Computers and Electronics in Agriculture 227 (2024) 109556

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

European beekeepers' interest in digital monitoring technology adoption for improved beehive management

Wim Verbeke [a,*], Mariam Amadou Diallo [a], Coby van Dooremalen [b], Marten Schoonman [d], James H. Williams [c], Marie Van Espen [a], Marijke D'Haese [a], Dirk C. de Graaf [e]

[a] Ghent University, Department of Agricultural Economics, Coupure links 653, B-9000 Gent, Belgium
[b] Wageningen University & Research, Wageningen 6708 PB, the Netherlands
[c] Aarhus University, Department of Agroecology, C.F. Møllers Allé 4-8, 8000 Aarhus C, Denmark
[d] BEEP Foundation, Hoofdstraat 252, 3972 LK Driebergen-Rijsenburg, the Netherlands
[e] Ghent University, Department of Biochemistry and Microbiology, Krijgslaan 281 S2, B-9000 Ghent, Belgium

A R T I C L E I N F O

Keywords:
Apiculture
Apis *mellifera*
Digitalisation
Structural equation model
Survey
Technology adoption
Theory of planned behaviour

A B S T R A C T

This study investigates the adoption of Digital Beehive Monitoring Technology (DBMT) based on a survey with 844 beekeepers across 18 European countries, shedding light on their characteristics, current usage patterns, expected benefits, and the determinants influencing technology adoption. Notably, 79.1 % of beekeepers had yet to embrace any form of digital monitoring, while 20.9 % engaged in limited monitoring, primarily focused on hive weight. The perceived benefits of DBMT were explored, with hive management facilitation, colony health enhancement, winter loss reduction, and time-saving emerging as primary expectations. A quarter of beekeepers expressed uncertainty regarding these anticipated benefits, underscoring the need for increased awareness and education about the advantages of DBMT. Logistic regression is used to uncover key determinants influencing DBMT adoption, emphasizing the role of professionalism, regional disparities, and active participation in beekeepers' associations. The application of the Theory of Planned Behaviour (TPB) through Structural Equation Modelling reinforced the central role of beekeepers' personal attitudes in shaping their intention to adopt DBMT, with social norms and perceived behavioural control providing complementary albeit minor influences. The findings imply that hobbyist beekeepers may be more involved in beekeeping as a nature-centric activity, whereas professional beekeepers demonstrate a greater inclination toward digitalisation. With the so-called social tipping point of 25 % for technology adoption being almost reached, this study provides a timely empirical perspective on the European beekeeping sector's evolution towards digitalisation, so-called Apiculture 4.0.

1. Introduction

1.1. Background and rationale

The honey bee (*Apis mellifera*) plays a crucial role in providing pollination services to agri- and horticulture, and in procuring apiary products such as honey, pollen, propolis and beeswax. Honey bees are therefore of great societal, environmental, and economic concern. Yet, the challenges facing the beekeeping sector are multiple. For more than three decades, beekeepers have experienced high honey bee colony winter losses due to a range of health-related threats such as parasites, pathogens, pesticides exposure, and reduced floral resources (Goulson et al., 2015; Vanbergen and the I.P. Initiative, 2013). These factors are in some cases exacerbated by limited beekeeper experience and inadequate beekeeping management training (Jacques et al., 2017) to deal with continuing and emerging challenges facing beekeepers, including adverse climate change impacts in specific regions (Van Espen et al., 2023). These high winter losses are persisting over time (Gray et al., 2020). Meanwhile, digitalisation is rapidly transforming the agri-food sector in its quest for becoming more sustainable and resilient (Finger,

* Corresponding author.
E-mail addresses: wim.verbeke@ugent.be (W. Verbeke), mariamamadou.diallo@ugent.be (M.A. Diallo), coby.vandooremalen@wur.nl (C. van Dooremalen), marten@beep.nl (M. Schoonman), jhw@agro.au.dk (J.H. Williams), marie.vanespen@ugent.be (M. Van Espen), marijke.dhaese@ugent.be (M. D'Haese), dirk.degraaf@ugent.be (D.C. de Graaf).

https://doi.org/10.1016/j.compag.2024.109556
Received 11 March 2024; Received in revised form 7 October 2024; Accepted 11 October 2024
Available online 28 October 2024

2023). The transition towards digital agriculture – also referred to as Agriculture 4.0 (Araújo et al., 2021) – can provide opportunities for innovation, employing digital technologies to tackle contemporary and future challenges in the beekeeping or apicultural sector too. In their horizon scanning exercise with experts, Willcox et al. (2023: 2) effectively identified "greater availability of technology and automation to remotely monitor bee colony health" as the main opportunity facing managed bees in European agricultural systems. Meanwhile, Shepherd et al. (2020: 5083) mentioned that "for the potential of digital technologies [in agriculture] to be truly realised, the technology has to be implemented on a large scale" and further that "history suggests this [diffusion and adoption of digital technologies in agriculture] could be a slow process". Enabling digital technologies (e.g., sensors and networks) are increasingly available, and with numerous digital products on the market (e.g., hive monitoring systems), beekeepers have started embracing digital beekeeping tools. Meanwhile, the world's beekeepers have been referred to be "a profession particularly slow to adopt" technologies such as apiary management software (Hassler et al., 2021: 13). However, at present and to the best of our knowledge, information about the state and insight into the drivers of uptake of digital technologies in the European beekeeping sector remains limited. This is precisely where the present research comes into play.

