used in the health monitoring of cattle.	Cattle	R.R.
Chandra et al. (2022)	To present IoT-based smart collars for vital and activity monitoring of cattle.	Cattle	A.R.
Gehlot et al. (2022)	To explore technological interventions in dairy cattle to improve their ecosystem.	Cattle	R.R.
Darwis et al. (2022)	To present a digital smart collar to be utilized in real-time monitoring of the health and development of cattle.	Cow	A.R.
Sallam et al. (2022)	To present a cow collar for tracking cow activities.	Cow	A.R.
Campiotti et al. (2022)	To design, manufacture, and test a collar to monitor sheep behavior.	Sheep	A.R.
Riaboff et al. (2022)	To review current literature on the prediction of livestock behavior from raw accelerometer data.	Livestock	R.R.
Wu et al. (2022)	To track cattle physiological states utilizing a neural network model and wearable electronic sensors.	Cattle	A.R.
Džermeikaitė et al. (2023)	To review wearable bio-sensing technologies used for early illness diagnosis, management, and operations for livestock.	Cattle	R.R.
Alipio and Villena (2023)	To review current biosensors and intelligent wearables used in agricultural cattle health monitoring and develop classification for them.	Cattle	R.R.
Neethirajan (2023b)	To review potential of wearable sensor technologies in livestock health monitoring.	Livestock	R.R.
Yuan et al. (2023)	To present a wearable device for pregnancy identification of rabbits.	Rabbits	A.R.
Mao et al. (2023)	To review current research on automated animal activity recognition based on wearable sensors and deep learning algorithms.	Livestock	R.R.

*R.R.: Review research.
*A.R.: Applied research.

of livestock animals enhances their welfare, wearables might affect animals' natural behaviors and cause stress and discomfort (Neethirajan, 2024). Additionally, using these technologies makes farmers reduce livestock animals to tracking devices and consider only their productivity, causing the objectification of animals (Bos et al., 2018).

Overall, as a promising technology in the face of improving animal welfare, livestock wearable technologies have been well-documented by many review studies concerning sensing technologies used for livestock health management (Alipio and Villena, 2023; Džermeikaitė et al., 2023; Neethirajan, 2023b). Besides review studies, there is also applied research on the design and presentation of livestock wearables regarding sensing technologies (i.e., Casas et al., 2021; Chung et al., 2020; Nunes et al., 2021; Yuan et al., 2023; Zhang et al., 2020). All the relevant research on livestock wearable technologies is summarized in Table 1.

4. Research gaps

After a comprehensive literature survey, it can be noted that the extant literature still lacks research handling livestock wearable technologies from the perspective of farmers by helping them by identifying and ranking the key features essential for livestock wearable technologies and guiding them to select the best livestock wearables to be used for livestock health management. Additionally, there is research on the design of livestock wearable technologies, such as wearable ear tags (i.e., Pandey et al., 2021), wearable accelerometers (i.e., Riaboff et al., 2022), and smart collars (i.e., Chandra et al., 2022; Darwis et al., 2022; Campiotti et al., 2022). However, none of these studies guide farmers about which sensor features are more necessary than others and which livestock wearable is best for livestock health management utilizing MCDM methods or their uncertain versions. Consequently, driven by these gaps in the literature, this research aims to identify the critical design features regarding WSCs and to rank the alternative WSC prototypes developed in the Metaverse universe, allowing farmers to select the best device for livestock health management.

4.1. Criteria for features of livestock wearables regarding livestock health management

Drawing upon a thorough survey of relevant research and expert opinions, such as farmers and veterinarians, eight main features as evaluation criteria (*C1, C2, …, C8*) that livestock wearable technologies should have for livestock health management are determined in this research.

C1–Metabolic activity tracker: Tracking the metabolic activities of farm animals, including their temperature, blood oxygen saturation, sweat, pulse, respiration, and heart rate variability, is crucial for livestock health management since the anomalies in the metabolic activity of animals can lead to several health problems and even death of farm animals (Neethirajan, 2017). Nonetheless, farmers are not always together with their animals and cannot physically monitor the metabolic activities of especially free-moving farm animals (Neethirajan, 2020a). Thus, it is critical to design livestock wearables with biosensors that track the metabolic activity of farm animals.

C2–Movement and behavior analyzers: Changes in the movements and behaviors of farms can indicate health problems (Neethirajan, 2017). When the walking, lying, standing, or posture of farm animals change, it can stem from sickness (Neethirajan, 2020b). Thus, to protect and improve the health of farm animals, livestock wearables should have sensors that track their behavior and movements, including positions, gait features, food intake, activity levels, sleep, obesity control, and calories burned.

C3–Location tracker: Real-time location trackers can pinpoint the exact position of animals within a specific field (Neethirajan, 2020b). Additionally, global positioning system (GPS) based sensor networks help farmers to either reduce or prevent wild animal attacks and theft in livestock (Aquilani et al., 2022). Thus, GPS technology can be integrated into livestock wearables to track farm animals' location and placement.

C4–Antibiotic detection: Farm animals can have antibiotic resistance if farmers frequently and unconsciously use antibiotics in livestock farms (Neethirajan, 2017). Since it is difficult to treat animals when they are immune to antibiotic treatment, farmers can lose their animals (Xu et al., 2023). Thus, livestock wearables can be designed with biosensors to detect the antibiotic levels of the animals.

C5–Disease detection: The diseases of farm animals can stem from several reasons, including mastitis, viruses (Cai et al., 2023), bacteria, pathogens (Ulucan-Karnak et al., 2023), and β-hydroxybutyrate (Neethirajan, 2017). Since early detection of disease in farm animals enables farmers to treat the animals or to prevent the spread of disease in whole herds (Džermeikaitė et al., 2023), early disease detection features also seem essential for improving livestock health and decreasing farm animal deaths.

C6–Sound and stress analyzers: The sound of animals can ensure critical information about their emotional state, such as stress level, and allows animal caretakers to calibrate conditions to keep them comfortable (Olczak et al., 2023). Besides, the high noise level is sometimes one of the essential indicators of health problems of farm animals (Sadeghi et al., 2023). Consequently, while designing a livestock wearable, sound analyzers must be used to detect stress levels or other health problems of farm animals.

C7–Solar-powered battery: Primarily, livestock wearables must continuously work to collect real-time data about the current state of the free-moving animals grazing outside the farm and under the sun (Tzanidakis et al., 2023). Thus, livestock wearables can be designed with solar-powered battery charging for a prolonged life span of wearables.

C8–Price: Recently, there has been a considerable decrease in the number of livestock caretakers due to economic reasons (Simitzis et al., 2021). Since the price of livestock wearables for livestock health management would lead to financial burdens on farmers, the cost of the device per every livestock animal can influence their decision to adopt this technology, as it affects the adoption of wearables for humans. Consequently, price could also be a key factor for evaluating and selecting the best livestock wearables for livestock health management.

4.2. WSC alternatives

Once the importance of livestock production in meeting the growing global demand for animal products is considered, using livestock wearable technologies for livestock health management seems a critical step for livestock welfare (Yin et al., 2023). However, adopting livestock wearable technologies is not as common as adopting wearables designed for humans and pets, such as dogs and cats (Brophy et al., 2021). As a result, though there are several start-ups for pet wearable technologies, such as FitBark and Whistle, the wearables used in livestock are still in their infancy (Waterhouse et al., 2019). On the other hand, there is an effort to develop livestock wearables, such as smart ear tags, ankle and tail bracelets, belly belts, and wearable smart collars worn directly by animals (Neethirajan, 2023b).

WSC is mainly selected in this research because smart collars are worn on the neck of the animals, and the neck is a suitable place to collect precise data about the physiological state, behavior, and movement of animals through sensors (Alipio and Villena, 2023). Additionally, there are various WSC alternatives in the marketplace, such as Smarttag Neck and Aficollar, but they must be improved with accurate features for better livestock health management (Lee and Seo, 2021). Thus, drawing upon the Metaverse technologies used mainly in the NPD process, the digital twins of five alternative WSCs for livestock health management are conceptualized based on feedback from farmers and veterinarians. These conceptual alternatives are given below:

A1 – It is the digital twin of the first and the cheapest WSC prototype. It is only equipped with movement and behavior analyzer and location tracker features with a remarkable price advantage.

A2 – It is the digital twin of the second WSC prototype. It offers metabolic activity and location trackers, sound and stress analyzers, and solar-powered battery features with a considerable price advantage. However, it lacks movement and behavior analyzers and antibiotic and disease detection features.
A3 – It is the digital twin of the third WSC prototype. It only has metabolic activity and location tracker features as well as antibiotic and disease detection features for livestock health management.
A4 – It is the digital twin of the fourth WSC prototype. Though it has several features, including a metabolic activity tracker, movement and behavior analyzers, location tracker, antibiotic detection, and solar-powered battery life, it lacks two features, including disease detection and sound and stress analyzers.
A5 – It is the digital twin of the fifth and the most expensive WSC prototype. It has all features except antibiotic detection and solar-powered battery life.

5. Research methodology

The basic approaches in the proposed decision-making model are explained in the following subtitles.

