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Approaches, challenges and recent advances in automated bee counting devices: A review

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Abstract

For nearly 100 years, electronic bee counters have been developed using various technologies to track the foraging activity of mostly honey bee colonies. These counters should enable remote monitoring of the hives without disturbing natural flight behaviour while generating precise scientific data. However, there are few counters on the market that are able to fulfil this task. One main challenge is the lack of standardised methods to validate a counter's precision, as validation is crucial to categorise and judge the data produced by the counter, especially for scientific purposes. Another challenge is the interpretation of flight data to measure the effects of environmental or anthropogenic sources. Nevertheless, recent developments in the field are promising. This review describes the historic development of automated bee flight measurements and critically compares validation methods to encourage their improvement. To increase the comparability of future analyses of bee counters, current advances in data interpretation are also presented.

KEYWORDS
bee flight measurement, connected hives, electronic bee counter, foraging activity, remote monitoring, robbers test, validation method

1 | INTRODUCTION

In 1925, the world's first electronic bee counter was described by Lundie (1925). Since then, many devices have been developed, employing the state-of-the-art technology of the time they were assembled. The technology used in the very first models was clearly dominated by a combination of mechanical parts and electrical circuits. As technology advanced, different sensor types were used to improve the seemingly simple process of counting incoming and outgoing bees from a hive. Although there are a variety of devices, the measuring technology can be narrowed down to five major technological fields. Recently, a trend can be seen regarding the utilisation of certain technologies. Optical sensors have dominated the field for more than 40 years. However, within the last decade, the number of video-based counters has rapidly increased (Figure 1).

I will show that every new generation of devices came with new challenges and limitations; some have remained from day one, and others have recently emerged from new insights. Currently, no commercial counter is available that would be sufficient for scientific needs considering the precision and reliability required for use in field-scale experiments or long-term monitoring of honey bee colonies.

One reason for this is the lack of standardised methods for determining the precision of a bee counter. However, such a method is essential for the comparability of the counts and, more importantly, for the correct interpretation of the overall data. To date, 63% of the scientific articles included in this work do not provide the precision of their counter or a validation method. Of the articles that state the precision, 17% do not provide the method used to validate the device. Notably, most articles lacking a reference to validation were published

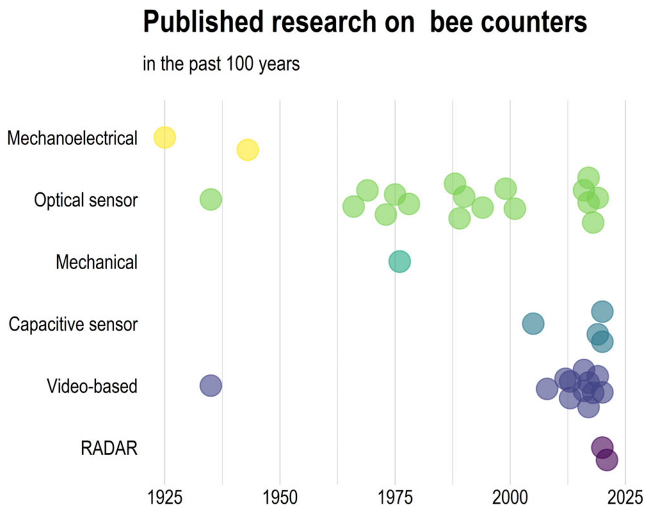

FIGURE 1 Published scientific articles included in this review that describe or use bee counters, categorised by their source technology and plotted by publication date. Each circle represents the year where a new bee counter was introduced or described in an article (total number of articles $n = 38$, see Table 1). Optical sensors have dominated the field for more than 40 years. However, within the last decade, there has been a rapid increase in video-based counters

before 2000. Nevertheless, the lack of validation and corresponding methods remains a major gap that needs to be addressed in the future development of such counters (a) for comparability and (b) to provide a solid baseline for justification of data interpretation. Correct data interpretation is key for the usage of such counters for bee-related ecological, biological, or ecotoxicological research. For example, currently, there is the hope that loss of forager bees because of pesticide applications could be a useful endpoint of regulatory risk assessment, but this would require that the uncertainty of the forager counts be as low as possible to precisely indicate the background mortality. It is therefore critical to connect hardware and software engineering with beekeeping and bee biology to form a proper baseline for the creation of precise counters.

The current development of bee counters can be seen as a process that is still affected by, and can learn from, past experiences. This review presents the major steps during historical development and highlights the main technologies on which the different counters are based, as well as their strengths and weaknesses. An overview of the areas in which bee counters can be used is also presented. The current methods for counter validation are critically compared to give new momentum for improvement. Last, this work compiles indices that focus on simple data interpretation from any bee counter that measures incoming and outgoing bee traffic and discusses their meaningfulness.

A review of the scientific and grey literature was conducted between October 2020 and May 2021 using a variety of approaches described in the supplemental material (see Supplementary Table 1. Data Collection).

1.1 | Field of use

The general field of use of electronic bee counters can be divided into two main areas: (a) scientific application and (b) precision beekeeping, but with several crossover interests. The first area includes the basic drive to develop such a counter, which will become clear in the subsequent sections of historical development in this review.

From the very beginning, scientific applications included the flight behaviour of honey bees, for example, to find a measure for colony productivity (Lundie, 1925; Marceau, Boily, & Perron, 1990) or specific traits among different bee races (Danka & Beaman, 2007). With an automated counting device, the operator can conclude the food availability, food requirements and age structure of a bee colony (reviewed in Meikle & Holst, 2015) and can provide valuable insights into other behavioural traits, such as swarming, colony defence, or robbing.

In addition, the spread of pests can be studied in previously impossible detail. Optical counters can register individual Varroa mites on bees. With this capability, dispersal routes can be better investigated, and the reinvasion behaviour of *Varroa destructor* can be described in detail (Chazette, Becker, & Szczerbicka, 2016; Bjerge et al., 2019; Bilik et al., 2021).

Another important scientific application is in ecotoxicology. The standard use of dead bee traps to record daily losses of bees throughout an entire season is cumbersome and fraught with pitfalls (Accorti, Luti, & Tarducci, 1991). Over longer time periods, bees become accustomed to the traps and empty them, making an accurate count of dead bees impossible. An automatic counter can record the balances of daily bee flight (Struye, 1999) and is particularly useful for visualising the effects of pest control applications in the field. Under field conditions, the direct acute effects can be inferred from flight behaviour (Struye et al., 1994; reviewed in Pham-Delègue, Decourtye, Kaiser, & Devillers, 2002) as well as the sublethal effects over time (Ngo et al., 2019; reviewed in Meikle & Holst, 2015).

For the second and more applied use of bee counters, beekeepers could benefit from extrapolating the previously mentioned characteristics of counter data. Combined monitoring parameters at the colony level, such as temperature, humidity, weight, acoustics and flight activity, are the core data of precision beekeeping (reviewed in Zacepins, Brusbardis, Meitalovs, & Stalidzans, 2015).

Incorporated into a wireless sensor network (WSN), data collection can be automated at a high level, and beekeepers would be able to see any relevant development of their colonies without having to manually inspect the hives (Hong et al., 2020; Jiang et al., 2016).

The benefits of remote prediction of swarm events include inspecting hives only when needed rather than regularly (Aumann et al., 2021). Furthermore, the data collected can indicate when honey flow stops and colonies need to be relocated or fed to maintain health or being able to find sites with higher honey yields (Wakjira et al., 2021). Doing so minimises the beekeeper's resource use and maximises hive productivity (Catania & Vallone, 2020). This could be particularly beneficial for beekeepers in emerging and developing countries, where significant profit maximisation would help generate income and combat unemployment. Ultimately, this could lead to improved protection of the environment and an increased quality of life and higher living standards in these countries (Gratzer, Susilo, Purnomo, Fiedler, & Brodschneider, 2019; Gratzer, Wakjira, Fiedler, & Brodschneider, 2021).