Preventing loss of honey bee colonies requires a better understanding beyond assessing the effects of short and long-term stressors on individual bees (Ulgezen et al., 2021; van Dooremalen et al., 2018) and/or identifying potential risk factors, e.g., via surveillance studies (Olate-Olave et al., 2021). For beekeepers, it is essential to anticipate losses early enough to apply mitigating actions (van Dooremalen and van Langevelde, 2021). Therefore, advanced methods for early warning of potential honey bee colony losses are urgently needed (van Dooremalen et al., 2018; van Dooremalen and van Langevelde, 2021). To estimate the health status of a honey bee colony, beekeepers currently still largely rely on physical interventions, consisting of manually opening the hives and visually inspecting the colony for anomalies, such as, e.g., the presence of parasites or viruses, symptoms of diseases, and colony traits like queen and brood presence and status, colony and brood size, and honey and pollen storage. Taking apart the hive components for inspections disturbs colonies, entails risking injury and loss of bees and queens, and may provoke defensive behaviour in the bees or robbing across adjacent hives. Moreover, such visual inspections using classical measurements only provide a momentary snapshot of a colony. Considering the complex and dynamic characteristics of honey bee colonies, momentary data are most likely unsuitable for mapping and predicting changes in the colony health status or colony losses (Ulgezen et al., 2021; van Dooremalen and van Langevelde, 2021). Manual monitoring is also labour-intensive and physically challenging for beekeepers, which may eventually result in beekeepers turning away from their hobby or business, like Potts et al. (2010) showed in the beekeepers' response to increased costs and labour as a consequence of the emergence of the *Varroa destructor* parasite. Therefore, automated monitoring tools and related digital technologies could have considerable potential as possible predictors for colony health status and losses. They are non-disruptive for the bees, and could significantly aid and simplify hive management, so long the technology is readily available and affordable.

Digital agriculture is defined as the collection and use of detailed digital information to guide decisions along the agricultural value chain, including technological advances, such as, improved sensor capability, data connectivity, and computer-based artificial intelligence decision support and self-learning systems (Shepherd et al., 2020). Key technologies and methods involved in digital agriculture are the Internet of Things (IoT), sensors, data analytics, image processing, and communication technologies. Agricultural digitalisation has been recognised to have great potential, not only economically by, e.g., increasing productivity and lowering costs, but also by playing an important role in preserving the environment and improving farmers' working conditions (Maffezzoli et al., 2022).

Like many economic sectors and contemporary production systems, beekeeping is also moving towards digitalisation. In 2022, Hadjur et al. (2022) provided a comprehensive overview of the advances in precision beekeeping and connected and smart beehives. Their survey covered the available architecture of connected beehives, types of sensors, data transmission systems, power supply, costs, as well as methods and levels of data collection and data analytics that emerged during the last decade. They noted that more affordable commercial solutions should be developed to meet beekeepers' interests, e.g., to improve hive management information for more efficient beekeeping. They expressed their hope that more and more beehives would become connected to provide new apiary knowledge. Since the publication of this survey, several additional studies on this topic emerged. For example, Aydin and Aydin (2022) focused on the software architecture for open data resulting from wireless sensory network (WSN-) based beehive monitoring, and they discussed the potential of microservice architecture in this respect. Arribas and Hortelano (2023) presented a system using spatial thermal data to monitor the behaviour of honey bees during the winter when hives cannot be opened. Real-time heat maps produced based on temperature sensor data and IoT technologies allow providing insights into the health and strength of honey bee colonies. Zaman and Dorin (2023) provided another review of available technologies and ICT resources for beehive monitoring, including diverse sensor technologies (e.g. weight, temperature, humidity, gas), accelerometers, vibration detectors, and thermal imaging. They also provided a framework that may assist in the adaptation and innovation of these technologies, and distinguished between operational monitoring, investigative monitoring, and predictive monitoring – the latter being referred to as becoming the new frontier in sensor-assisted beehive monitoring. Degenfellner and Templ (2024) used and deployed machine learning to translate beehive weight and weight level shift data into predictive insights for hive monitoring. Their data were collected on a continuous basis by means of a load cell-equipped weighing platform and transmitted via an antenna through a mobile device. Bilik et al. (2024) provided an overview of more than 50 research projects that combine machine learning and computer vision techniques for automated beehive monitoring, mostly used for bee traffic, pollen and varroa detection with potential for assessing the health status of honey bee colonies. Despite the growing interest in this topic as exemplified by the aforementioned papers, none of these recent studies addressed the likelihood and determinants of adoption by the ultimate target user groups of beekeepers.

Technological developments driving the digital agriculture revolution (Shepherd et al., 2020) allow for more continuous measurements in beehives through the use of sensors, data transfer and storage, novel analytical techniques, and improved connectivity. Such technological developments provide an opportunity to find indicators of changes in the status of a biological system (Scheffer et al., 2018). Indeed, measurements from in-hive sensors allow gathering high resolution information on honey bee colony dynamics (Meikle and Holst, 2015), while at the same time providing a more non- or low-disturbing monitoring method for the bees (Meikle and Holst, 2015; Ulgezen et al., 2021; van Dooremalen and van Langevelde, 2021). Several studies emphasise the value of using weight, temperature, humidity, sound and vibrations to measure colony resources, activity and growth (Meikle and Holst, 2015; Zacepins et al., 2015). An important step to indirectly assess colony performance is the interpretation of the raw data (Braga et al., 2020a, 2020b; Cecchi et al., 2020; Meikle et al., 2017), which benefits from a machine learning or artificial intelligence approach (Braga et al., 2020b; Meikle and Holst, 2015; Metlek and Kayaalp, 2021). For example, Braga et al. (2020b) developed a high precision classification model based on a supervised machine learning approach to estimate the health status of honey bee colonies and to indicate an imminent colony collapsing state to beekeepers. In a similar vein, Bencsik et al., (2023) demonstrated that it is possible to estimate the number of foraging bees, colony size and strength and eventual risk of colony loss from the change measured in-hive carbon dioxide using CO_2 gas sensors.