5.1. Decision-making with facial expressions

The quality of expert opinions in decision-making models is important in many respects. In this context, experts from whom opinions will be provided must have comprehensive knowledge of the subject. Therefore, quality expert opinions help make more accurate decisions. Moreover, quality expert opinions enable a clearer understanding of the problems in the decision-making process. Thus, it is possible to obtain more accurate analysis results. On the other hand, quality expert opinions contribute to a more reliable decision-making process. Thus, better strategies can be developed based on the results obtained. In summary, correctly integrating experts in the decision-making process allows quality decisions.

It is vital to consider the facial expressions of experts to reduce uncertainties in decision-making processes. This situation is essential to include emotional intelligence in the analysis process. The main reason for this condition is that experts' facial expressions reflect the emotional states of the decision-making process. In other words, issues such as the expert's uneasiness and indecision can be included in the analysis process. Thus, it is possible to achieve more realistic analysis results (Megahed & Mohammed, 2020; Lee et al., 2023; Zhao et al., 2023; Li et al., 2023). Decision-making processes are not only based on logic and data; human factors can also be considered. The facial action coding system (FACS) considers people's emotions during analysis. In this framework, 46 distinct action units (AUs) are taken into consideration. With the help of this issue, uncertainties in the evaluation process can be minimized.

5.2. Quantum-based fuzzy sets with golden ratio

Quantum theory is considered to express tiny particles' behaviors, so it is helpful to make sensitive evaluations. Because of this advantage, this approach can be used to predict values. Further, uncertainty is relatively high in particle analysis, so detailed and precise analyses can be performed with quantum theory. One of the most critical problems in the decision-making process is high uncertainty, which closely concerns the accuracy of the results. For this reason, there are various searches to increase confidence in the decisions made (Kou et al., 2023). Hence, the quantum mechanism is integrated with a spherical fuzzy decision-making model to minimize uncertainties in the process. In the literature, some researchers have proposed some solid quantum spherical fuzzy methodologies to solve challenging real-world problems for effective decision-making, such as evaluating sectors in the stock exchange (Kayacık et al., 2022), ranking sustainable industries (Hacioglu et al., 2023), assessing fintech ecosystem (Ali et al., 2023), evaluating investment alternatives (Kou et al., 2023), analyzing bank mergers (Albinali et al., 2023), and identifying investor risk profile (Rahadian et al., 2024). Quantum spherical fuzzy situation is detailed in Eqs. (1)–(3).

$$Q(|u>) = \varphi e^{j\theta} \tag{1}$$

$$|\varsigma> = \{|u_1>, |u_2>, \cdots, |u_n>\} \tag{2}$$

$$\sum_{|u>\subseteq|\varsigma>} |Q(|u>)| = 1 \tag{3}$$

In these equations, ς demonstrates a collection of exhaustive events and φ^2 provides the amplitude-based result. On the other side, θ defines the phase angle and u indicates an event. Spherical fuzzy sets, $\widetilde{A}_S$, are the extensions of the classical fuzzy numbers. The main superiority of these sets is considering different degrees in the evaluation process to handle the uncertainties in the process. These sets are identified in Eqs. (4) and (5).

$$\widetilde{A}_S = \left\{ \langle u, (\mu_{\tilde{A}_S}(u), v_{\tilde{A}_S}(u), h_{\tilde{A}_S}(u)) | u \in U \right\} \tag{4}$$

$$0 \leq \mu^2_{\tilde{A}_S}(u) + v^2_{\tilde{A}_S}(u) + h^2_{\tilde{A}_S}(u) \leq 1, \forall_u \in U \tag{5}$$

In this framework, $\mu_{\tilde{A}_S}$ denotes the membership degree, $v_{\tilde{A}_S}$ indicates non-membership degree and $h_{\tilde{A}_S}$ refers to the hesitancy degrees. With the help of Eqs. (6)-(8), Quantum theory is integrated to the Spherical fuzzy numbers.

$$\left|\varsigma_{\tilde{A}_S}> = \left\{ \langle u, (\varsigma_{\mu_{\tilde{A}_S}}(u), \varsigma_{v_{\tilde{A}_S}}(u), \varsigma_{h_{\tilde{A}_S}}(u)) | u \in 2^{\left|\varsigma_{\tilde{A}_S}>\right.} \right\}\right. \tag{6}$$

$$\varsigma = \left[\varsigma_\mu . e^{j2\pi.\alpha}, \varsigma_v . e^{j2\pi.\gamma}, \varsigma_h . e^{j2\pi.\beta}\right] \tag{7}$$

$$\varphi^2 = |\varsigma_\mu(|u_i>)| \tag{8}$$

where $\varsigma_{\mu_{\tilde{A}_S}}$ identifies the membership, $\varsigma_{v_{\tilde{A}_S}}$ refers to the non-membership, and $\varsigma_{h_{\tilde{A}_S}}$ explains the hesitant degrees. The amplitudes of quantum membership, non-membership, and hesitancy degrees are shown as ς_μ, ς_v , and ς_h. On the other side, phase angles are defined by α, γ, and β. For the calculation of the degrees in this proposed model, golden ratio (G) is considered. The calculation process is given in Eqs. (9) and (10).

$$\varsigma_v = \frac{\varsigma_\mu}{G} \tag{9}$$

$$\varsigma_h = 1 - \varsigma_\mu - \varsigma_v \tag{10}$$

The computation operations are explained in Eqs. (11)–(17).

$$\alpha = |\varsigma_\mu(|u_i>)| \tag{11}$$

$$\gamma = \frac{\alpha}{G} \tag{12}$$

$$\beta = 1 - \alpha - \gamma \tag{13}$$

$$\lambda^{*}\widetilde{A}_{\varsigma}=\left\{\left(1-\left(1-\varsigma_{\mu_{\tilde{A}}}{}^{2}\right)^{\lambda}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(1-\left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}\right)^{\frac{1}{2}}},\varsigma_{\nu_{\tilde{A}}}{}^{\lambda}e^{j2\pi\cdot\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{\lambda}},\left(\left(1-\varsigma_{h_{\tilde{A}}}{}^{2}\right)^{\lambda}-\left(1-\varsigma_{\mu_{\tilde{A}}}{}^{2}-\varsigma_{h_{\tilde{A}}}{}^{2}\right)^{\lambda}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(\left(1-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}-\left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}\right)^{\frac{1}{2}}}\right\},\lambda>0 \tag{14}$$

$$\widetilde{A}_{\varsigma}{}^{\lambda}=\left\{\varsigma_{\mu_{\tilde{A}}}{}^{\lambda}e^{j2\pi\cdot\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{\lambda}},\left(1-\left(1-\varsigma_{\nu_{\tilde{A}}}{}^{2}\right)^{\lambda}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(1-\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}\right)^{\frac{1}{2}}},\left(\left(1-\varsigma_{\nu_{\tilde{A}}}{}^{2}\right)^{\lambda}-\left(1-\varsigma_{\nu_{\tilde{A}}}{}^{2}-\varsigma_{h_{\tilde{A}}}{}^{2}\right)^{\lambda}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}-\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\right)^{\lambda}\right)^{\frac{1}{2}}}\right\},\lambda>0 \tag{15}$$

$$\widetilde{A}_{\varsigma}\oplus\widetilde{B}_{\varsigma}=\left\{\left(\varsigma_{\mu_{\tilde{A}}}{}^{2}+\varsigma_{\mu_{\tilde{B}}}{}^{2}-\varsigma_{\mu_{\tilde{A}}}{}^{2}\varsigma_{\mu_{\tilde{B}}}{}^{2}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}+\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^{2}-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}},\varsigma_{\nu_{\tilde{A}}}\varsigma_{\nu_{\tilde{B}}}e^{j2\pi\cdot\left(\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)\right)},\left(\left(1-\varsigma_{\mu_{\tilde{B}}}{}^{2}\right)\varsigma_{h_{\tilde{A}}}{}^{2}+\left(1-\varsigma_{\mu_{\tilde{A}}}{}^{2}\right)\varsigma_{h_{\tilde{B}}}{}^{2}-\varsigma_{h_{\tilde{A}}}{}^{2}\varsigma_{h_{\tilde{B}}}{}^{2}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(\left(1-\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}+\left(1-\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2}-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}}\right\} \tag{16}$$

$$\widetilde{A}_{\varsigma}\otimes\widetilde{B}_{\varsigma}=\left\{\varsigma_{\mu_{\tilde{A}}}\varsigma_{\mu_{\tilde{B}}}e^{j2\pi\cdot\left(\frac{\alpha_{\tilde{A}}}{2\pi}\right)\left(\frac{\alpha_{\tilde{B}}}{2\pi}\right)},\left(\varsigma_{\nu_{\tilde{A}}}{}^{2}+\varsigma_{\nu_{\tilde{B}}}{}^{2}-\varsigma_{\nu_{\tilde{A}}}{}^{2}\varsigma_{\nu_{\tilde{B}}}{}^{2}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}+\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^{2}-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}},\left(\left(1-\varsigma_{\nu_{\tilde{B}}}{}^{2}\right)\varsigma_{h_{\tilde{A}}}{}^{2}+\left(1-\varsigma_{\nu_{\tilde{A}}}{}^{2}\right)\varsigma_{h_{\tilde{B}}}{}^{2}-\varsigma_{h_{\tilde{A}}}{}^{2}\varsigma_{h_{\tilde{B}}}{}^{2}\right)^{\frac{1}{2}}e^{j2\pi\cdot\left(\left(1-\left(\frac{\gamma_{\tilde{B}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}+\left(1-\left(\frac{\gamma_{\tilde{A}}}{2\pi}\right)^{2}\right)\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2}-\left(\frac{\beta_{\tilde{A}}}{2\pi}\right)^{2}\left(\frac{\beta_{\tilde{B}}}{2\pi}\right)^{2}\right)^{\frac{1}{2}}}\right\} \tag{17}$$

5.3. The quantum spherical fuzzy extension of DEMATEL

The DEMATEL technique is used to compute the weights of different factors. In this model, this approach is integrated with quantum Spherical fuzzy sets. The details are indicated below.