2 | COUNTER TECHNOLOGIES

2.1 | Mechanoelectrical

Historically, the first electronic bee counter described in the literature dates back almost 100 years to the work of Lundie, who started his experiments in 1922. He utilised small portals where bees had to pass through a tunnel on which end a balance arm was attached. The balance was adjusted to let the bodyweight of the bee trigger the arm, resulting in electrical contact forwarding the impulse to a counter (Figure 2). Thirty of these portals were combined in one hive unit—15 for the incoming and 15 for the outgoing traffic of forager bees arranged about each other. Each portal was connected to a telephone message register (counter) that read the total impulses hourly (Lundie, 1925).

Adapting the principle of this apparatus, Fabergé introduced a device claiming to have overcome some of Lundie's issues. He implemented a system in which all impulses from one set of portals fed into only one counter, yielding a graph of exits and a graph of entrances that could be printed simultaneously on the same sheet of paper (Fabergé, 1943).

Lundie (1925) considered 12 factors that introduced errors in the count in his work. The majority of these factors were caused by the complexity of the mechanics and the resulting high maintenance required. Freeing the counter's parts from bee debris and fixing mechanical issues required an almost daily cleaning interval.

Although Fabergé (1943) improved the design in terms of recording, no other mechanoelectrical counters were described besides these two. Lundie's apparatus functioned for a whole season and gave valuable data, as he also recorded the hive weight and environmental factors such as the temperature and daily sunshine hours. Both counters were the only affordable way to establish an electronic counter, as the photoelectronic technique was very expensive at that time (Brittain, 1935).

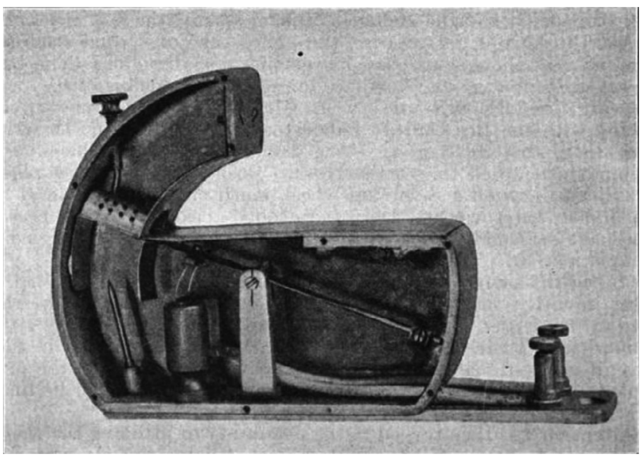

FIGURE 2 A single portal for incoming or outgoing bees from Lundie's first mechanoelectrical bee counter (Lundie, 1925)

The latest approach to implement a mechanoelectrical design was published by Liu et al. (1990) in a preliminary test. They considered microswitches as counting units to generate electric impulses whenever a bee walked over the trigger, that is, when the bodyweight would push it down. However, they rejected this idea because this technique could injure or handicap the bee passing through.

The counter proposed by Chauvin is notable although it is only mechanical and not mechanoelectrical (Chauvin, 1976). He constructed a movable cylinder through which the bees had to pass when leaving the hive. The cylinder was connected to a recording pen that registered the traffic on a paper roll. Parts of the device were treated with a repellent to guide bee traffic as favoured by the author. It was stated that a continuous operation for 4 months was possible. Although practically interesting with a simple setup, technically saving data on paper in a field trial does not provide enough safety for data loss, and the mechanical approach was not applied in future devices.

2.2 | Sensor-based

After Lundie introduced a mechanoelectrical counter, the subsequent generations of devices focused on sensor technology fuelled by the invention and availability of cheap photocell and later light-emitting diode (LED) and transistor technology. For over 20 years throughout the 70s, 80s and 90s, photocells were predominantly used (Figure 1). When imaging technology became available in the last two decades, the focus turned from LED advanced optical sensors to video-based systems, most recently enhanced by machine learning algorithms.

2.2.1 | Optical sensors

Photoelectric

In optoelectronics, a light barrier is a system that detects the interruption of a light beam and displays it as an electrical signal. In this way, automatic devices can detect moving objects without contact. Examples include obstacle detection for automatically closing doors and intruder detection through alarm systems. Light barriers consist of a light beam source, the transmitter or emitter, and a sensor, the receiver for the radiation (ELOVIS, 2021).

The first device with this technique was introduced by Brittain in 1935. His design and other early attempts used a simple photocell or light-dependent resistor (Erickson et al., 1975; Kerfoot, 1966; Spangler, 1969). Restricted by pricey components (up to 100 USD at the time), the design implemented only one gate that counted, assuming it to be a representative sample of the whole bee traffic. Other solutions implemented only small colonies on a single frame or a few frames and did not provide measurement of a full colony (Erickson et al., 1975). This was seen as a compromise until a solution for complete flight traffic was available.

In these designs, different, rather unreliable, and/or unfavourable light sources were used as transmitters. Even daylight was used as a light source, which has the huge disadvantage of being inconsistent and massively dependent on the environment. Continuous function of the device cannot be maintained (Kerfoot, 1966; Spangler, 1969). Using a simple light bulb as a light source provides more consistency but introduces two major biases: (a) the heat generated by the lamp may affect the bee's movement and behaviour, and (b) emitted visible light may act as an obstruction alone or in combination with the heat, especially at dawn or night. An additional factor is the durability of such analogue components.

Although some experimenters have suggested addressing light source issues by using red light (Erickson et al., 1975), limitations because of the use of only one photocell per counting corridor reveal further disadvantages. Devices needed a separator that split up incoming and outgoing bees to count them accordingly, especially when there was much traffic that came with the honey flow and stronger colonies. Spangler (1969) tried to guide bee traffic with a specially designed 'maze', separating incoming bees from outgoing bees (Figure 3). This study described a rather complex system for how bees could enter and leave without crossing and be double-counted by walking forth and back or counted as one by two bees walking closely together (Struye et al., 1994).

This 'maze' was criticised to restrict or slow down normal activity at the hive entrance (Erickson et al., 1975). Another method to improve the separation of incoming and outgoing bees was the implementation of airflow to the system. Erickson et al. (1975) installed separate entrance and exit tubes with counters. In addition, they installed a fan on top of the hive body that resulted in an intake of fresh air at the exit tubes and a low airflow out through the entrance tubes. However, this technique was not adopted and was further enhanced by others.

With the rapid progress in semiconductor fabrication in the 1960s, new technology became affordable, and Buckley et al. (1978) were the first to use a phototransistor instead of a simple photocell in a full hive setup. This affordable LED technology has been widely used in sensor-based bee counters.

Infrared

By using LED technology, most of the described disadvantages of the light source disappeared, and the first commercially successful bee counter was developed in the 90s by Struye, Borremans, and Jacobs (1991). With LEDs and modern computer technology for data recording, it was possible to use more than one light barrier that bees had to cross while entering or leaving the hive. This made it possible to detect the movement direction of bees and use only one passageway for entries and exits, making the aforementioned constructions to separate bee traffic obsolete. Because of their compact size (Figure 4), it was also much easier to implement more than one passage, which is very important to maintain a certain flow of bees during times of high-frequency forager passing (Liu et al., 1990).

Although this advanced technology overcame problems from the past, new difficulties appeared very soon. As most counters were tested with hives of low strength, testing full-sized colonies revealed serious new difficulties. At times of high honey flow where several bees enter the corridors one after another at a high frequency, counting errors occurred (Struye et al., 1994). Similar issues appeared from bees changing directions in the corridors or bees aggregating in front of the hive entrance because of high temperatures in the summer or lack of space in the brood chamber (Danka & Beaman, 2007; Souza Cunha et al., 2020).