Ongoing developments in the beekeeping sector include software such as websites and mobile apps to register and store hive observations, interventions and managerial actions (beekeeping administration), hardware such as measurement sensors and printed circuit boards to control the measurements and transmit data wirelessly, databases to store data, algorithms to process the data, and applications to feed information back to the beekeeper. All these digital elements together form a platform with a data pipeline. Hence, in this paper we refer to Apiculture 4.0 as the transition towards digital beekeeping, a parallel to the concept of Agriculture 4.0. In this context, Apiculture 4.0 boils down to a set of remote, non-invasive, wireless or IoT-based beehive or honey bee colony monitoring tools and data analytics. In this paper we will refer to this set of tools as 'Digital Beehive Monitoring Technology' (DBMT) and study its current and future adoption among beekeepers in Europe.

1.2. Scope, objectives and framework

Both beekeepers and honey bee colonies can benefit from DBMT applications as indicated previously. By measuring the hive continuously, beekeepers can be informed and even warned about the status of their bee colonies. Sensor data from beehives combined with environmental data, e.g., landscape and weather information, can be transferred to an application allowing beekeepers to remotely monitor the health status of their bee colonies. DBMT is a non-invasive means to know if a colony needs the beekeepers' assistance because of health issues (e.g., the expression of a disease or lack of food resources) and helps beekeepers with managerial and production decisions (e.g., deciding about the optimal time for honey harvesting or disease treatment). However, DBMT is not a matured field yet. As more sensors, knowledge on honey bee colonies and their health factors, and application of data science such as machine learning become available, new applications to support the beekeepers are still being developed. Open source code and designs allow for swift developments in the public space and permit researchers, beekeepers, and others to collaborate in the development of new applications.

Apart from the challenges imposed by the emerging technologies themselves, Shepherd et al. (2020: 5087) mentioned that "there is plenty of evidence to suggest that the main barriers to uptake will be socio-ethical [rather than merely technological]". This refers amongst others to equitable sharing of the benefits the technology can offer and identifying those who will embrace the technology and potentially benefit from it, versus those who will not. In their search for priority research questions pertaining to the digitalisation of agriculture, Ingram et al. (2022) identified and prioritised seven key themes that would benefit from a stronger evidence base, to help steer policy formulation including 'understanding benefits and uptake of data and technologies'. Within each theme, priority research questions were categorised into 'gold', 'silver' and 'bronze'. The present research fits specifically within the theme on understanding benefits and uptake, which basically refers to factors that determine and support adoption and benefit or hamper farmers' (i.e., beekeepers' in our case) capacity to adopt digital technologies. One of the priority research questions within this theme – classified as 'silver' by Ingram et al. (2022: 7) – asks: "What factors influence the uptake of digital technologies on farms (i.e., apiaries in our case)?" This is one of the research questions explicitly addressed in the present study. Related priority research questions refer to benefits and their distribution as well as identifying users who might be (dis) advantaged with respect to the adoption of digital technologies.

With the overall aim to bridge a part of the aforementioned knowledge gaps, the objectives of the present study are threefold: (1) to characterise European beekeepers who are implementing (at least some kind of) digital monitoring in their beekeeping operation versus those who are not; (2) to assess the benefits beekeepers seek or expect from the adoption of DBMT; and (3) to identify key determinants of beekeepers' intention and adoption behaviour related to DBMT. Specifically with respect to third objective, this study embraces the Theory of Planned Behaviour (TPB) as the conceptual framework to identify and assess the determinants of beekeepers' intentions to adopt DBMT.[1]

According to the TPB, behavioural intention (INT), which refers to an individual's readiness to perform the concerned behaviour (i.e., adopting DBMT), is assumed to be a direct antecedent of behaviour, which is the individual's observable response (i.e., implementing DBMT at least to some degree, in this present study). Behavioural intention is in turn influenced by three possible determinants: personal attitude toward the behaviour; social (or subjective) norm; and, perceived behavioural control (Ajzen, 2002, 1991). Attitude toward the behaviour (ATT) refers to how positively or negatively a person evaluates the target behaviour (i.e., in this case, to how positively or negatively a beekeeper evaluates the adoption of DBMT). Social Norms (SN) refer to perceived social influence or pressure to perform or not perform the behaviour (Ajzen, 1991). In the context of beekeeping, social norms may refer to the eventual influence of other beekeepers, beekeepers' associations or other people or organisations that matter to the beekeeper.[2] Perceived behavioural control (PBC) refers to the perceived ease or difficulty with which the individual believes they can perform the behaviour. PBC thus encompasses perceptions of resource and technology facilitation conditions (i.e., perceptions of how easy or difficult the beekeeper perceives the adoption of DBMT to be). This component accounts for eventual incomplete voluntary control over the intended behaviour, e.g., because of a lack of financial resources, technical skills or accessibility of the technology. These three antecedents to behavioural intention are argued to develop from three sets of beliefs, namely behavioural beliefs in the case of personal attitude, normative beliefs referring to social norms, and control beliefs related to PBC (Ajzen, 1991).