Step 1: Evaluations are taken from the selected experts.

Step 2: A decision matrix is created by Eq. (18).

$$\varsigma_{k}=\begin{bmatrix}0 & \varsigma_{12} & \cdots & \cdots & \varsigma_{1n}\\ \varsigma_{21} & 0 & \cdots & \cdots & \varsigma_{2n}\\ \vdots & \vdots & \ddots & \cdots & \cdots\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ \varsigma_{n1} & \varsigma_{n2} & \cdots & \cdots & 0\end{bmatrix} \tag{18}$$

The aggregated values are calculated by Eq. (19).

$$\varsigma=\left\{\left[1-\prod_{i=1}^{k}\left(1-\varsigma_{\mu_i}{}^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}e^{2\pi\cdot\left[1-\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}},\prod_{i=1}^{k}\varsigma_{\nu_i}{}^{\frac{1}{k}}e^{2\pi\cdot\prod_{i=1}^{k}\left(\frac{\gamma_i}{2\pi}\right)^{\frac{1}{k}}},\left[\prod_{i=1}^{k}\left(1-\varsigma_{\mu_i}{}^{2}\right)^{\frac{1}{k}}-\prod_{i=1}^{k}\left(1-\varsigma_{\mu_i}{}^{2}-\varsigma_{h_i}{}^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}e^{2\pi\cdot\left[\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^{2}\right)^{\frac{1}{k}}-\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^{2}-\left(\frac{\beta_i}{2\pi}\right)^{2}\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}}\right\} \tag{19}$$

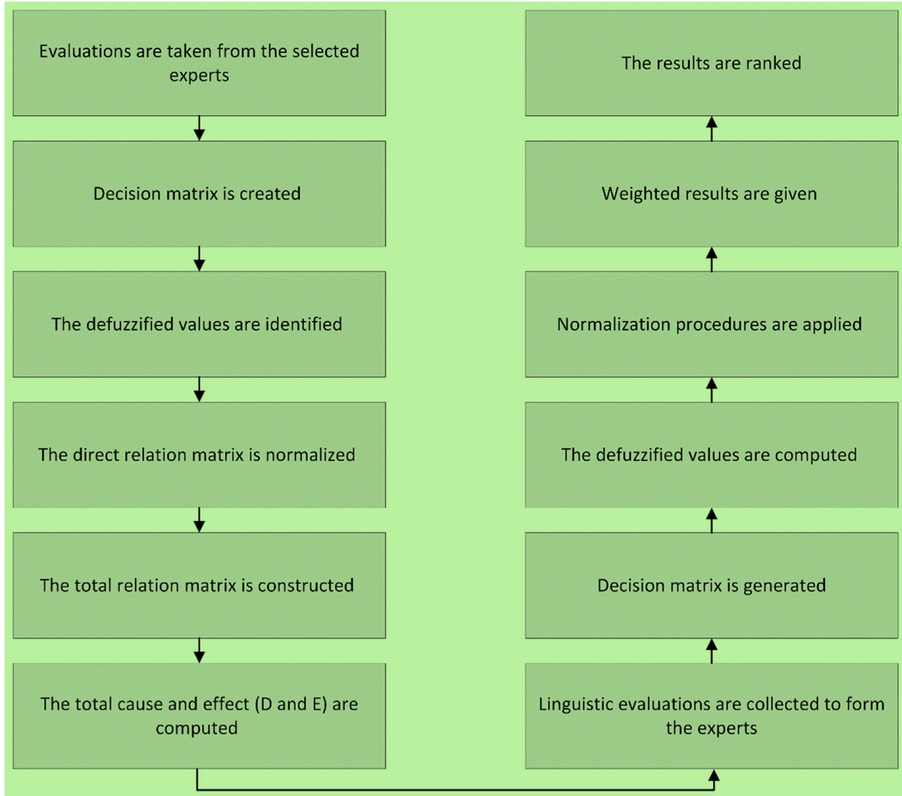

Fig. 1. The flowchart of the analysis.

Step 3: The defuzzified values are identified with Eq. (20).

$$Def\varsigma_i = \varsigma_{\mu_i} + \left(\frac{\varsigma_{\mu_i}}{\varsigma_{\mu_i} + \varsigma_{h_i} + \varsigma_{v_i}}\right) + \left(\frac{\alpha_i}{2\pi}\right) + \left(\frac{\left(\frac{\alpha_i}{2\pi}\right)}{\left(\frac{\alpha_i}{2\pi}\right) + \left(\frac{\gamma_i}{2\pi}\right) + \left(\frac{\beta_i}{2\pi}\right)}\right) \tag{20}$$

Step 4: The direct relation matrix is normalized by Eqs. (21) and (22).

$$B = \frac{\varsigma}{max_{1 \le i \le n} \sum_{j=1}^{n} \varsigma_{ij}} \tag{21}$$

$$0 \le b_{ij} \le 1 \tag{22}$$

Step 5: The total relation matrix is constructed with Eq. (23).

$$\lim_{k \to \infty} \left(B + B^2 + \cdots + B^k\right) = B(I - B)^{-1} \tag{23}$$

Step 6: The total cause and effect (D and E) are computed by Eqs. (24) and (25).

$$D = \left[\sum_{j=1}^{n} e_{ij}\right]_{nx1} \tag{24}$$

$$E = \left[\sum_{i=1}^{n} e_{ij}\right]_{1xn} \tag{25}$$

The total of these values is used to weight the items. Additionally, threshold value in Eq. (26) is considered to identify causal directions.

$$\alpha = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left[e_{ij}\right]}{N} \tag{26}$$

Table 2
Selected criteria for the wearable technology selection.

Criteria	Definition	References
C1-Metabolic activity tracker	It refers to biosensors tracking temperature, blood oxygen saturation, pregnancy, sweat, pulse, respiration, heart rate variability.	Neethirajan (2017, 2020a)
C2-Movement and behavior analyzers	It refers to sensors tracking positions, gait feature, food intake, activity levels, watering, eating habits, fattening, obesity control, sleep and calories burned and muscle injuries.	Neethirajan (2017, 2020b)
C3-Location tracker	It refers to GPS technology which detects the exact location of animals.	Neethirajan (2017)
C4-Antibiotic detection	It refers to biosensors that easily detect antibiotic levels in blood and muscle of animals and warn farmers if the level is upper than a maximum range	Neethirajan (2017)
C5-Disease detection	It refers to biosensors detecting influenza virus, bacteria, pathogens, β-hydroxybutyrate to provide early diagnosis.	Džermeikaitė et al. (2023), Neethirajan (2017)
C6-Sound and stress analyzers	It refers to sound analyzers to detect stress level and other problems regarding livestock from their sounds.	Olczak et al. (2023)
C7-Solar powered battery	It refers to charging via daylight.	Tzanidakis et al. (2023)
C8-Price	It refers to the cost of device for farmers.	Simitzis et al. (2021)

5.4. The quantum spherical fuzzy extension of MOORA

MOORA is considered for alternative ranking. In this study, this technique is used with quantum Spherical fuzzy sets. The steps of this integration are indicated as follows.

Table 3
Emotional expressions and action unit combinations.