Several authors highlighted the importance of not interfering with the normal behaviour of bees in any way to collect legitimate and unbiased data (Chen et al., 2012; Erickson et al., 1975; Fabergé, 1943; Rickli et al., 1989; Struye et al., 1991). Struye et al. (1991) postulated the following requirements for a 'stand-alone continuous monitoring

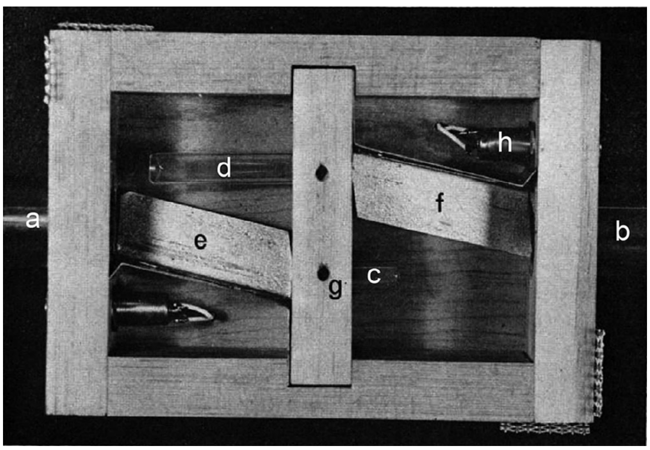

FIGURE 3 Top view of the bee counter. (a) Tube leading from the hive; (b) tube leading to outside; (c) outgoing counter tube; (d) incoming counter tube; (e) ledge leading to the outgoing tube; (f) ledge leading to the incoming tube; (g) light beam hole; (h) phone jack connecting to photocell [From Spangler (1969)]

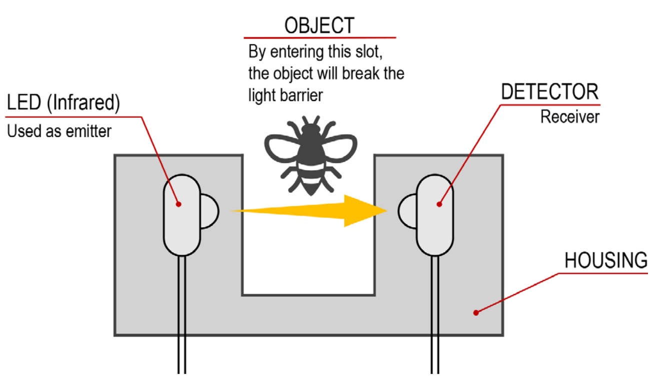

FIGURE 4 Basic setup of an optical sensor in a counting unit utilised in a bee corridor. Usually, two of these sensors are implemented per corridor to track the direction of movement of the bee [After Pešović et al. (2017)]

field device': (a) monitoring of all colony sizes, (b) no influence on normal bee behaviour, (c) ventilation and orientation should not be compromised, (d) completely autonomous functioning under field conditions, (e) user-friendly and low-maintenance construction, (f) affordable enough to monitor more than one colony and (g) low energy consumption to allow for continuous operation. These requirements still apply today.

Struye et al. (1994) were also the first to clearly state that a key issue in improving counters lies in the identification and elimination of erratic bee movement in the channels. They also implemented user-friendly maintenance automation in which their apparatus (named 'BeeScan') brought up an error message when one channel was blocked (by a dead bee, for example) and there was no registration because of a lack of activity. Increasing counter accuracy was the aim of Struye (1999) as well as other authors who suggested improving precision, that is, by adding more than two sensors per passage (Pešović et al., 2017). However, no LED counter is described in the literature that features this suggestion.

Some of the above-described difficulties remain a challenge for modern counters. Because Struye et al. (1991) postulated their requirements, little has happened to improve this stage of sensor technology. Schöne (1996) suggests that the average walking speed of a worker bee is 20–120 mm s^{-1}, so the bee should break two light barriers in succession within 50–300 ms (Pešović et al., 2017). Interruption outside this timeout period is considered incorrect counting, which could provide the basis for an algorithm to correct data appropriately. Further consideration of this suggestion was provided recently by Pešović et al. (2017), and it could benefit a correction algorithm that tries to work out so-called borderline cases such as erratic bee movement between sensors or bees getting stuck there somehow (Bermig et al., 2020).

In one of the latest developments, infrared optical sensors were integrated into a WSN. The WSN provides automatic and remote data tracking that collects input from the connected sensors in real time to a gateway. This gateway manages data storage and availability to its users, making it possible to access and inspect the whole system from around the globe (Jiang et al., 2016). Such a network is not limited to sensor-based counters and is open for any kind of device providing relevant input.

Finally, using the infrared light spectrum has the advantage of being invisible to the bee's eye, which lowers any potential influence on natural behaviour. Using a noncontact method over a contact method in sensor technology reduces the possibility of harming bees when triggering the sensor.

Nevertheless, one major disadvantage of optical sensors should be highlighted. Debris and other contaminations by outgoing foragers, particularly returning foragers, make frequent maintenance necessary to keep the sensors clean and working (Bromenshenk et al., 2015; Rickli et al., 1989; Struye et al., 1994). Interestingly, it was not mentioned how long such a maintenance interval would be. Furthermore, another obvious disadvantage of optical sensors lies in the registration precision of bees entering or leaving the hives in batches where several bees enter or leave the hive one after another (Liu et al., 1990; Struye et al., 1994). As described by Struye et al. (1994), algorithms are necessary to detect and clear data of this issue (see also Bermig et al., 2020). Another suggestion to solve this problem was to use capacitive sensors (Campbell et al., 2005; Rickli et al., 1989).

2.2.2 | Capacitive sensors

Although past literature noted the advantages of a capacitive sensor system to assess the flight activity of bees, few research works have implemented this technology so far although it is cheap, robust and quite simple. The bee body, like that of all organisms, consists of a certain proportion of water. Therefore, it has a dielectric signature that is detectable by its capacitance measured between two electrodes, the so-called capacitors (Perrault & Teachman, 2016). Alterations because of temperature, humidity and debris inside the corridors of the counter tend to be compensated for by assessing the difference in capacitance, that is, the dielectric constant, between the two capacitors. The bees' direction of motion can be tracked by the pair of electrodes responding to a change in capacitance. Its velocity can be calculated by the time required to walk from one set to the other set of electrodes. Interestingly, the change in capacitance is proportional to the body size of the bee; larger bees cause a greater change in capacitance (Campbell et al., 2005), which makes it theoretically possible to differentiate between all three castes of honey bees (Figure 5).

Campbell et al. (2005) tested the sensor with live bee specimens. *A. mellifera* and *Bombus* sp., *Andrena* sp. and *Megachile rotundata* were included in their experiments. They demonstrated that an increase in bee mass was followed by an increase in voltage. Although there was an overall linear relationship between those two factors, there was still significant variability, particularly for the honey bee and *Andrena*, making identification of different species difficult.

The authors suggest that the different shapes of the bees may be the reason for this. *Bombus* species are generally more robust and compact, while the *Andrena* and leafcutter species are longer and thinner. More than 10 years after Campbell's publication, this technology was adopted by Perrault and Teachman (2016) to create a solitary bee counter for *Osmia* sp. with an Arduino single-board microcontroller. The authors believe that with this technique, it is possible to

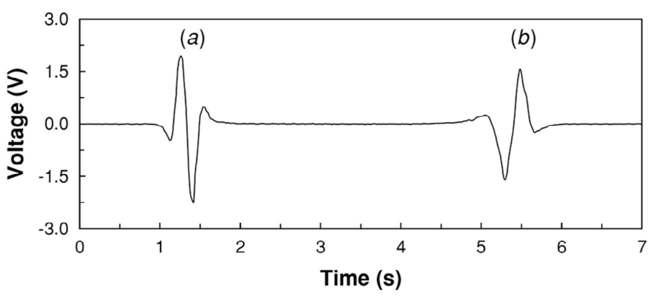

FIGURE 5 Typical asymmetric double pulses produced by bees in a capacitive ring sensor. Pulse (a) is a larger bee exiting the hive, and pulse (b) is a smaller bee entering the hive [After Campbell et al. (2005)]

determine the volume of nesting material and food collected by a single bee as well as the type of bee involved. Their sensors detected fluctuations in capacity caused by bee movements in the nesting tube. This could allow for evaluation of activity patterns to determine how long the bees spend outside the nest, how active they are when they return and how these changes depend on the time of day or other alterations in environmental conditions that influence their behaviour. By employing deep learning algorithms over the course of a year, the authors believe it should be possible to predict how much pollen each bee has collected and indicate the general health status of the brood. Therefore, a better understanding of the dynamics of pollinators other than honey bees could be promoted.