Finally, PBC is expected to moderate the effect of behavioural intention on behaviour, in the sense that a favourable intention may drive the behaviour only in case PBC is strong enough, which means that facilitating conditions are present to a satisfactory degree at least. Using quantitative pan-European beekeeper survey data, this paper will test the validity of the TPB model for assessing determinants of beekeepers' adoption of DBMT. For a visualisation of the TPB model, we refer to the results section where the model and analytical findings concerning the hypothesised paths in the TPB model are presented.

2. Materials and methods

2.1. Survey, questionnaire and measurement scales

Primary data were collected through a cross-sectional quantitative survey with European beekeepers (n = 844). Part of an online questionnaire was developed to assess beekeepers' current use, interest and future intention to adopt DBMT. The overall survey was introduced to the participants as a study on healthy and sustainable beekeeping in general and it was conducted within the frame of the EU Horizon 2020 project B-GOOD (de Graaf et al., 2022; van Dooremalen et al., 2014).

[1] We refer to the corresponding Results section (3.5) for a graphical representation of the TPB model.

[2] The possible presence of social influences justifies the choice of the TPB model rather than the Technology Acceptance Model (TAM) as the conceptual framework for this study. The TAM focuses on personal attitudes and perceptions, notably the perceived usefulness and the perceived ease of use of a technology. This model has proven to be useful also in the context of beekeeping when technology adoption is determined by individual perceptions (e.g., Hassler et al., 2021). These are implicitly contained in the Attitude and Perceived Behavioural Control components of our study's TPB model, next to Social Norms. It has been suggested that the TPB may be more powerful than the TAM in technology adoption decisions where social influences play a role (e.g., Cheng, 2019).

The survey addressed characteristics of the beekeepers, their beekeeping operation, personal attitudes and management practices in relation to beekeeping, honey bee colony health and its monitoring, environmental quality and climate change, and interest in digital technologies for beekeeping. This paper focuses on analysing the data collected in the latter part of the survey, notably beekeepers' interest in adopting DBMT. Key characteristics of the study sample are summarised in Table 1 (first column) and have also been described in Van Espen et al. (2023).

Within the survey section on DBMT, participants were first asked to indicate to what extent they are currently digitally monitoring different hive parameters including weight, temperature, humidity, sound, and number of bees in (at least some of) their beehives. Each parameter was accompanied by a binary ("no"/"yes") measurement scale and they were presented in a randomised order to avoid order bias. The question formulation specified that 'to monitor' does not simply mean 'to measure' but rather 'to check, observe and interpret over a period of time'. Responses to this question were included in the TPB model as measures of observed behaviour (see section 3.5). Participants were also asked to indicate what percentage of their beehives are currently digitally monitored as reported in the preceding question. Next, beekeepers were asked about the benefits they seek from (present or future) adoption of DBMT. Five potential benefits were assessed, including 'to save time', 'to save costs', 'for easier beehive management', 'to decrease colony loss', and 'to enhance colony health', each on a five-point Likert scale ranging from 1="totally disagree" to 5="totally agree". The list of possible benefits was informed by the promises of current and near-future DBMT as reviewed from literature.

Finally, participants were exposed to a list of 13 statements referring to personal attitude (three behavioural belief statements), social norms (three normative belief statements), perceived behavioural control (three control belief statements), and behavioural intention (four statements). As reported previously in section 1.2, according to the TPB, intentions towards adopting a new technology are hypothesised to be predicted by the perception that the adoption of the technology is personally desirable (personal attitude toward the behaviour), supported by social norms (subjective or social norms), and practically feasible (perceived behavioural control). Each statement was scored on a five-point Likert scale ranging from 1="totally disagree" to 5="totally agree". The precise formulation of the statements is provided in the results section (we refer to Table 2). Before exposing participants to the TPB-statements, they were informed that "digital hive monitoring means checking, observing and interpreting data collected by means of electronic devices for beekeeping that are connected to other devices or networks over time; examples of digital hive monitoring technologies in beekeeping include hive monitoring and colony surveillance tools, swarm detection systems, or bee counting devices, and using a digital logbook". It was further specified that these questions pertain to "at least some, but not necessarily all of your hives". The anticipated timeframe for adoption was specified in the question formulation as "in the next two years". The 13 TPB-statements were presented in one set with a randomised order to avoid order bias. The use of multiple items to measure each construct allows to obtain observed measurements which constitute an unobserved latent construct in the TPB model that will be estimated by means of Structural Equations Modelling (SEM).

The questionnaire also included questions probing for socio-demographic characteristics of the beekeeper (e.g., age, gender, education, country) and characteristics of their beekeeping operation, of which the following were relevant to the present study: number of beehives, number of years active as a beekeeper, beekeepers association membership and eventual role in the management of the association, urban–rural location (five-point scale ranging from 1="purely urban" to 5="purely rural"), total and average (i.e., per productive hive) honey production (kg) in 2021, average colony winter loss over the last five years (percentage, categorical), and whether the beekeeper self-qualifies as a hobbyist versus professional (five-point scale ranging from 1="purely hobbyist" to 5="fully professional").