Emotions	AUs	Pair combinations of AUs	Scales for Criteria	Scales for Alternatives	Possibility Degrees	Fuzzy Numbers
Contempt (Disdain)	7,10,14,15	(7,10),(7,14),(7,15), (10,14),(10,15),(14,15)	No influence (n)	Weakest (w)	0.40	$\left[\sqrt{0.16}\,e^{j2\pi.0.4}, \sqrt{0.10}\,e^{j2\pi.0.25}, \sqrt{0.74}\,e^{j2\pi.0.35}\right]$
Intermediate Emotion	1 AU of Contempt + 1 AU of Surprise	(7,1),(7,2),(7,5), (7,27), (10,1),(10,2), (10,5),(10,27), (14,1), (14,2),(14,5),(14,27), (15,1),(15,2),(15,5), (15,27)	Somewhat influence (s)	Poor (p)	0.45	$\left[\sqrt{0.20}\,e^{j2\pi.0.45}, \sqrt{0.13}\,e^{j2\pi.0.28}, \sqrt{0.67}\,e^{j2\pi.0.27}\right]$
Surprise	1,2,5,27 1 AU of Contempt + 1 AU of Happy	(1,2),(1,5),(1,27), (2,5),(2,27),(5,27) (7,6),(7,12),(7,25), (7,26), (10,6),(10,12), (10,25),(10,26),(14,6), (14,12), (14,25),(14,26),(15,6), (15,12),(15,25),(15,26)	Medium influence (m)	Fair (f)	0.50	$\left[\sqrt{0.25}\,e^{j2\pi.0.50}, \sqrt{0.15}\,e^{j2\pi.0.31}, \sqrt{0.60}\,e^{j2\pi.0.19}\right]$
Intermediate Emotion	1 AU of Surprise + 1 AU of Happy	(1,6),(1,12),(1,25), (1,26),(2,6),(2,12), (2,25),(2,26),(5,6), (5,12),(5,25),(5,26), (27,6),(27,12),(27,25), (27,26)	High influence (h)	Good (g)	0.55	$\left[\sqrt{0.30}\,e^{j2\pi.0.55}, \sqrt{0.19}\,e^{j2\pi.0.34}, \sqrt{0.51}\,e^{j2\pi.0.11}\right]$
Happiness	6,12,25,26	(6,12),(6,25),(6,26), (12,25),(12,26),(25,26)	Very high influence (vh)	Best (b)	0.60	$\left[\sqrt{0.36}\,e^{j2\pi.0.6}, \sqrt{0.22}\,e^{j2\pi.0.37}, \sqrt{0.42}\,e^{j2\pi.0.03}\right]$

Table 4
Observation results of facial expressions for the criteria.

Expert 1

	C1	C2	C3	C4	C5	C6	C7	C8
C1		(10,26)	(10,26)	(14,2)	(14,2)	(27,25)	(14,2)	(14,2)
C2	(10,1)		(10,1)	(14,15)	(10,1)	(2,6)	(14,15)	(14,2)
C3	(10,1)	(14,27)		(14,2)	(10,1)	(2,6)	(10,1)	(10,1)
C4	(14,27)	(10,26)	(10,26)		(14,2)	(25,26)	(10,1)	(10,1)
C5	(7,12)	(2,6)	(2,6)	(10,26)		(25,26)	(27,25)	(14,2)
C6	(14,15)	(14,2)	(14,15)	(14,27)	(14,15)		(14,27)	(10,1)
C7	(14,2)	(10,26)	(7,12)	(14,27)	(14,27)	(7,12)		(10,1)
C8	(7,12)	(5,12)	(2,6)	(10,26)	(14,2)	(25,26)	(10,26)	

Expert 2

	C1	C2	C3	C4	C5	C6	C7	C8
C1		(10,26)	(2,6)	(10,1)	(10,1)	(25,26)	(7,12)	(14,2)
C2	(14,2)		(7,12)	(10,1)	(10,1)	(2,6)	(10,1)	(10,1)
C3	(10,1)	(14,27)		(14,15)	(14,27)	(10,26)	(14,15)	(14,15)
C4	(10,1)	(7,12)	(2,6)		(14,27)	(27,25)	(14,27)	(14,27)
C5	(10,1)	(7,12)	(2,6)	(10,26)		(25,26)	(10,26)	(10,1)
C6	(14,15)	(14,15)	(14,2)	(14,15)	(14,2)		(14,27)	(10,1)
C7	(10,1)	(7,12)	(7,12)	(14,27)	(10,1)	(2,6)		(10,1)
C8	(14,2)	(7,12)	(27,25)	(10,26)	(10,1)	(25,26)	(10,26)	

Expert 3

	C1	C2	C3	C4	C5	C6	C7	C8
C1		(2,6)	(2,6)	(10,26)	(10,1)	(25,26)	(7,12)	(7,12)
C2	(14,27)		(10,26)	(14,27)	(10,1)	(2,6)	(14,27)	(14,2)
C3	(14,15)	(14,15)		(14,27)	(7,14)	(10,26)	(14,27)	(14,15)
C4	(10,1)	(7,12)	(7,12)		(10,1)	(2,6)	(14,27)	(14,27)
C5	(10,1)	(10,26)	(27,25)	(10,26)		(25,26)	(7,12)	(7,12)
C6	(7,14)	(14,27)	(14,15)	(14,2)	(7,14)		(14,2)	(10,1)
C7	(14,27)	(10,26)	(27,25)	(7,12)	(14,2)	(25,26)		(10,1)
C8	(14,27)	(10,26)	(27,25)	(7,12)	(14,2)	(25,26)	(14,2)	

Expert 4

	C1	C2	C3	C4	C5	C6	C7	C8
C1		(14,27)	(10,1)	(7,12)	(14,27)	(10,26)	(27,25)	(10,26)
C2	(10,1)		(10,1)	(7,12)	(10,1)	(7,12)	(7,12)	(14,27)
C3	(10,1)	(14,27)		(10,26)	(10,1)	(10,26)	(7,12)	(14,27)
C4	(14,15)	(14,15)	(14,27)		(7,14)	(14,27)	(7,12)	(7,14)
C5	(14,27)	(7,12)	(7,12)	(2,6)		(2,6)	(25,26)	(10,26)
C6	(10,1)	(10,1)	(10,1)	(10,1)	(10,1)		(10,26)	(10,1)
C7	(14,15)	(14,2)	(14,15)	(14,15)	(10,1)	(14,15)		(10,1)
C8	(14,27)	(14,27)	(14,27)	(10,26)	(10,1)	(15,26)	(2,6)	

Table 5
Average values of quantum spherical fuzzy numbers for the criteria.

	C1	C2	C3	C4
C1		$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$	$\left[\sqrt{0.27}e^{j2\pi.0.52}, \sqrt{0.16}e^{j2\pi.0.32}, \sqrt{0.57}e^{j2\pi.0.17}\right]$	$\left[\sqrt{0.23}e^{j2\pi.0.48}, \sqrt{0.14}e^{j2\pi.0.29}, \sqrt{0.64}e^{j2\pi.0.24}\right]$
C2	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$		$\left[\sqrt{0.23}e^{j2\pi.0.48}, \sqrt{0.14}e^{j2\pi.0.29}, \sqrt{0.64}e^{j2\pi.0.24}\right]$	$\left[\sqrt{0.21}e^{j2\pi.0.45}, \sqrt{0.12}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.28}\right]$
C3	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$		$\left[\sqrt{0.21}e^{j2\pi.0.45}, \sqrt{0.12}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.28}\right]$
C4	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$	$\left[\sqrt{0.23}e^{j2\pi.0.48}, \sqrt{0.14}e^{j2\pi.0.29}, \sqrt{0.64}e^{j2\pi.0.24}\right]$	$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$	
C5	$\left[\sqrt{0.22}e^{j2\pi.0.47}, \sqrt{0.13}e^{j2\pi.0.29}, \sqrt{0.65}e^{j2\pi.0.25}\right]$	$\left[\sqrt{0.26}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.20}\right]$	$\left[\sqrt{0.29}e^{j2\pi.0.54}, \sqrt{0.18}e^{j2\pi.0.33}, \sqrt{0.54}e^{j2\pi.0.15}\right]$	$\left[\sqrt{0.26}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.20}\right]$
C6	$\left[\sqrt{0.17}e^{j2\pi.0.41}, \sqrt{0.10}e^{j2\pi.0.25}, \sqrt{0.73}e^{j2\pi.0.33}\right]$	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$	$\left[\sqrt{0.18}e^{j2\pi.0.43}, \sqrt{0.11}e^{j2\pi.0.26}, \sqrt{0.71}e^{j2\pi.0.31}\right]$	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$
C7	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$	$\left[\sqrt{0.24}e^{j2\pi.0.48}, \sqrt{0.14}e^{j2\pi.0.30}, \sqrt{0.62}e^{j2\pi.0.22}\right]$	$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$	$\left[\sqrt{0.21}e^{j2\pi.0.45}, \sqrt{0.12}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.28}\right]$
C8	$\left[\sqrt{0.22}e^{j2\pi.0.47}, \sqrt{0.13}e^{j2\pi.0.29}, \sqrt{0.65}e^{j2\pi.0.25}\right]$	$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$	$\left[\sqrt{0.28}e^{j2\pi.0.52}, \sqrt{0.16}e^{j2\pi.0.32}, \sqrt{0.58}e^{j2\pi.0.19}\right]$	$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$