Bermig et al. (2020) describe a system called 'BeeCheck' in which seven capacitive sensors per corridor were implemented with an algorithm that provides a solution to the difficulties described above and by other authors, such as erratic bee movement in the corridor or bees coming into contact while moving through the gates (Rickli et al., 1989; Struye et al., 1994).

They noted that the high variation in the walking speed of bees is still a challenge. In addition, slow-moving bees or long stays in the corridor, and bees that are passing each other or running close behind each other can lead to erroneous measurements. Therefore, an algorithm is required to map the daily balance of incoming and outgoing bees as accurately as possible, factoring out these variations or borderline cases (Bermig et al., 2020).

In terms of easy-to-apply technology, capacitive sensors seem to be superior to the technologies introduced thus far. 'BeeCheck' can be maintained with low effort, as no frequent cleaning of the components is necessary. It is independently operable for more than 3 months on battery power and exchangeable data memory. The apparatus is currently improved within the consortium of the 'VIBee' project (www.vibee-project.net). However, the limitations of this technology are similar to those using narrow corridors or entrance tubes, generating the abovementioned borderline cases. Moreover, ambient air humidity may affect the dielectric constant of moving objects, affecting the sensitivity of the counter and ultimately creating false positives rather than negatives. This could be fixed with waterproof housing for the counter.

2.2.3 | Electromagnetic sensors

RFID

A counter that records the total bee traffic (i.e., activity) is often incapable of capturing the foraging behaviour of single bees. However, some research questions make it necessary to focus on individuals. To date, direct or video observations have been used in combination with coloured labels, numbers, or both to differentiate between the subjects of interest (Odemer, Nilles, Linder, & Rosenkranz, 2018). As a result of a continuous decrease in the size and weight of transponders in the last two decades, radio-frequency identification (RFID) technology has been established for bee monitoring.

RFID tags allow for automated and continuous monitoring of individual bee flight activity 24 hr a day, easily outperforming human observers (reviewed in Nunes-Silva et al., 2019). The technology integrates two main components: a transponder (a tag combined with an antenna that is glued on the bee's thorax) and a reader usually installed at the hive entrance. The antenna emits radio signals at a certain frequency that activates the tag. The tag then communicates its stored data, such as an identification number (or ID), to the reader using a modulated signal. The ID is then recognised along with a timestamp when the tagged bee was last detected at the entrance (Tenczar, Lutz, Rao, Goldenfeld, & Robinson, 2014).

Although RFID technology is not designed to measure the full trafficking of a colony, it has some notable advantages. RFID chips are designed to be fitted to individuals (workers, drones, queens) to study the behaviour of a specific cohort of bees (reviewed in Nunes-Silva et al., 2019). Therefore, it is possible to precisely determine the onset of flights of freshly hatched bees, flight duration, number of flights, or homing success.

In addition, both technologies, a whole-hive bee counter and individual markers could be combined to increase the resolution of behaviour observation at both the colony and individual level. One reason why this RFID technology is not yet extensively used is the relatively high price, especially of the tags, which are reusable only by sacrificing the bee if the tagged individual can be caught after the observation.

Currently, an OECD guideline is under development (OECD, 2020) where this technology will be used to determine sublethal effects in the regulation of plant protection products (i.e., the homing success of worker bees to measure sublethal effects); more frequent use of RFID technology and a drop in prices could be consequences.

RADAR

To date, there have only been two studies using RAdio Detection And Ranging (RADAR) technology to measure incoming and outgoing bees from a hive. The beehive activity monitor of Souza Cunha et al. (2020) consists of a Doppler radar, a signal conditioning amplifier, a microcontroller for data acquisition and processing, a real-time clock for time stamping the data, a micro SD card for data storage and a power management block.

By measuring the total energy output of the Doppler radar at low frequency, the flight activity of bees can be determined (Figure 6). This Doppler effect produces velocity data from objects at a distance. A microwave signal bounces off the target, and a computer analyses how the motion of the bee has altered the frequency of the returned signal. This creates a variation that enables direct and highly accurate measurements of the radial component of a target's velocity relative to the radar (Souza Cunha et al., 2020).

In Aumann et al. (2021), a similar approach was used to monitor rather simple activity events of flying honey bees. Swarming, robbing and orientation flights could be indicated with root-mean-squared counts, also known as the quadratic mean (Jones, 2018), which correlates with the total power in the Doppler spectrum. This indicates bee activity without providing exact numbers. Therefore, evaluating the

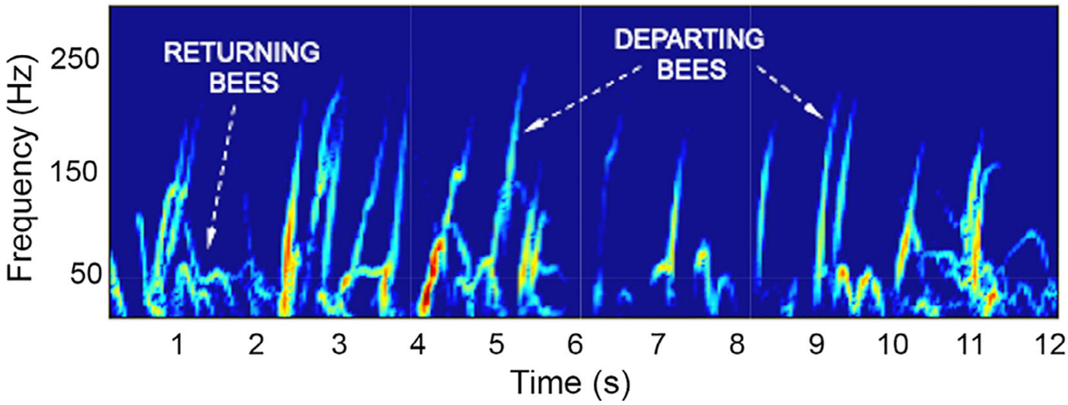

FIGURE 6 Time–frequency–intensity heat map plot from a 10.5 GHz Doppler radar. The frequencies of forager bees are displayed as vertical tracks approaching 90–150 Hz with yellow and red banding. Tracks can be seen extending throughout the 12 s timeframe of the recording from left to right [After Souza Cunha et al. (2020)]

data and comparing precision with other counters is rather difficult at this stage of development. Future improvements are currently being developed. For example, the software can be used to predict radar cross-sections of flying bees as a precursor to detecting and tracking them (Alzaabi et al., 2021). Overall, RADAR could be a promising technology in terms of the low cost, durability and possibility of combination with sensor- or video-based counters.

2.3 | Imaging/video-based systems

In 1935, Patterson was the first to describe an image-based bee counter. He illuminated the entrance gates of a bee colony and, by means of a wide-angle lens, focused the images of 24 gates onto a single strip of continuously moving 35 mm positive film. A single bee passage was recorded as an interruption of a solid line; this resulted in very high labour to count these interruptions, and the running cost of the film was considerable at the time (approximately 20.3 m film per minute).

Since then, video-based counters were not considered for a long time because of technical complexities and costs. They can be seen as a development of the recent decade (Figure 1; Table 1). Concurrent with the global increase in available smartphone technology in the late 2000s, camera lenses implemented in these phones were the result of lower prices because of the high availability on the world market (Thusu, 2012). As a side effect, this trend made it possible to develop affordable video-based devices such as bee counters in the early 2010s.