2.2. Data collection procedure

The master version of the questionnaire was developed and pre-tested in English with the collaboration of those members of the research project consortium who are also beekeepers. The questionnaire and all related informed consent literature were translated into 11 additional European languages, pre-tested, checked for linguistic equivalence, and web-programmed in Qualtrics for online administration. Data collection was completed during October 2021-January 2022. The survey was accessed through a dedicated website where study participants could select their native (or preferred) language version for

Table 1

Sample characteristics (n, %) and logistic regression model results explaining determinants of using digital beehive monitoring technology (binary variable, 20.9 % yes): coefficient estimates (β), standard errors (S.E.), z- and p-values, odds ratios (OR) and 95 % confidence intervals (95 % CI) (n = 844).

Variables	n (%)	β	S.E.	z	p	OR [95 % CI]
European region						
Northern Europe (reference)	78 (9.2)					
Western Europe	455 (53.9)	0.81	0.40	2.05	0.041	2.27 [1.04–4.96]
Eastern Europe	156 (18.5)	0.93	0.41	2.28	0.023	2.53 [1.14–5.61]
Southern Europe	155 (18.4)	0.65	0.42	1.56	0.118	1.92 [0.85–4.32]
Type of beekeeper						
Purely hobbyist (reference)	396 (46.9)					
Neither purely hobbyist nor professional	288 (34.1)	0.89	0.24	3.76	<0.001	2.43 [1.53–3.85]
Rather or fully professional	160 (19.0)	1.60	0.28	5.7	<0.001	4.97 [2.86–8.62]
Years active as a beekeeper						
Up to 3 years or less (reference)	144 (17.1)					
From 4 to 15 years	435 (51.5)	0.61	0.32	1.88	0.060	1.84 [0.97–3.46]
16 or more years	265 (31.4)	0.76	0.34	2.23	0.026	2.14 [1.10–4.19]
Managerial role in beekeepers association as chairperson, secretary or board member						
No (reference)	629 (74.5)					
Yes	215 (25.5)	0.47	0.20	2.39	0.017	1.60 [1.09–2.37]
Constant	844 (100.0)	−3.53	0.48	−7.39	0.000	0.03 [0.01–0.07]

Goodness of fit statistics: Wald $chi^2(8) = 72.50$, $p < 0.001$; pseudo $R^2 = 0.095$.

Table 2
Theory of Planned Behaviour (TPB) measurement items and constructs, final confirmatory factor analysis (CFA) properties and factor loadings (all factor loading p-values < 0.001), and Cronbach's alpha reliability coefficients (n = 844).

Measurement items and constructs	Factor loading
Attitude (ATT) (Cronbach's alpha = 0.914)	
I feel that using digital hive monitoring would be a good idea for my beehives within the next two years (ATT1)	0.881
I would enjoy using digital hive monitoring would be a good idea for my beehives within the next two years (ATT2)	0.864
I feel that using digital hive monitoring would be important for me and my beehives within the next two years (ATT3)	0.906
Social Norms (SN) (Cronbach's alpha = 0.891)	
Most people whose opinions I value think I should use digital hive monitoring within the next two years (SN1)	0.880
Most people who are important to me think I should use digital hive monitoring within the next two years (SN2)	0.875
Many beekeepers who are like me think I should use digital hive monitoring within the next two years (SN3)	0.816
Perceived Behavioural Control (PBC) (Cronbach's alpha = 0.714)	
I have the financial resources to implement digital hive monitoring in my beehives in the next two years (PBC1)	0.606
I have the technical know-how to implement digital hive monitoring in my beehives in the next two years (PBC2)	0.615
I can easily obtain digital hive monitoring equipment for my beehives in the next two years (PBC3)	0.829
Behavioural Intention (INT) (Cronbach's alpha = 0.958)	
I intend to use digital hive monitoring in my beehives within the next two years (INT1)	0.936
I plan to use digital hive monitoring in my beehives within the next two years (INT2)	0.930
I will try to use digital hive monitoring in my beehives within the next two years (INT3)	0.915
I am determined to use digital hive monitoring in my beehives within the next two years (INT4)	0.912
Behaviour (Cronbach's alpha = 0.782)	
Do you digitally monitor the weight of at least some your hives?(WEIGHT)	0.634
Do you digitally monitor the temperature inside at least some of your hives? (TEMP)	0.887
Do you digitally monitor the humidity inside at least some of your hives? (HUMID)	0.767
Do you digitally monitor the sound of at least some of your hives? (SOUND)*	(0.543)*
Do you use a digital bee counter for at least some of your hives? (COUNT)*	(0.378)*

Goodness of fit statistics: Root Mean Square Error of Approximation (RMSEA) = 0.041; pclose > 0.05; Comparative Fit Index (CFI) = 0.987; Tucker-Lewis Index (TLI) = 0.983; Standardized Root Mean Square Residual (SRMR) = 0.043; * Factor loadings from initial CFA including all measurement items – based on these factor loadings being < 0.6, the final CFA was run without these two items. All observed variables (measurement items) were accompanied by the statement "Please indicate to what extent you agree or disagree with the following statement?" and assessed on a five-point Likert scale ranging from 1="Strongly agree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree" to 5="Strongly agree".