	C5	C6	C7	C8
C1	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$	$\left[\sqrt{0.32}e^{j2\pi.0.57}, \sqrt{0.20}e^{j2\pi.0.35}, \sqrt{0.48}e^{j2\pi.0.09}\right]$	$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$	$\left[\sqrt{0.23}e^{j2\pi.0.48}, \sqrt{0.14}e^{j2\pi.0.29}, \sqrt{0.64}e^{j2\pi.0.24}\right]$
C2	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$	$\left[\sqrt{0.29}e^{j2\pi.0.54}, \sqrt{0.18}e^{j2\pi.0.33}, \sqrt{0.54}e^{j2\pi.0.15}\right]$	$\left[\sqrt{0.21}e^{j2\pi.0.45}, \sqrt{0.12}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.28}\right]$	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$
C3	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$	$\left[\sqrt{0.26}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.20}\right]$	$\left[\sqrt{0.21}e^{j2\pi.0.45}, \sqrt{0.12}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.28}\right]$	$\left[\sqrt{0.18}e^{j2\pi.0.43}, \sqrt{0.11}e^{j2\pi.0.26}, \sqrt{0.71}e^{j2\pi.0.31}\right]$
C4	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$	$\left[\sqrt{0.30}e^{j2\pi.0.55}, \sqrt{0.19}e^{j2\pi.0.34}, \sqrt{0.51}e^{j2\pi.0.11}\right]$	$\left[\sqrt{0.22}e^{j2\pi.0.47}, \sqrt{0.13}e^{j2\pi.0.29}, \sqrt{0.65}e^{j2\pi.0.25}\right]$	$\left[\sqrt{0.19}e^{j2\pi.0.44}, \sqrt{0.12}e^{j2\pi.0.27}, \sqrt{0.69}e^{j2\pi.0.29}\right]$
C5		$\left[\sqrt{0.35}e^{j2\pi.0.59}, \sqrt{0.21}e^{j2\pi.0.36}, \sqrt{0.44}e^{j2\pi.0.06}\right]$	$\left[\sqrt{0.29}e^{j2\pi.0.54}, \sqrt{0.18}e^{j2\pi.0.33}, \sqrt{0.54}e^{j2\pi.0.15}\right]$	$\left[\sqrt{0.23}e^{j2\pi.0.48}, \sqrt{0.14}e^{j2\pi.0.29}, \sqrt{0.64}e^{j2\pi.0.24}\right]$
C6	$\left[\sqrt{0.18}e^{j2\pi.0.43}, \sqrt{0.11}e^{j2\pi.0.26}, \sqrt{0.71}e^{j2\pi.0.31}\right]$		$\left[\sqrt{0.22}e^{j2\pi.0.47}, \sqrt{0.13}e^{j2\pi.0.29}, \sqrt{0.65}e^{j2\pi.0.25}\right]$	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$
C7	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$	$\left[\sqrt{0.28}e^{j2\pi.0.52}, \sqrt{0.16}e^{j2\pi.0.32}, \sqrt{0.58}e^{j2\pi.0.19}\right]$		$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$
C8	$\left[\sqrt{0.20}e^{j2\pi.0.45}, \sqrt{0.13}e^{j2\pi.0.28}, \sqrt{0.67}e^{j2\pi.0.27}\right]$	$\left[\sqrt{0.34}e^{j2\pi.0.58}, \sqrt{0.21}e^{j2\pi.0.36}, \sqrt{0.45}e^{j2\pi.0.07}\right]$	$\left[\sqrt{0.25}e^{j2\pi.0.50}, \sqrt{0.15}e^{j2\pi.0.31}, \sqrt{0.60}e^{j2\pi.0.19}\right]$	

Table 6
Score function of the criteria for quantum spherical fuzzy sets.

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.000	1.507	1.559	1.405	1.305	1.761	1.507	1.405
C2	1.305	0.000	1.405	1.313	1.305	1.654	1.313	1.305
C3	1.261	1.261	0.000	1.313	1.261	1.553	1.313	1.216
C4	1.261	1.412	1.507	0.000	1.261	1.664	1.356	1.261
C5	1.356	1.553	1.654	1.553	0.000	1.863	1.660	1.405
C6	1.169	1.261	1.216	1.261	1.216	0.000	1.356	1.305
C7	1.261	1.453	1.466	1.313	1.305	1.577	0.000	1.305
C8	1.356	1.507	1.609	1.500	1.305	1.811	1.507	0.000

Step 1: Linguistic evaluations are collected to form the experts.
Step 2: By the help of Eq. (27), decision matrix is generated.

$$X_k = \begin{bmatrix} 0 & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & 0 & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & 0 \end{bmatrix} \quad (27)$$

Step 3: The defuzzified values are computed via Eq. (20).

Step 4: Normalization procedures are applied with Eq. (28).

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}}. \quad (28)$$

Step 5: Positive and negative effects are analyzed owing to Eq. (29).

$$Y_i = \sum_{j=1}^{h} X_{ij}^* - \sum_{j=h+1}^{n} X_{ij}^* \quad (29)$$

Step 6: Weighted results are given by Eq. (30).

$$Y_i^* = \sum_{j=1}^{h} W_j X_{ij}^* - \sum_{j=h+1}^{n} W_j X_{ij}^* \quad (30)$$

Step 7: The results are ranked.

6. Analysis results

The steps of the analysis are given in Fig. 1. This analysis has two

Table 7
Normalized relation matrix.

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.000	0.136	0.141	0.127	0.118	0.159	0.136	0.127
C2	0.118	0.000	0.127	0.119	0.118	0.150	0.119	0.118
C3	0.114	0.114	0.000	0.119	0.114	0.141	0.119	0.110
C4	0.114	0.128	0.136	0.000	0.114	0.151	0.123	0.114
C5	0.123	0.141	0.150	0.141	0.000	0.169	0.150	0.127
C6	0.106	0.114	0.110	0.114	0.110	0.000	0.123	0.118
C7	0.114	0.132	0.133	0.119	0.118	0.143	0.000	0.118
C8	0.123	0.136	0.146	0.136	0.118	0.164	0.136	0.000

stages, including the weighting of the criteria with the extended DEMATEL and the ranking of the alternatives with the extended MOORA. The detailed results are given in the following sections.

6.1. The weighting of the criteria

In this study, it is aimed to evaluate alternative wearable technologies for livestock health management. To this end, selected eight criteria mentioned above are summarized in Table 2.

An expert team consists of four experts, ages between 37 and 58. Of these four experts, two are academicians interested in the NPD process, DTs, and Metaverse. Besides, one of the four experts is breeding cattle for butchers, while the other works as a farmer with an animal farm manager. These people evaluate the factors by considering the values in Table 3, visualizing some necessary information about the above-mentioned alternatives (Table 4).

Table 3 gives the linguistic information about the evaluations with the AUs (Action Units) and the fuzzy sets regarding the criteria.

Average values are given in Table 5.

Score values are determined in Table 6.

The normalized values are computed as in Table 7.

Total relation matrix is created in Table 8.

The weights are presented in Fig. 2. Further, the causal directions and weighting results are given in Table 9.

Table 9 informs us about the causal directions. Based on this table, disease detection (C5), metabolic activity tracker (C1), and price (C8) are the most influencing criteria. Moreover, *disease detection* affects all other criteria. *Metabolic activity tracker* affects criteria other than *disease detection*, whereas price affects criteria other than *metabolic activity tracker* and *disease detection*. However, the sound and stress analyzer (C6) is influenced by all other criteria. Regarding the importance weights of criteria, *sound and stress analyzer* is the foremost criterion, followed by *disease detection, price, solar-powered battery* (C7), and *location tracker* (C3). Nevertheless, movement and *behavior analysis* (C2), *metabolic activity tracker* (C1), and *antibiotic detection* (C4) are found to be the least crucial criteria in this research, respectively.

Table 8
Total relation matrix.

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.886	1.090	1.132	1.058	0.992	1.273	1.096	1.020
C2	0.928	0.901	1.049	0.984	0.928	1.185	1.013	0.948
C3	0.893	0.968	0.900	0.949	0.893	1.137	0.977	0.909
C4	0.933	1.022	1.065	0.886	0.933	1.195	1.024	0.953
C5	1.039	1.142	1.189	1.116	0.930	1.337	1.156	1.066
C6	0.858	0.937	0.967	0.915	0.861	0.977	0.949	0.886
C7	0.931	1.023	1.060	0.990	0.934	1.187	0.913	0.954
C8	1.005	1.101	1.147	1.076	1.002	1.290	1.107	0.918

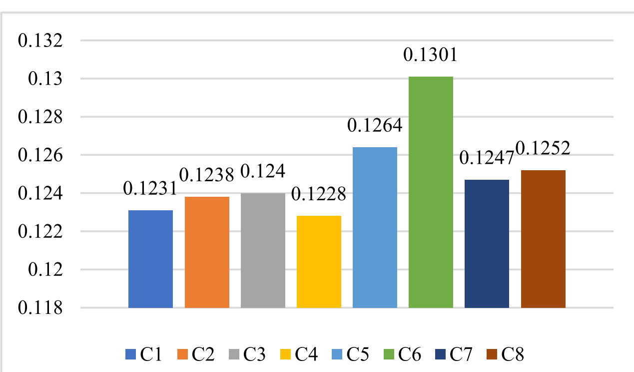

Fig. 2. Weights of the criteria.

Table 9
Influence and weights of the criteria.

	D	E	D + E	D-E	Weighting results	Impact directions
C1	8.547	7.472	16.019	1.075	0.1231	C1→(C2,C3,C4, C6,C7,C8)
C2	7.935	8.183	16.119	−0.248	0.1238	C2→(C3,C6)
C3	7.625	8.509	16.134	−0.884	0.1240	C3→(C6)
C4	8.011	7.973	15.984	0.037	0.1228	C4→(C2,C3,C6, C7)
C5	8.975	7.475	16.450	1.500	0.1264	C5→(C1,C2,C3, C4,C6,C7,C8)
C6	7.350	9.582	16.932	−2.232	0.1301	–
C7	7.993	8.234	16.227	−0.241	0.1247	C7→(C2,C3,C6)
C8	8.646	7.654	16.300	0.993	0.1252	C8→(C2,C3,C4, C6,C7)

6.2. Ranking of the alternatives

In the second part of the proposed model, alternatives are ranked. For this purpose, 5 different porotypes as alternatives are selected that are A1, A2,…, A5. Observation results are depicted in Table 10.