One of the first models that can be considered a hybrid of video, optical infrared LEDs, and individual tags was presented by Chen et al. (2012). They used a camera to record individually marked bees under infrared light at the hive entrance, automatically registered by an algorithm. Bees were labelled with a circular character-encoding tag. To identify these tags in the video, an algorithm (Hough transformation) was used to detect the presence of the marked bees (Tarsha-Kurdi, Landes, & Grussenmeyer, 2007). A 12,000-bee strong colony could be monitored for 15 consecutive days.

This approach combines several advantages of the aforementioned technologies and can be seen as an alternative to RFID tagging. Important benefits are the reduced costs compared to RFID transponders and the range of applications. For instance, bees labelled in this way can be deployed to study the possible effects of electric fields such as mobile communications radiation (3G–5G) under field conditions without major interference as expected with an RFID device that would suffer from EMF radiation. A similar counter was employed by Dussaubat et al. (2013) to investigate the effects of a *Nosema ceranae* infection on the flight behaviour of honey bees.

The device of Chen et al. (2012) was subject to the same limitations as RFID technology (see Section 2.2.3). To date, it has been an exception to most other video-based counters and has not been described except in Dussaubat et al. (2013).

The principles of a modern video-based counter usually include three parts: (a) bee detection; image transformation algorithms are necessary to make the bee image stand out from the background and differentiate it from other forms. Methods such as background subtraction, shape matching processes, ellipse approximations and hybrid segmentation using both intensity and depth images can be applied (Chiron et al., 2013; Ngo et al., 2019). In the second part (b), tracking bees (targets) by assuming their future positions to determine whether they are going in or flying out of the hive is accomplished by different algorithms. The most widely used approaches are Kalman filters, iterative-Hungarian algorithm tracking (Ngo et al., 2019; Sahbani & Adiprawita, 2016; Yang, Collins, & Beckerleg, 2018), or 3D multitarget tracking based on a combined Kalman filter and global nearest neighbour (Chiron et al., 2013; Konstantinova, Udvarev, & Semerdjiev, 2003; Magnier et al., 2018; Ngo et al., 2019). Kalman filters are algorithms that calculate a kind of memory of past measurements and use and continuously update this memory to determine parameters, for example, the position of an object with high precision (Zarchan & Musoff, 2015). For instance, such filters are employed in every satellite navigation device and smartphone. The final part (c) counts the bees from the results obtained from the first two algorithms. As pictured in Figure 1 and Table 1, the utilisation of such

TABLE 1 Automated bee counting devices that were described in the scientific literature (i.e., in journal articles, preprints, conference proceedings and theses)

Type	Light source	Species	Validation method	Precision	Source
Mechanoelectrical	n.a.	*A. mellifera*	n.a.	n.a.	Lundie (1925)
	n.a.	*A. mellifera*	n.a.	n.a.	Fabergé (1943)
Optical sensor	Light bulb	*A. mellifera*	n.a.	n.a.	Brittain (1935)
	Daylight	*Agapostemon texanus*	n.a.	n.a.	Kerfoot (1966)
	Light bulb	*A. mellifera*	n.a.	n.a.	Spangler (1969)
	n.a.	*A. mellifera*	n.a.	n.a.	Burrill and Dietz (1981)
	Light bulb	*A. mellifera*	n.a.	n.a.	Erickson, Miller, and Sikkema (1975)
	Daylight	*A. mellifera*	n.a.	n.a.	Buckley, Davies, and Spindley (1978)
	Infrared (LED)	*A. mellifera*	Manual counting bees in front of the hive	97.7% (96.3–99.1%)	Marceau, Boily, and Perron (1988)
	Infrared (LED)	*A. mellifera*	Liebefeld Method (Imdorf et al., 1987)	Up to 7.5-fold higher loss rate than estimated	Rickli et al. (1989)
	Infrared (LED)	*A. mellifera*	n.a.	n.a.	Liu, Leonard, and Feddes (1990)
	Red light (LED)	*A. mellifera*	Flight cage	99.7–99.8%	Struye, Mortier, Arnold, Miniggio, and Borneck (1994)
	Infrared (LED)	*A. mellifera*	Robbers test	n.a.	Struye (1999)
	n.a.	*A. mellifera*	n.a.	n.a.	Bromenshenk (2001)
	Infrared (LED)	*A. mellifera*	Manual counting bees on video	84.92% incoming and 85.95% outgoing	Jiang et al. (2016)
	Infrared (LED)	*A. mellifera*	n.a.	n.a.	Pešović, RanĎić, and Stamenković (2017)
	Infrared (LED)	*A. cerana*	n.a.	n.a.	Qiuzi et al. (2017)
	n.a.	*A. mellifera*	n.a.	n.a.	Clarke and Robert (2018)
	Infrared (LED)	*A. mellifera*	Manual counting bees on video images	95.57% incoming and 96.11% outgoing	Son et al. (2019)
Mechanical	n.a.	*A. mellifera*	n.a.	n.a.	Chauvin (1976)
Capacitive sensor	n.a.	*Bombus* sp. *A. mellifera* *Andrena* sp. *Megachile rotundata*	n.a.	86.80%	Campbell, Dahn, and Ryan (2005)
	n.a.	*Osmia* sp.	n.a.	n.a.	Perrault and Teachman (2016)
	n.a.	*A. mellifera*	Robbers test and manual counting bees on video	~95%+	Bermig et al. (2020)
	n.a.	*A. mellifera*	n.a.	n.a.	Hong et al. (2020)
Video-based	n.a.	*A. mellifera*	n.a.	n.a.	Patterson (1935)
	n.a.	*A. mellifera*	n.a.	94%	Campbell, Mummert, and Sukthankar (2008)
	Infrared (LED)	*A. mellifera*	n.a.	n.a.	Chen, Yang, Jiang, and Lin (2012)
	n.a.	*A. mellifera*	n.a.	n.a.	Chiron, Gomez-Krämer, and Ménard (2013)
	n.a.	*A. mellifera*	n.a.	96–97%	Dussaubat et al. (2013)
	n.a.	*A. mellifera*	Manual counting bees on video images	80.5–85.5% (total bees on flight board within a margin of 10 bees)	Kulyukin and Reka (2016)

TABLE 1 (Continued)

Type	Light source	Species	Validation method	Precision	Source
	n.a.	*A. mellifera*	Manual counting bees on video images	95.3% incoming and 88.8% outgoing	Tu, Hansen, Kryger, and Ahrendt (2016)
	n.a.	*A. mellifera*	Manual counting bees on video images	94–99% (total bees on flight board within a margin of 10–15 bees)	Kulyukin (2017)
	n.a.	*A. mellifera*	n.a.	n.a.	Tashakkori, Hernandez, Ghadiri, Ratzloff, and Crawford (2017)
	n.a.	*A. mellifera*	Manual counting bees on video images	75%	Magnier, Ekszterowicz, Laurent, Rival, and Pfister (2018)
	n.a.	*A. mellifera*	Manual counting bees on video images	93.9%	Ngo, Wu, Yang, and Lin (2019)
	n.a.	*A. mellifera*	n.a.	n.a.	Tausch, Schmidt, and Diehl (2020)
	n.a.	*A. mellifera*	Manual counting bees on video images	97.5% (82.4–100%)	Kulyukin, Mukherjee, Minichiello, and Truscott (2021)*
RADAR	n.a.	*A. mellifera*	Manual counting bees in front of the hive/BeeScan (Struye, 1999)	76.6% visual, 70.3–76.3% BeeScan	Souza Cunha et al. (2020)
	n.a.	*A. mellifera*	n.a.	n.a.	Aumann, Aumann, and Emanetoglu (2021)

Note: An online search was conducted using Google Scholar, ResearchGate and literature references in review articles. The search process is further described in the supplementary material. *Without claiming completeness*.
Note: (n.a.) not applicable or not available.
Note: (*) The author(s) used the same technique but different counting algorithms. Therefore, in Figure 1, only the first of these publications were considered.
Note: (+) personal communication.

algorithms has just started in recent years and was strongly triggered by affordable video techniques. Therefore, it can be assumed that development in this sector will most likely have a substantial influence on future bee counters, especially when combined with deep learning approaches (see Section 2.3.1).