completion. Participants were recruited primarily through distributing the survey's web link via national beekeepers' associations who posted the survey invitation on their websites, newsletters, and/or social media posts addressed to their members. In addition, beekeepers were contacted and invited to take part in the study by the involved partner research institutes. The target population of the survey were active beekeepers in the European countries where the survey link was distributed. In line with van der Zee et al. (2013), the study qualifies as a self-administered internet survey using a non-random participant self-selection sampling method. Ethics approval for the beekeeper survey was granted by the UZ Gent / UGent Medical Ethics Committee (ref. nr. BC-10610 – August 2021). The full questionnaire (master English version in pdf format) and the data (SPSS format) of this study are available on the B-GOOD Bee Health Data Portal.[3]

2.3. Statistical analysis

Participant's socio-demographic and their beekeeping operation's characteristics were summarised using descriptive statistics. Differences between groups (based on, e.g., age, gender, degree of professionalism) in current usage and benefits sought from using DBMT were assessed using cross-tabulation and chi-square statistics in case of two categorical variables, and independent samples t-tests or one-way ANOVA F-tests in case of categorical and metric variables. A new binary variable was created indicating whether a beekeeper was already implementing some digital monitoring of beehives (see section 3.4 for more detail). Bivariate associations between this new binary variable and beekeeper and beekeeping characteristics were tested through cross-tabulation and chi-square statistics. Next, a logistic regression model was estimated with this binary variable as the dependent variable and selected explanatory variables to identify a set of determinants of adoption of DBMT among European beekeepers. Finally, Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) were implemented to test the contribution of personal attitudes (ATT), social norms (SN) and perceived behavioural control (PBC) in shaping beekeepers' intention to adopt (INT) – and adoption of – DBMT as stipulated in the conceptual TPB-model. To assess the goodness-of-fit of the CFA and SEM model, the following statistics were used: the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), pclose, and the Standardised Root Mean Square Residual (SRMR). Generally, the SEM model is considered to fit well if the CFI and TLI are greater than 0.9 (Bagozzi and Yi, 2012; Hair et al., 2013), the RMSEA is less than 0.05, pclose is greater than 0.05, and the SRMR is less than 0.08 (Thakkar, 2020). Statistical analyses were performed using SPSS 25 and Stata 17.

3. Results

3.1. Beekeeper and beekeeping characteristics

A total of 844 beekeepers completed the survey representing 18 European countries. Participants were classified based on their country of residence into four European regions (Northern, Western, Eastern, Southern Europe) based on the United Nations Geoscheme for Europe classification. Beekeepers' age ranged from 18 to 91 years (mean age = 53 years), 80.7 % identified as male, and almost half of the participants (44.8 %) had been active as a beekeeper for more than 10 years. The size of their beekeeping operations ranged from 1 to 6,100 beehives, with an

[3] Link for access to the survey questionnaire and data: https://beehealthdata.org/datasets/ba6a57b1-78f4-4f59-874f-84575d3acce9.

average of 72.4 beehives (S.D. = 265.0). Almost one fifth (19.0 %) of the participants self-classified as being ‘rather professional’ or ‘fully professional’ based on the size of their beekeeping operation; the large majority (81.0 %) self-classified as ‘purely hobbyist’, ‘rather hobbyist’ or ‘neither hobbyist nor professional’. Most beekeepers indicated keeping bees in a (mainly) rural area (89.0 %). Average honey production amounted to 17.2 kg/hive (S.D. = 13.9 kg/hive) among beekeepers who reported to have produced honey in 2021 (93.0 % of the total sample). Almost half of the beekeepers (48.2 %) reported honey bee colony winter loss rates of less than 10 % on average during the previous five years (up to 2021); the other half reported to have lost more than 10 % of their colonies on average, with more than one fifth of the total sample (21.1 %) reporting to have incurred more than 20 % winter losses on average.

3.2. Current use of DBMT

Fig. 1 illustrates that the large majority (n = 668; 79.1 %) of the participating beekeepers did not yet digitally monitor any potentially relevant hive parameter, namely weight, temperature, humidity, sound, or number of bees. Digital monitoring – if already implemented – was mostly limited to one parameter while only a few beekeepers (n = 24; 2.8 %) monitored four or all five parameters included in the survey. Among those who used some kind of digital monitoring (n = 176; 20.9 %), most were monitoring weight (81.8 %) followed by temperature (47.7 %), humidity (34.7 %), sound (29.5 %), and number of bees (5.7 %). Beekeepers who were already digitally monitoring at least one hive parameter indicated doing so for 6.3 % (S.D. = 19.6) of their hives on average. The share of beehives being digitally monitored was significantly higher among beekeepers with less than 15 hives (who indicated to monitor on average 13.5 % of their hives) versus beekeepers with 15–50 hives (5.1 %) and beekeepers with more than 50 hives (2.3 %) (ANOVA F = 5.12; p = 0.007). These numbers indicate that most beekeepers (independent of the size of their beekeeping operation) implement DBMT on one or two hives only, which can thus be considered ‘indicator’ hives, e.g. one per apiary or location. Only six beekeepers indicated monitoring all of their hives; their total number of beehives ranged from 1 to 30 and half of them were purely hobbyists and/or less than five years active as a beekeeper.