Average values are computed in Table 11.

Score values are indicated in Table 12.

These values are normalized in Table 13.

The ranking results are showed in Fig. 3 and depicted in Table 14.

It is concluded that the third WSC prototype (A3) is the most critical alternative for this situation. Furthermore, the fourth WSC prototype (A4) and the second WSC prototype (A2) are other essential alternatives.

The sensitivity analysis is also applied to 8 scenarios by changing the weight values of the criteria consecutively. The ranking results for the scenarios considered are given in Table 15.

The ranking results with several cases illustrate that the changing weighting results lead to similar results for the alternatives. It means that the introduced framework's findings are logical, and thus, A3 is the most desirable WSC prototype.

7. Discussion and implications

In the face of growing demand for food driven by increasing population growth, providing animal welfare and efficiency in animal production are becoming extremely important for consumers, researchers, intensive livestock industry practitioners, and policymakers (Neethirajan, 2023a). To track farm animals' health, movement, and behavior, livestock wearables, in which several sensors are embedded, have been designed and produced in recent years (Tzanidakis et al., 2023). In reducing farm management costs, increasing operational efficiency, providing sustainability, and improving animal welfare, livestock wearables are vital in the intensive livestock industry (Džermeikaitė et al., 2023). However, most sensor technology-driven wearable devices apply to humans and provide accurate data to improve human health and well-being (Zhang et al., 2021). Thus, compared to wearables worn by humans and pets, livestock wearables are still in progress, though there is an increasing need for these devices for livestock health management.

On the other hand, the research on livestock wearables is increasing

Table 10
Observation results of facial expressions for the alternatives.

Expert 1								
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	(7,14)	(2,25)	(2,25)	(7,14)	(7,14)	(10,2)	(7,14)	(2,25)
A2	(27,12)	(7,14)	(2,25)	(10,2)	(10,2)	(27,12)	(27,12)	(5,27)
A3	(27,12)	(7,14)	(2,25)	(27,12)	(27,12)	(10,2)	(10,2)	(7,5)
A4	(27,12)	(2,25)	(27,12)	(27,12)	(27,12)	(7,5)	(2,25)	(7,5)
A5	(27,12)	(2,25)	(2,25)	(5,27)	(6,26)	(2,25)	(7,5)	(7,14)
Expert 2								
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	(10,2)	(2,25)	(5,27)	(14,15)	(14,15)	(14,15)	(14,15)	(2,25)
A2	(6,26)	(7,14)	(5,27)	(10,2)	(10,2)	(10,2)	(2,25)	(27,12)
A3	(6,26)	(14,15)	(5,27)	(27,12)	(6,26)	(7,14)	(14,15)	(5,27)
A4	(6,26)	(27,12)	(5,27)	(27,12)	(5,27)	(7,14)	(2,25)	(10,2)
A5	(25,26)	(27,12)	(5,27)	(5,27)	(25,26)	(7,5)	(10,2)	(7,14)
Expert 3								
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	(14,15)	(14,6)	(5,27)	(7,14)	(7,14)	(7,5)	(14,15)	(2,25)
A2	(25,26)	(10,2)	(5,27)	(7,5)	(14,15)	(5,27)	(27,12)	(14,6)
A3	(6,26)	(5,27)	(5,27)	(27,12)	(25,26)	(7,5)	(14,15)	(10,2)
A4	(6,26)	(5,27)	(5,27)	(27,12)	(7,5)	(7,5)	(2,25)	(10,2)
A5	(25,26)	(14,6)	(14,6)	(10,2)	(6,26)	(14,6)	(14,15)	(7,14)
Expert 4								
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	(7,14)	(6,26)	(25,26)	(7,14)	(7,14)	(7,14)	(7,14)	(25,26)
A2	(2,25)	(6,26)	(25,26)	(14,15)	(14,15)	(27,12)	(27,12)	(27,12)
A3	(27,12)	(6,26)	(6,26)	(6,26)	(6,26)	(14,15)	(14,15)	(5,27)
A4	(2,25)	(25,26)	(6,26)	(25,26)	(7,14)	(7,14)	(27,12)	(10,2)
A5	(2,25)	(25,26)	(25,26)	(14,15)	(6,26)	(2,25)	(14,15)	(14,15)

Table 11
Average values of quantum spherical fuzzy numbers for the alternatives.

	C1	C2	C3	C4
A1	$\begin{bmatrix}\sqrt{0.17}\,e^{j2\pi.0.41},\\ \sqrt{0.10}\,e^{j2\pi.0.25},\\ \sqrt{0.73}\,e^{j2\pi.0.33},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.31}\,e^{j2\pi.0.55},\\ \sqrt{0.19}\,e^{j2\pi.0.34},\\ \sqrt{0.51}\,e^{j2\pi.0.13},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.29}\,e^{j2\pi.0.54},\\ \sqrt{0.18}\,e^{j2\pi.0.33},\\ \sqrt{0.54}\,e^{j2\pi.0.15},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.16}\,e^{j2\pi.0.45},\\ \sqrt{0.10}\,e^{j2\pi.0.25},\\ \sqrt{0.74}\,e^{j2\pi.0.35},\end{bmatrix}$
A2	$\begin{bmatrix}\sqrt{0.33}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.49}\,e^{j2\pi.0.11},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.31}\,e^{j2\pi.0.55},\\ \sqrt{0.19}\,e^{j2\pi.0.34},\\ \sqrt{0.51}\,e^{j2\pi.0.13},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.29}\,e^{j2\pi.0.54},\\ \sqrt{0.18}\,e^{j2\pi.0.33},\\ \sqrt{0.54}\,e^{j2\pi.0.15},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.19}\,e^{j2\pi.0.44},\\ \sqrt{0.12}\,e^{j2\pi.0.27},\\ \sqrt{0.69}\,e^{j2\pi.0.29},\end{bmatrix}$
A3	$\begin{bmatrix}\sqrt{0.33}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.49}\,e^{j2\pi.0.11},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.34}\,e^{j2\pi.0.58},\\ \sqrt{0.21}\,e^{j2\pi.0.36},\\ \sqrt{0.45}\,e^{j2\pi.0.07},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.29}\,e^{j2\pi.0.54},\\ \sqrt{0.18}\,e^{j2\pi.0.33},\\ \sqrt{0.54}\,e^{j2\pi.0.15},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.32}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.48}\,e^{j2\pi.0.09},\end{bmatrix}$
A4	$\begin{bmatrix}\sqrt{0.33}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.49}\,e^{j2\pi.0.11},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.31}\,e^{j2\pi.0.55},\\ \sqrt{0.19}\,e^{j2\pi.0.34},\\ \sqrt{0.51}\,e^{j2\pi.0.13},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.29}\,e^{j2\pi.0.54},\\ \sqrt{0.18}\,e^{j2\pi.0.33},\\ \sqrt{0.54}\,e^{j2\pi.0.15},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.32}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.48}\,e^{j2\pi.0.09},\end{bmatrix}$
A5	$\begin{bmatrix}\sqrt{0.33}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.49}\,e^{j2\pi.0.11},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.31}\,e^{j2\pi.0.55},\\ \sqrt{0.19}\,e^{j2\pi.0.34},\\ \sqrt{0.51}\,e^{j2\pi.0.13},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.29}\,e^{j2\pi.0.54},\\ \sqrt{0.18}\,e^{j2\pi.0.33},\\ \sqrt{0.54}\,e^{j2\pi.0.15},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.22}\,e^{j2\pi.0.47},\\ \sqrt{0.13}\,e^{j2\pi.0.28},\\ \sqrt{0.63}\,e^{j2\pi.0.26},\end{bmatrix}$