However, as promising as it may be, the technique has some notable limitations. As with photography, every video-based system inevitably depends on the lighting conditions. In an outside setting, these conditions can vary significantly with the time of day, season and weather (Campbell et al., 2008).

Counters without an additional light source are dependent on sunlight, which is not permanently available 24 hr a day. This makes continuous recording of traffic difficult. Introducing a light source other than the infrared spectrum can cause behavioural alterations of foragers and nest bees, which reflect a major disturbance to the natural habits of a colony. Moreover, to cover the whole flight area in front of a hive from a short distance when mounted near the entrance, wide-angle lenses are typically used. From early on, such imaging systems encountered issues with false-negative registration of bees at the edges of the frame because of optical restrictions and distortions of the lens. False positives occur when bees fly toward the camera and appear larger than usual, generating multiple detections, or by occasional shades, leaves, or blades of grass wrongly counted as bees. Complex areas such as a crowded flight board can also cause false-positive events (Campbell et al., 2008; Chiron et al., 2013; Kulyukin & Reka, 2016).

Moreover, as expected with any tracker algorithm, the efficiency decreases as the number of targets increases (Chiron et al., 2013). Honey bee colonies tend to strongly vary in flight traffic depending on the available food sources, health status and weather conditions (reviewed in Marchal et al., 2020). To evaluate counters of any type, ground truth or empirical evidence needs to be obtained by a reference device with a known precision or by human evaluators. Both can be troubled by very high densities of honey bees, where one cannot reliably measure in–out activity, as bees are almost impossible to separate visually. To improve the process, stronger algorithms and better image quality might solve some of the problems, as suggested in Magnier et al. (2018). Last, video data generate large amounts of disk space that cannot easily be transferred from storage to the user online. When future high-speed 5G networks are more commonly accessible, this issue should be overcome.

2.3.1 | AI-based systems and deep learning

Artificial intelligence (AI) is a branch of computer science focused on algorithms that mimic intelligent learning and problem solving.

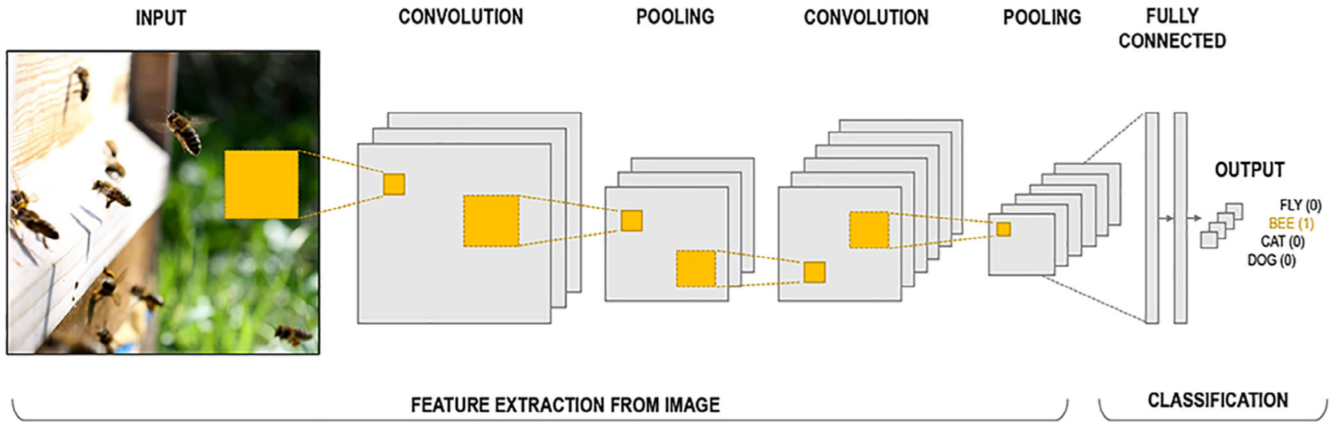

FIGURE 7 Convolution and pooling layers act as feature extractors from the input image, while fully connected layers act as a classifier. Because the input image is a bee, the target probability is 1 for the bee class and 0 for the other three classes

An important and increasingly used approach within AI is deep learning, a class of machine learning algorithms that uses multiple layers of a neural network to progressively extract higher-level features from the raw input data. Neural networks are algorithms that can be trained to detect certain signals, for example, images. Most commonly applied to analysing visual imagery, a convolutional neural network (CNN) is employed as a class of deep neural networks that basically represents an input–output mapping. When combined with video-based counters, it can be a powerful tool to detect more than honey bees flying in and out of their hives.

The CNN converts raw sensory data on the input side (e.g., a picture) into a classification or keywording (e.g., a text description of the object shown in the picture). The input data are entered into the network, where a series of intermediate layers in the network subsequently extract increasingly abstract 'features' of the image. A feature is an attribute that the network 'learns' from the data (Figure 7).

Based on such algorithms, Marstaller, Tausch, and Stock (2019) and Tausch et al. (2020) presented a visual monitoring system to detect the flight activity and background mortality of honey bee hives.

An advantage of using deep learning algorithms in visual bee counters is the ability to extract features from image data other than honey bees alone. As demonstrated by Babic, Pilipovic, Risojevic, and Mirjanic (2016), Yang et al. (2018) and Yang and Collins (2019), deep learning can be utilised to differentiate between pollen and nonpollen foragers to detect corbicular pollen carriers. By utilising regional data on flowering periods from possible bee-attractive food plants, correlations of pollen colour could indirectly indicate food availability in the flight radius and season of observation. This could provide valuable input for developing policies that support diverse and continuous food supply in rural and agricultural landscapes. Ideally, these AI-based counters could be embedded in monitoring programs or WSNs to evaluate such policies (Ratnayake, Dyer, & Dorin, 2021).

Moreover, it is also possible to detect Varroa-infested bees when a phoretic mite is attached to the bee body (Bjerge et al., 2019; Schurischuster, Remeseiro, Radeva, & Kampel, 2018). For instance, Bjerge et al. (2019) developed a so-called Infestation Level Estimator algorithm to analyse image data by counting the number of bees and estimating the positions of Varroa mites found. It seems only logical to implement feature extraction to detect all genera of bees, such as drones, queens and workers, as well as other insects that possibly threaten hives, such as the small hive beetle *Aethina tumida* or the Asian hornet *Vespa velutina* (reviewed in Abou-Shaara & Staron, 2019).

Another possibility to utilise deep learning to detect Varroa mites is object detection. Bilik et al. (2021) implemented YOLO (you only look once) and SSD (single shot detector) object detectors in a real-time computer vision-based honey bee inspection system. This system can be used as an online monitoring tool where video or photo data are analysed. Finally, nonscientific use by beekeepers to quickly screen their apiary or monitoring area for current Varroa prevalence could be enabled and may benefit future treatment strategies. By applying generic counters with such features, technological advances could ultimately be used for nationwide health monitoring, in which food availability and parasitation levels can be remotely tracked and, through rapid intervention, situations could be improved.

In addition, deep learning techniques are used for automated pollen detection when combined with multispectral imaging flow cytometry (Dunker et al., 2021). This is a very promising development in the field of palynology, as it requires less effort and expertise to perform a reliable pollen analysis. Combined with a bee counter and pollen trap, monitoring of food resources for pollinators at the landscape scale could be established to measure the impact of steps to improve bee nutrition as well as to monitor pollinator health.

3 | COUNTER VALIDATION METHODS

A prerequisite and very important step in developing a bee counter is validation. It is necessary to assemble the appropriate apparatus that does not interfere with bee behaviour and to use components that are inexpensive, durable and functional to maintain a stand-alone continuous monitoring field device. Without validation, the device may be recoding incoming and outgoing numbers of bees with an unknown precision.