3.3. Benefits sought from using DBMT

Beekeepers expect DBMT to predominantly facilitate their hive management and related beekeeping management decisions, followed by enhancing honey bee colony health, decreasing colony winter loss and overall time-saving, which can all contribute to easier and more effective hive management. Only about one quarter of the beekeepers expect that DBMT would provide a benefit in terms of lowering their operational costs, which indicates they are accounting for the additional investment required for the adoption of this technology. Interestingly, for each of the possible benefits about one fifth to one quarter of the beekeepers are undecided, thus neither expecting nor not expecting hive monitoring technology to provide the respective benefit. This suggests beekeepers’ doubts or limited awareness about possible benefits that hive monitoring technology may provide to beekeeping (Fig. 2). Beekeepers who were already monitoring at least one hive parameter in some of their hives systematically reported stronger expected benefits from adopting DBMT than beekeepers who were not yet implementing any kind of digital hive monitoring, with $p < 0.001$ for ‘easier management’, ‘saving time’ and ‘saving costs’ and $p < 0.05$ for ‘enhancing colony health’ and ‘decreasing colony winter loss’ based on independent samples t-tests.

3.4. Determinants of using DBMT

A new binary variable (further referred to as ‘using DBMT’; with ‘yes’ for 20.9 % (n = 176) of the total sample) has been created indicating whether the beekeeper reported already using DBMT, of some kind. Based on bivariate analyses, using DBMT was significantly more common among beekeepers who qualified as ‘rather or fully professional’ based on the size of their beekeeping operation (40.6 % of these beekeepers classified as ‘using DBMT’) (chi-square = 63.19; $p < 0.001$); who are located in Eastern Europe (32.1 %) (chi-square = 18.38; $p < 0.001$); who migrate their bees for honey production (i.e., implement so-called ‘transhumance’) (31.5 %) (chi-square = 27.17; $p < 0.001$); who assume a role as chair, secretary or board member in a beekeepers association (29.8 %) (chi-square = 13.89; $p < 0.001$); by beekeepers with secondary or lower education (27.3 %) (chi-square = 11.29; p = 0.004); and who are active with beekeeping for 16 or more years (25.6 %) (chi-square = 7.29; p = 0.026). Using DBMT was not significantly associated with gender, age, and urban versus rural location. Beekeepers who were

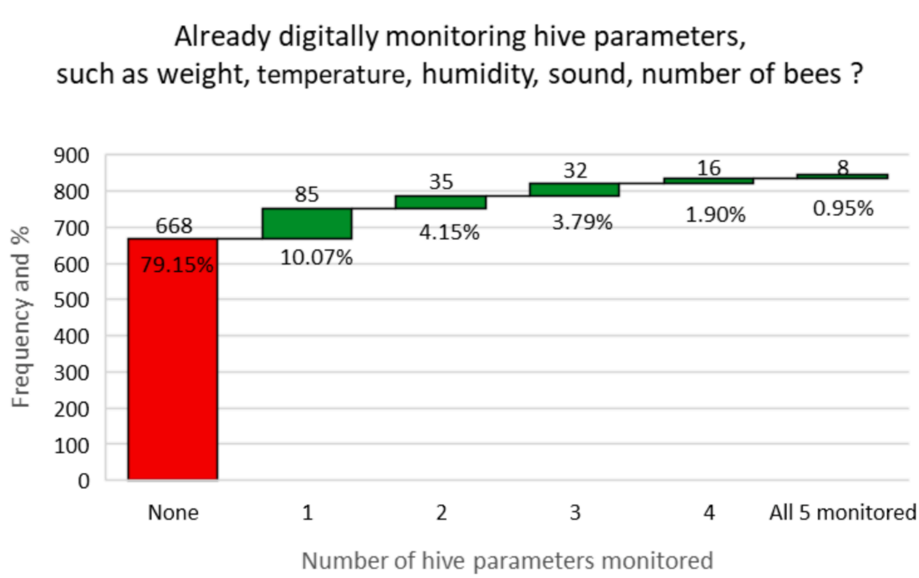

Fig. 1. Frequency distribution (n and %) of beekeepers who are digitally monitoring none (red bar) vs. up to five hive parameters including weight, temperature, humidity, sound and number of bees (n = 844). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

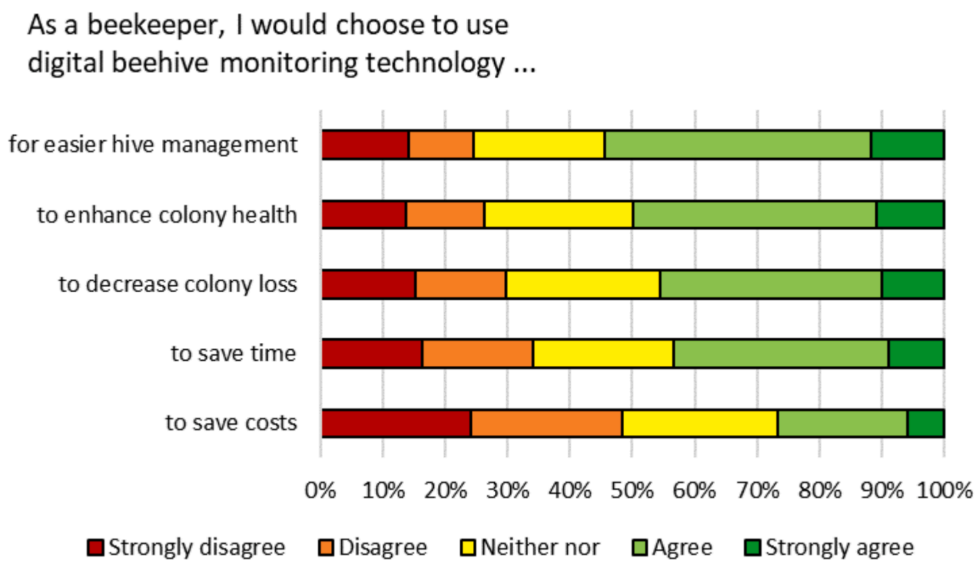

Fig. 2. Beekeepers' benefits sought from using digital beehive monitoring technology (%, n = 844).

classified as 'using DBMT' did not differ significantly from other beekeepers with respect to honey yield per hive and colony winter loss rate.