	C5	C6	C7	C8
A1	$\begin{bmatrix}\sqrt{0.16}\,e^{j2\pi.0.45},\\ \sqrt{0.10}\,e^{j2\pi.0.25},\\ \sqrt{0.74}\,e^{j2\pi.0.35},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.18}\,e^{j2\pi.0.43},\\ \sqrt{0.11}\,e^{j2\pi.0.26},\\ \sqrt{0.71}\,e^{j2\pi.0.31},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.16}\,e^{j2\pi.0.45},\\ \sqrt{0.10}\,e^{j2\pi.0.25},\\ \sqrt{0.74}\,e^{j2\pi.0.35},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.32}\,e^{j2\pi.0.57},\\ \sqrt{0.20}\,e^{j2\pi.0.35},\\ \sqrt{0.48}\,e^{j2\pi.0.09},\end{bmatrix}$
A2	$\begin{bmatrix}\sqrt{0.18}\,e^{j2\pi.0.43},\\ \sqrt{0.11}\,e^{j2\pi.0.26},\\ \sqrt{0.71}\,e^{j2\pi.0.31},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.27}\,e^{j2\pi.0.52},\\ \sqrt{0.16}\,e^{j2\pi.0.32},\\ \sqrt{0.57}\,e^{j2\pi.0.17},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.30}\,e^{j2\pi.0.55},\\ \sqrt{0.19}\,e^{j2\pi.0.34},\\ \sqrt{0.51}\,e^{j2\pi.0.11},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.28}\,e^{j2\pi.0.52},\\ \sqrt{0.16}\,e^{j2\pi.0.32},\\ \sqrt{0.58}\,e^{j2\pi.0.19},\end{bmatrix}$
A3	$\begin{bmatrix}\sqrt{0.35}\,e^{j2\pi.0.59},\\ \sqrt{0.21}\,e^{j2\pi.0.36},\\ \sqrt{0.44}\,e^{j2\pi.0.06},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.18}\,e^{j2\pi.0.43},\\ \sqrt{0.11}\,e^{j2\pi.0.26},\\ \sqrt{0.71}\,e^{j2\pi.0.31},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.17}\,e^{j2\pi.0.41},\\ \sqrt{0.10}\,e^{j2\pi.0.25},\\ \sqrt{0.73}\,e^{j2\pi.0.33},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.24}\,e^{j2\pi.0.48},\\ \sqrt{0.14}\,e^{j2\pi.0.30},\\ \sqrt{0.62}\,e^{j2\pi.0.22},\end{bmatrix}$
A4	$\begin{bmatrix}\sqrt{0.24}\,e^{j2\pi.0.48},\\ \sqrt{0.14}\,e^{j2\pi.0.30},\\ \sqrt{0.62}\,e^{j2\pi.0.22},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.18}\,e^{j2\pi.0.43},\\ \sqrt{0.11}\,e^{j2\pi.0.26},\\ \sqrt{0.71}\,e^{j2\pi.0.31},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.30}\,e^{j2\pi.0.55},\\ \sqrt{0.19}\,e^{j2\pi.0.34},\\ \sqrt{0.51}\,e^{j2\pi.0.11},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.20}\,e^{j2\pi.0.45},\\ \sqrt{0.13}\,e^{j2\pi.0.28},\\ \sqrt{0.67}\,e^{j2\pi.0.27},\end{bmatrix}$
A5	$\begin{bmatrix}\sqrt{0.35}\,e^{j2\pi.0.59},\\ \sqrt{0.21}\,e^{j2\pi.0.36},\\ \sqrt{0.44}\,e^{j2\pi.0.06},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.27}\,e^{j2\pi.0.52},\\ \sqrt{0.16}\,e^{j2\pi.0.32},\\ \sqrt{0.57}\,e^{j2\pi.0.17},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.18}\,e^{j2\pi.0.43},\\ \sqrt{0.11}\,e^{j2\pi.0.26},\\ \sqrt{0.71}\,e^{j2\pi.0.31},\end{bmatrix}$	$\begin{bmatrix}\sqrt{0.16}\,e^{j2\pi.0.45},\\ \sqrt{0.10}\,e^{j2\pi.0.25},\\ \sqrt{0.74}\,e^{j2\pi.0.35},\end{bmatrix}$

Table 12
Score function of the alternatives for quantum spherical fuzzy sets.

	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.169	1.709	1.660	1.120	1.120	1.216	1.120	1.759
A2	1.811	1.402	1.660	1.261	1.216	1.559	1.705	1.604
A3	1.811	1.447	1.660	1.759	1.863	1.216	1.169	1.405
A4	1.811	1.709	1.660	1.759	1.420	1.216	1.705	1.305
A5	1.811	1.709	1.660	1.363	1.920	1.559	1.216	1.120

Table 13
Normalized decision matrix.

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.307	0.477	0.447	0.339	0.325	0.399	0.356	0.540
A2	0.476	0.392	0.447	0.382	0.352	0.511	0.542	0.493
A3	0.476	0.404	0.447	0.533	0.540	0.399	0.371	0.432
A4	0.476	0.477	0.447	0.533	0.412	0.399	0.542	0.401
A5	0.476	0.477	0.447	0.413	0.556	0.511	0.386	0.344

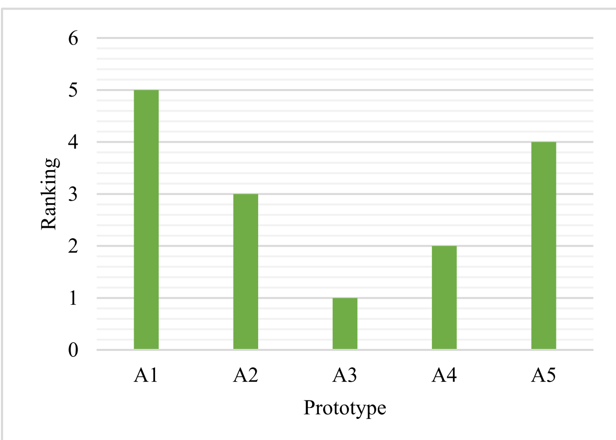

Fig. 3. Ranking results.

Table 14
Weighted and ranking values.

Alternatives	Non-cost Values	Non-beneficial Values	Weighted Scores	Ranking Results
A1	0.288	0.111	0.177	5
A2	0.335	0.115	0.220	3
A3	0.348	0.102	0.246	1
A4	0.349	0.111	0.238	2
A5	0.326	0.126	0.201	4

daily, contributing to the development and improvement of livestock wearables. Most of the extant research on livestock wearables has concentrated on sensor technologies concerning their use purposes, such as monitoring movement, behavior (i.e., Muminov et al., 2019; Pons et al., 2017; Riaboff et al., 2022), and health (i.e., Neethirajan et al., 2017) of livestock; for future of the sensor-driven wearable devices (i.e., Zhang et al., 2021); and concerning classification of sensors embedded into livestock wearables (i.e., Alipio and Villena, 2023; Go et al., 2022; Irshad et al., 2021). Additionally, there are several applied research on the design of specific livestock wearables, such as smart collars (i.e., Campiotti et al., 2022; Chandra et al., 2022; Darwis et al., 2022; Pratama et al., 2019). However, there is no direct research in the relevant literature on evaluating and selecting the optimum WSC for livestock. Thus, which criteria are prioritized in assessing and choosing the best WSC to be worn by farm animals to track their movement, behavior, and health status are still questionable from the farmers' perspective. Thus, the uniqueness of the research stems from the scarcity of research on evaluating and selecting the optimum WSC for livestock in extant literature.

Based upon a thorough review of relevant research on smart collar, key evaluation criteria essential for design of WSC are determined as features including *metabolic activity tracker* (Neethirajan, 2017; 2020a), *movement and behavior analyzers* (Neethirajan, 2017; 2020b), *location tracker* (Aquilani et al., 2022; Neethirajan, 2020b), *antibiotic detection* (Neethirajan, 2017; Xu et al., 2023), *disease detection* (Džermeikaitė et al., 2023; Neethirajan, 2017), *sound and stress analyzer* (Olczak et al., 2023; Sadeghi et al., 2023), *solar-powered battery* (Tzanidakis et al., 2023), and *price* (Simitzis et al., 2021). Regarding the overall ranking of criteria in this paper, the *sound and stress analyzer* (0.1301) is the foremost criterion that must be considered in the new WSC development process. Research on extant literature reveals that the sound of livestock is one of the significant indicators of awareness of livestock's health and welfare, supporting our study's results (Olczak et al., 2023). Some research presents that farm animals make a sound with high frequency when there is an emergency case, such as illness, wounding, or lameness (Widaningsih et al., 2023). Besides, sound analysis is an excellent way to measure the stress level of farm animals, influencing their productivity (Neethirajan, 2017). Hence, concerning operational efficiency and animal welfare, the sound and stress analyzer is unsurprisingly selected as the foremost feature essential for the design of WSC.

Similar to the results of previous studies in the relevant literature, the sound and stress analyzer is followed by *disease detection* (0.1264), *price* (0.1252), *solar-powered battery* (0.1247), *location tracker* (0.124), *movement and behavior analyzer* (0.1238), and *metabolic activity tracker* (0.1231). That is, disease detection is found to be the second crucial feature essential for WSC. To protect animal welfare, it is important to early detect the diseases of farm animals (Džermeikaitė, et al., 2023). The virtue of early detection of disease through sensors sending vital signs, timely intervention can be facilitated, and the risk of the spread of disease within herds can be mitigated (Widaningsih et al., 2023). Besides, early disease detection and stress detection can lower the use of antibiotics and other medical interventions by promoting more sustainable farming practices (Park and Han, 2023). The following significant criterion is identified as price. In recent years, there has been a gradual decrease in farm animal caretakers because of economic reasons (Simitzis et al., 2021). Herein, since livestock wearables must be used for every farm animal to provide overall farm efficiency and animal welfare, these additional costs can also add more burden to the shoulders of farmers. Thus, price is the third most important concern for farmers.

Regarding overall rankings, "solar-powered battery" is the fourth important feature for WSC. To collect continuous information about the health and movement of farm animals, even when the animals are grazing outside the farm, farmers need livestock wearables with long battery life for working wireless sensors (Neethirajan, 2017). Since

Table 15
Ranking results with sensitivity analysis.