A bee counter that is used for scientific purposes needs to be validated by applying standard methods. This would make it possible to compare the performance of different types of counters and foster the development of the best technology. Of the counters presented in Table 1, 58% did not indicate a validation method, which was criticised by Rickli et al. (1989). They found that, without validation, neither the devices nor the data generated could be compared. Of the papers that stated a method, manual counting of bees on video or in front of the hive was the most common (75%). The remaining studies used specific methods.

This lack of standardisation clearly indicates that there is an urgent need for methods that are easy to apply and comparable among the different types of counters. In this section, the two most promising approaches are described, that is, visual observation and the robbers test. Moreover, the user should be aware of the counter's principle precision and have a means to monitor the current precision of counters in operation. This would correspond to checking the precision of a laboratory balance, which can easily be gauged by using calibration weights. While this routine significantly reduces the opportunity for problems to remain undetected, most balances these days have additional self-check systems of various levels of sophistication that provide some degree of confidence that the system is operating correctly. This should also be implemented in bee counter systems, as realised by Struye et al. (1994) and Bromenshenk et al. (2015).

3.1 | Visual observation

Manual counting of bees to compare the flight activity with the numbers provided by the counting device seems reasonable to be the first step in evaluating a counter's performance. Counting the entire traffic of one flight day of a full-sized honey bee colony would be impossible for a human observer when carried out manually, but with the help of the video technique, this task is partly solvable. However, it still requires an operator that has to align both datasets appropriately.

Manual evaluation of video footage to determine counting precision requires a standardised approach. Jiang et al. (2016) suggested the following equations to calculate the percentage error (PE) in measuring incoming and outgoing bees. The actual number (AN) represents the number of bees assessed visually, and the counted number (CN) defines the bees counted by the device:

$$\mathrm{PE_{in}} = \left[\frac{\mathrm{AN_{in}} - \mathrm{CN_{in}}}{\mathrm{AN_{in}}}\right] \times 100 \tag{1}$$

and

$$\mathrm{PE_{out}} = \left[\frac{\mathrm{AN_{out}} - \mathrm{CN_{out}}}{\mathrm{AN_{out}}}\right] \times 100 \tag{2}$$

The average percentage error (AvgPE) of the incoming and outgoing precision was defined as

$$\mathrm{AvgPE_{in}} = \frac{\sum \mathrm{PE_{in}}}{\mathrm{Trial_{total}}} \tag{3}$$

and

$$\mathrm{AvgPE_{out}} = \frac{\sum \mathrm{PE_{out}}}{\mathrm{Trial_{total}}} \tag{4}$$

Note that $\mathrm{Trial_{total}}$ represents the total number of test trial observations during the experimental validation period.

Bermig et al. (2020) suggest using colonies of 5,000–10,000 bees to obtain flight traffic a human observer can handle. Moreover, they suggest evaluating 3-min videos at a 0.3 playing speed (slow motion) to capture all movements appropriately.

The foraging conditions at the apiary are an important factor when manually assessing bee flight. Favourable conditions with temperatures above 14°C (Clarke & Robert, 2018) and mass flowering food sources are on the higher end of the scale, providing solid large flight traffic. However, Jiang et al. (2016) highlight that lower temperatures are suitable to cover the lower range of flight traffic. Including both scenarios and detecting a possible gradient in the precision of the counter is equally important.

Possible limitations of this method include its impracticability to capture periods of very high traffic. Tu et al. (2016) reported that it was impossible for human observers to count bees on the flight board because of the vast number of bees and as a result of various layers of incoming and outgoing bees. Even with second-by-second resolved pictures from a video, counting bees accurately is not possible (Chiron et al., 2013). Moreover, behavioural traits such as short-term flights from newly assigned hive bees, aggregating bees at the hive entrance because of higher temperatures, or any other behaviour that interferes with a clear vision of the entrance could bias the count (Danka & Beaman, 2007; Souza Cunha et al., 2020). These challenges also indicate that it is important to clearly define what we mean by 'flight activity' detected by counters. It is actually the number of bees leaving and entering the hive, but it does not necessarily reflect all of the foraging activity.

Nevertheless, manual counting is suitable for achieving a certain degree of 'ground truth'. At least for a level of flight activity that can be handled by a human observer, considering that precision tends to decrease with traffic (Jiang et al., 2016). This is important in terms of setting a minimum level of comparability.

3.2 | Robbers test

In contrast to the manual validation of bee traffic, Struye et al. (1994) were the first to introduce a simple but solid validation method managed without human participation called the 'robbers test'.

In this method, the counter is placed under an empty box with a food source attracting honey bees to encourage them to 'rob' the box. Bees have to access the food by entering and leaving through the counter. At the end of the day, the sum of in and outgoing bees has to be zero, as bees tend to fly home after the temperature drops lower and daylight is reduced. Any deviation from zero is considered a benchmark of the precision of the device.

This can be outlined as the first standardised approach to measure the precision of a bee counter, independent of a human observer. Apart from Bermig et al. (2020), no one had applied this test, probably because of the lack of visibility, as it was merely published in the proceedings of a conference (ICPPR; Struye, 1999).

Bermig et al. (2020) suggest using more standardised conditions such as a tunnel tent instead of free-ranging foragers to limit access to the counter to one single colony and limit the risk that robbing spreads to weaker colonies at the apiary. This makes it possible to select a gradient of colony strengths, as different authors noted that most counters lose precision with increasing traffic (Jiang et al., 2016; Struye et al., 1994). However, a limitation of the tunnel is that the flight traffic may not be as intense as with free-flying bees.

Taking this into account, future research should focus on the development of a robust validation method to make the performance of a bee counter transparent and reproducible. The robbers test has the potential to become such a standard method. Bermig et al. (2020) and Struye et al. (1994) calculated their counter's total percentage error (PE_{total}) with the following equations:

$$CN_{diff} = CN_{in} - CN_{out} \tag{5}$$

For the CN_{diff}, it was chosen to subtract the total number of incoming bees (CN_{in}) from the total number of outgoing bees (CN_{out}). Usually, one assumes the other way would be more appropriate to measure how many bees remained outside the hive after a flight day. However, in robbers tests, traffic is first generated by incoming bees and not *vice versa*. Note that CN is the counted number of either incoming or outgoing bees (see 3.1).

$$PE_{total} = \left[\frac{100}{CN_{in}}\right] \times CN_{diff} \tag{6}$$

where $PE_{total} > 0$ means that x% of incoming bees remained in the box and suggests checking the box after each flight day for dead bees inside the box. These bees should be added to CN_{out} as a correction. $PE_{total} < 0$ means that y% more bees flew out than came in, which is not possible and indicates inaccuracy of the counter. $PE_{total} = 0$ would be 100% precision or 0% error of the device.

4 | DATA INTERPRETATION

Rickli et al. (1989) and Struye (1999) were the first to specify indices related to how data from bee counters can be used to provide evidence for the health and vitality status of a honey bee colony, later complemented by Ngo et al. (2019). Like the validation of the counters, such indices are very important in terms of the standardisation and comparability of the created dataset. Moreover, these indices contain clearly specified terms that allow for interpretation and visualisation of the data.

As a basic feature, a bee counter should ideally record incoming and outgoing bees 24 hr a day. Although no flight activity is expected before sunrise and after sunset, activity may be detected at the hive entrance during events such as fanning because of hot temperatures and should be recorded. Therefore, the time resolution should be as high as possible to cover the slightest possible fluctuation that may represent an unnatural flight behaviour indicating internal or external interference. A 1 min interval has proven to be sufficient for that purpose (Bermig et al., 2020).

If we take a pesticide spray scenario as an example, it would make sense to compare flight data from a treated and untreated area where bees were foraging before, during, and after the spray application (event) as indicators for (sublethal) effects. Sublethal effects may involve, for example, delayed return or departure of bees to neighbouring colonies. To do so, extracting timeframes with cumulative flight counts (C) from incoming and outgoing bees as a function of the hour (hr) can be resolved with the following equations:

$$C_{in}(hr) = \sum_0^{59} C_{in}(min) \tag{i}$$

and

$$C_{out}(hr) = \sum_0^{59} C_{out}(min) \tag{ii}$$

This can be condensed to cumulative flight counts per day (d) if the event may not need such a high resolution to be displayed using Equations (iii) and (iv):

$$C_{in}(d) = \sum_0^{23} C_{in}(hr) \tag{iii}$$

and

$$C_{out}(d) = \sum_0^{23} C_{out}(hr) \tag{iv}$$

These indices can be applied to compare events of significant change in flight behaviour such as swarming or pesticide exposure by feeding (Ngo et al., 2019; Struye et al., 1994). Moreover, it may be of higher interest to examine incoming (i.e., returning) bees when events tend to affect foragers on their trip outside of the hive in terms of homing success. Examination of outgoing bees may be more relevant when internal exposure is expected as the source of the event.

To quantify the total daily loss (L) of a honey bee colony, Equation (v) can be used to determine the total number of bees that did not return to the hive at the end of the day. This measure has a more informative value to judge striking events such as forager loss because of a spray application or rotary mowers used on a blooming clover harvest, for instance.

$$L(d) = C_{out}(d) - C_{in}(d) \tag{v}$$

The same index was used by Bortolotti et al. (2003) to measure the effects of the neonicotinoid imidacloprid on the homing success of bees. In general, flight traffic hinges on internal factors such as the size, composition and health status of a colony, among others (Bermig et al., 2020; Clarke & Robert, 2018). These factors can vary significantly among different colonies. To avoid such bias, Struye (1999) and Ngo et al. (2019) suggested utilising a normalised or relative loss rate (LR) to better categorise the increase or decline of forager bees per time, independent of colony factors. With Equation (vi), the daily loss can be expressed as a ratio of the cumulative outgoing flight counts in per cent (%):

$$LR(d) = \left[\frac{C_{out}(d) - C_{in}(d)}{C_{out}(d)}\right] \times 100 \tag{vi}$$

Furthermore, the accumulated loss of foragers (L_{acc}) that had not returned to the hive during N days can be calculated by Equation (vii):

$$L_{acc}(N) = \sum\nolimits_1^N L(d) \tag{vii}$$

The accumulated loss rate (LR_{acc}) represents the percentage loss of bees during N days and can be calculated by Equation (viii):

$$LR_{acc}(N) = \sum\nolimits_1^N LR(d) \tag{viii}$$

Indices (vi) and (vii) are particularly useful to reveal external influences on bees' flight behaviour for both short-term and long-term periods (Ngo et al., 2019; Struye, 1999). For future work with electronic counting devices, the above-introduced indices can help interpret data and are critical to create comparable and standardised results as scientific output.

5 | CONCLUSIONS AND PERSPECTIVE

Since the first invention of an electronic bee counter, the research field has developed slowly. For a long time, sensor-based systems dominated the sector. The strength of sensors lies in their robustness and a rather simple design. However, there is still no commercial model available that can generate reliable scientific data. In the last decade, promising approaches have been made by using enhanced video-based systems to record flight activity utilising deep learning and artificial intelligence to disentangle the complex flight behaviour of honey bee superorganisms (Figure 1). We can observe trends in addition to recording incoming and outgoing bees. With the increased complexity and capabilities of the technique, it is possible to record many details, rendering sensor-based systems inferior. One example is automatic food source recognition to identify the pollen loads of returning foragers. Another detail that sensor-based counters cannot register is the presence of parasites attached to the bees' bodies, as in the use of an image recognition algorithm to observe the degree of infestation with Varroa mites (Cecchi, Spinsante, Terenzi, & Orcioni, 2020). In a future scenario, mites could be detected at the hive entrance, and statistics on the infestation rate could be made available by a web interface for neighbouring beekeepers. As an ultimate approach to fight *V. destructor* without chemicals, the coordinates of the mites could be detected, and a laser could be used to kill them (Chazette et al., 2016).

There is promising evidence that the implementation of video-based systems could be successful. The recent developments of computer vision and deep learning enable monitoring of biodiversity in a fully autonomous and noninvasive way for whole seasons, which is not limited to honey bees (Høye et al., 2021; Ratnayake et al., 2021). Such an instrument can also enhance the processing of samples in the laboratory, as automated imaging can provide a new way of identifying and counting specimens to measure the abundance of different bee pollinators. This was impressively demonstrated by Høye et al. (2021) with examples of sensors and devices relevant to the field of entomology. They provide evidence of how deep learning tools can easily convert big data streams into ecological information. This trend is currently commercialised with products to remotely monitor bee health for everyday beekeepers. Weather conditions, hive weight, brood temperature and flight data are recommended for monitoring. Although some techniques are well-engineered, the market is not transparent because of the lack of standards and without provision of counter precision, data may be useless, at least for scientific use.

This issue is also apparent in the current scientific literature. The majority of the reviewed articles did not provide any information on the validity of their bee counters. As a counter represents a precision tool similar to a laboratory balance, it is not enough to simply state that it counts incoming and outgoing bees. It is mandatory for correct data interpretation to understand the range of precision the device operates at. If the daily loss of forager bees accumulates to an unrealistic number suggesting that the hive would be empty after a week, it is questionable if such data can be trusted. By providing a PE after validation with a standard test method, the data are far more comparable and the user can judge it more easily. Therefore, there is an urgent need to define a common standard in counter validation. The advances in method development noted earlier in this review could form the basis for future validation concepts.

Once a device is validated, it is equally important to enable proper interpretation of the flight data. If counters are used to measure the ecotoxicological significance of plant protection products on bees' flight behaviour and ultimately on colony development, comparing daily incoming and outgoing bees from treated and untreated colonies may not provide enough resolution to detect sublethal effects. By utilising a normalised LR, however, the temporal resolution can easily be adapted to hourly or even smaller intervals independent of colony factors. Such 'indices' were first compiled by Rickli et al. (1989), Struye (1999) and Ngo et al. (2019) and slightly refined in this review.

The so-called background mortality of a honey bee colony indicates bees that die naturally outside the hive at a certain time (e.g., daily, weekly, in spring, in the summer hole, etc.) (Dukas, 2008). With a counter that has a stable and low error rate, even during periods of intense flight activity, it would be possible to reliably determine this mortality. However, as seen from the work presented here, standards for determining the error rate must be established to make such an approach feasible.

It is not yet possible to collect this kind of data accurately, particularly over longer time intervals. However, this would benefit environmental risk assessment for higher-tier studies. Obtaining accurate information on bee mortality rates induced solely by the substance of interest would be a valuable endpoint. In addition, the effects of a spray application could be measured in real time while the farmer is operating the field sprayer.

Identifying whether a certain loss of foragers poses a significant risk to the colony, for example, in terms of its winter mortality, would be difficult, if not impossible, to determine empirically but can be checked using simulation models that are sufficiently realistic (i.e., to simultaneously reproduce a range of observed features of a colony and its response to different environmental conditions). BEEHAVE is such a model (Becher et al., 2014). It has been thoroughly examined by the European Food Safety Authority (EFSA, 2015) and is considered suitable for simulating unstressed or reference colonies (EFSA, 2021). The EFSA has a model under development that will be based on the ALMaSS (Animal, Landscape and Man Simulation System) framework of representing agricultural landscapes and their management, including considerably more detail than BEEHAVE, with modules for diseases and pesticide effects (EFSA, 2016).

Considering the most recent development in bee counters, promising progress has been made, indicating a major leap toward solving the issues and shortcomings in the current decade. Connected hives and beekeeping networks will provide a tremendous amount of data, including bee traffic, weight change, weather conditions and overall colony development, providing indicators for bee and colony health. Compiling the current knowledge of state-of-the-art electronic counting devices should enable future work to be more focused to overcome the outlined issues.

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CONFLICT OF INTEREST

The authors declare that no competing interests exist.

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