Alternatives	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
A1	5	5	5	5	5	5	5	5
A2	3	3	3	3	2	2	3	3
A3	1	1	1	1	1	1	1	1
A4	2	2	2	2	3	3	2	2
A5	4	4	4	4	4	4	4	4

replacing batteries is time-consuming, it is important to use environmentally friendly and self-powered batteries like solar-powered batteries. Following solar-powered batteries, the location tracker is the fifth important feature of the design of WSC. By using livestock wearables equipped with GPS, farmers can track the real-time locations of their farm animals (Park and Han, 2023). So, when they are lost or under the attack of wild animals, farmers can intervene promptly at the point where they stand. Besides, livestock wearables equipped with location trackers can also prevent the theft of animals and provide information about field distribution behavior, such as feeding and ruminating (Tzanidakis et al., 2023).

Further, in this research, the movement and behavior analyzer is surprisingly identified as the sixth important feature for WSC, while the metabolic activity tracker is determined as the seventh important feature. However, previous research in the prevailing literature mainly emphasizes the importance of wearable sensor technologies in tracking animals' movement and behavior (Campiotti et al., 2022; Hendriks et al., 2020) and metabolic activities, such as heart rate and body temperature (Pratama et al., 2019). Lastly, based on overall rankings, the antibiotic detection feature (0.1228) is the last and the most negligible design feature for WSC. Antibiotic use in farm animals is mainly under the control of farmers. If they unconsciously and frequently use antibiotics, they can lead to antibiotic resistance in their animals (Neethirajan, 2017). However, this feature can be neglected in the design of WSC if the farmers are conscious of the outcome of the use of antibiotics.

On the other hand, prototype A3 is selected as the best WSC prototype for livestock health management once its features are considered. Further, A4 is determined as the second optimum WSC prototype to be worn by livestock, whereas A2 is identified as the third optimum WSC prototype for collecting relevant data about farm animals. Finally, A5, the most expensive prototype, and A1, the cheapest prototype with only movement and behavior analyzer and location tracker features, are found as the fourth and fifth WSC prototypes, respectively.

7.1. Theoretical implications

The concept of facial recognition is a prominent issue in understanding the emotional states of the decision-makers. In decision-making theory, linguistic expressions are generally considered when evaluating criteria and alternatives. From our methodological background, it is possible to recognize expert evaluations more accurately with the set of action units and coding systems, together with the integration of quantum mechanics and spherical fuzzy sets. Thus, the decision-making process could be handled properly in complex real-world business and economic problems under uncertainty.

Apart from methodological novelties, this research contributes to prevailing literature in some aspects. Whereas the extant research on livestock wearables mainly emphasizes the technological aspects of these devices, the research on understanding user aspects of these devices from the farmers' perspective is neglected. So, smallholder farmers are left in the lurch to decide which livestock wearables perfectly fit their expectations from the devices. Additionally, there is no research on evaluating and selecting livestock wearables in the form of WSC, which will help farmers choose the best WSC with accurate features. To fill these gaps, this research identifies the key features prioritized in the new WSC development process and selects the most optimum WSC among the alternative WSC prototypes with varying features created for this research. Besides, drawing upon the integration of DTs and virtual farms in Metaverse, this research shows that it can benefit from the Metaverse technologies in concept testing for WSC alternatives by creating DTs of WSC prototypes and farm animals in virtual farm settings. Thus, this research extends current research on livestock wearables by incorporating Metaverse and livestock management simultaneously within the context of SLF.

7.2. Managerial implications

In satisfying the meat demand of the growing world population, animal production is one of the biggest concerns of consumers, farmers, and policymakers. Though the livestock industry is compelled to grow globally, this necessary growth also leads to several environmental problems, such as climate change (Pozo et al., 2021). To mitigate all negative aspects of animal production, virtual environments within the Metaverse context can be a solution to finding and practicing more sustainable farming practices (Neethirajan, 2023a). Accordingly, in this research, utilizing Metaverse technologies, the WSC prototypes for livestock health management are created, and then the best one is selected based on the features that are prioritized according to their importance.

Though there is some research on smart collar technologies, no research directly identifies and ranks the essential features of WSC and selects the best WSC for farmers. Moreover, though many enterprises produce smart collars for livestock in the marketplace, these devices should be improved to serve livestock health management better. In this regard, this research initially determines the critical design features that WSC must have with a thorough review of the literature on wearable sensors. Afterward, five alternative WSC prototypes with different features are created for concept testing in Metaverse (Jeong et al., 2023). As a result, the first contribution of this research is to merge Metaverse technologies with livestock farming in the design and selection of optimum WSC for livestock health management through DTs within the context of SLF practices.

The other contribution of these results is for farmers once the complexity, price, and technological features of WSC are considered. By ranking the features essential for WSC concerning their significance values and presenting the best WSC to be used in livestock farming, the research findings assist the farmers who want to enhance their animal welfare and operational efficiency in selecting the optimum WSC. These results also guide industrial designers, engineers, and technology companies that want to improve WSC for better livestock health management. Though this research does not directly address the material selection of WSCs as a critical feature, using environmentally friendly, biocompatible, and biodegradable materials and adopting green manufacturing approaches could be proposed as sustainable practices lowering the negative environmental impact of producing WSCs (Liu et al., 2021). Moreover, as a sustainable approach, WSCs could be designed with environmentally friendly solar-powered batteries, which do not need any recycling process at their disposal (Neethirajan, 2017). Finally, since animal production is crucial to ensure global food security, policymakers can promote livestock wearables by incentivizing technological investment to farmers to have a more sustainable world. Herein, supporting the improvements in AI-based computing and machine learning will be necessary to immediately transform data into knowledge that can be employed for real-time farm management (Koltes et al., 2019). Using machine learning and data mining techniques in big data analysis can reduce some daunting challenges, such as genomic prediction, genotype assignment, mastitis detection, phenotype spoofing detection, and microbiome analysis (Morota et al., 2018). Also, by integrating data mining, data processing, and data analytics via AI and machine learning techniques with DTs, virtual farm conditions can provide feedback for controlling and managing physical conditions, enabling farmers to foresee any murky matters and optimize their operations (Gámez Díaz et al., 2020). Thus, AI and machine learning algorithms would optimize WSCs and connected tools such as smartphones and dashboards, data labeling, detection of ideal scenarios with high precision, and early prediction of diseases and stress (Neethirajan, 2023). Recent developments in machine learning and AI-based computing would also address several problems, including data privacy concerns, by promoting privacy-preserving data exchange systems (Neethirajan and Kemp, 2021a).

8. Conclusion

The growth in demand for animal products has necessarily changed the practices in livestock farming with more industrialized and intensive animal production methods. In the increasing demand for animal products to feed the growing world population, animal welfare and sustainability have become primary concerns for policymakers, consumers, and stakeholders in the livestock industry. As a result, wearable technologies are also re-designed based on the requirements of animal caretakers to protect animal health and increase animal production and overall farm efficiency. Since these devices are utilized for various purposes, they have several sensor technologies and different prices and features. Thus, farmers should consider many criteria regarding livestock wearables and select the best alternative without any cognitive dissonance. Hence, it is vital to analyze essential features of WSCs in terms of their importance weights and present the best WSC prototype to farmers. The neuro quantum spherical fuzzy decision-making approach offered in the present work allows us to decide the weights of WSC features through the extended DEMATEL and prioritize the WSC prototypes within Metaverse via the extended MOORA. The results reveal that sound and stress analyzers, disease detection, and price are the essential features that must be considered in the design and selection of WSC. Further, A3 is selected as the best WSC alternative to be used by farmers in livestock farming. A sensitivity check is also performed to depict the proposed framework's practicality and effectiveness. The superiorities of the proposed methodology are listed as the use of emotional intelligence and facial expressions in the decision-making process uniquely and the novel extension of the DEMATEL and MOORA methodologies by using the quantum mechanics and the spherical fuzzy sets with golden cuts.

Nonetheless, this research has some limitations, which would provide new avenues for further study. First, this research examines livestock wearables in the form of WSC, which are worn on the neck of farm animals. However, there are several forms of livestock wearables, such as belly belts and wearable ear tags. In this vein, other MCDM methods could be conducted to identify critical evaluation and selection criteria for other livestock wearable forms. Second, this research determines eight design features from the perspective of farmers. Yet, it ignores some potentially essential features, such as ergonomics of WSC in terms of size, weight and shape, biocompatibility, and discomfort to livestock animals, which are vital from the perspective of farm animals. Further research would also consider features that are also important for these animals. Third, this research shows the applicability of Metaverse technologies in NPD processes. However, the results attained from virtual environments for concept testing of WSC could be different from the real-world results, though Metaverse directly mimics the physical world. In this research, WSC prototypes are conceptualized and driven by experts' feedback and relevant literature. Then, key features necessary for WSC are prioritized, and the optimum alternatives with the best features are ranked by experts such as farmers and veterinarians. However, these conceptual prototypes are not subjected to real-life field testing and validation in this research. Thus, further research could focus on providing more fruitful insights into the real-life field testing and validation of the WSC prototypes, including feedback from farmers and veterinarians. Finally, the proposed methodology cannot consider the decision-makers' evaluation of the scope of the facial action coding system. Yet, it could be extended with sensor-based recognition applications. The results could also be processed with other MCDM techniques, such as TOPSIS and VIKOR, for further studies.

CRediT authorship contribution statement

Fatih Ecer: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **İlkin Yaran Ögel:** Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Hasan Dinçer:** Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Serhat Yüksel:** Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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