It should be noted that several of the above-mentioned variables that associate significantly with DBMT in bivariate analyses are interlinked, e.g. there are relatively more professional beekeepers from Eastern Europe (than from other European regions) in the study sample, and professional beekeepers are more likely to implement transhumance compared to hobbyist beekeepers. Therefore, to identify the variables that truly distinguish between already using versus not using DBMT, a multivariable logistic regression model was estimated with 'using DBMT' as the dependent binary variable. The results of the logistic regression model are presented in Table 1. The odds of using DBMT are respectively 2.3 and 2.5 times higher among beekeepers from Western and Eastern Europe compared to beekeepers from Northern Europe. The odds of using DBMT are almost 5 times higher among professional beekeepers compared to hobbyist beekeepers (OR = 4.97). Furthermore, the odds of using DBMT are more than two times higher among beekeepers who have been active for more than 16 years compared to those active less than three years (OR = 2.14). Finally, the odds of using DBMT increase by 60 % as a beekeeper assumes a managerial role in a beekeepers association such as being chairperson, secretary or board member.

3.5. Future adoption of DBMT: Theory of Planned Behaviour (TPB)

Data were further analysed using Stata version 17 to test the TPB model using a two-step modelling approach whereby the measurement model (step 1) and the structural model (step 2) were constructed separately (Acock, 2013).

3.5.1. Confirmatory factor analysis (CFA)

First, a CFA was conducted to test the adequacy of the measurement model and to examine evidence of the factorial structure and reliability of the latent constructs generated by the observed measures (i.e., the questionnaire items as listed in Table 2). Specifically, a five-factor model was fitted to the data that capture the latent constructs of Attitude (ATT), Social Norms (SN), Perceived Behavioural Control (PBC), intention (INT) and behaviour. According to the fit indices (RMSEA, CFI, TLI and SRMR) employed, the CFA (Table 2) indicates that the proposed five-factor model provides a good fit (RMSEA = 0.038, pclose > 0.05, CFI = 0.986, TLI = 0.983, SMRM = 0.040). Cronbach's alpha was used to evaluate the construct reliability. All Cronbach's alpha values ranged from 0.779 to 0.958, and were higher than the minimum cut-off value of 0.7 indicating that construct reliability was supported (Taber, 2018). Convergent validity was assessed by inspection of the factor loadings. The initial factor loadings of all measurement items were significant and higher than the suggested cut-off value of 0.6 except for the items 'Sound' and 'Count' (number of bees) within the latent construct Behaviour. Therefore, the CFA was run again without these two measurement items in the analysis. All factor loadings of the final CFA (Table 2) were significant and higher than 0.7, indicating good convergent validity of the model (Vellis, 2003). The overall CFA results suggest that the observed variables are indeed indicators of the latent constructs, and that the measurement model is valid and reliable. The resulting measurement model can therefore be used as a foundation for testing structural relationships between the latent constructs using Structural Equation Modelling (SEM) in the next analysis step.

3.5.2. Structural equations model (SEM)

Second, for determining the direction as well as the strength of the interrelationships between latent constructs as hypothesised in the TPB, SEM was employed. The SEM with the total sample of beekeepers (Fig. 3) showed a good fit to the data (chi-square = 231.270; $p < 0.001$; RMSEA = 0.041; pclose = 0.987; CFI = 0.987; TLI = 0.984; and SRMR = 0.043). Standardised weights (β) of all the explanatory variables were statistically significant at $p < 0.01$ levels (Table 3a). Among the constructs, Attitude showed the strongest positive and significant effect on intention to use DBMT ($\beta = 0.666$; $t = 20.720$; $p < 0.001$), indicating that personal attitude explains 44.4 % (square root of 0.666) of the variance in intention. Personal attitude – which is a rather stable construct that is based on an individual's personal beliefs, values, convictions and/or experiences over time – is herewith the most important predictor of behavioural intention as compared to other factors that may be more variable or context-dependent. Social Norms (SN) and Perceived Behavioural Control (PBC) were also positively contributing to intention (($\beta = 0.206$; $t = 5.570$; $p < 0.001$) and ($\beta = 0.145$, $t = 5.860$, $p < 0.001$), respectively), albeit both showing a much lower effect on intention. In line with the theory of reasoned action, Behavioural Intention showed a positive and significant – albeit relatively weak effect on Behaviour ($\beta = 0.273$; $t = 6.440$; $p < 0.001$). Moreover, PBC had a significant direct and positive effect on Behaviour ($\beta = 0.126$; $t = 2.650$; $p < 0.01$). The Sobel-test was applied to test the mediation effect of Behavioural Intention on the relationship between PBC and Behaviour using bootstrap methods. The results show that Behavioural Intention effectively mediates the effect of PBC on Behaviour ($\beta = 0.040$; $p < 0.01$) (see Table 3b), thus confirming that facilitating conditions

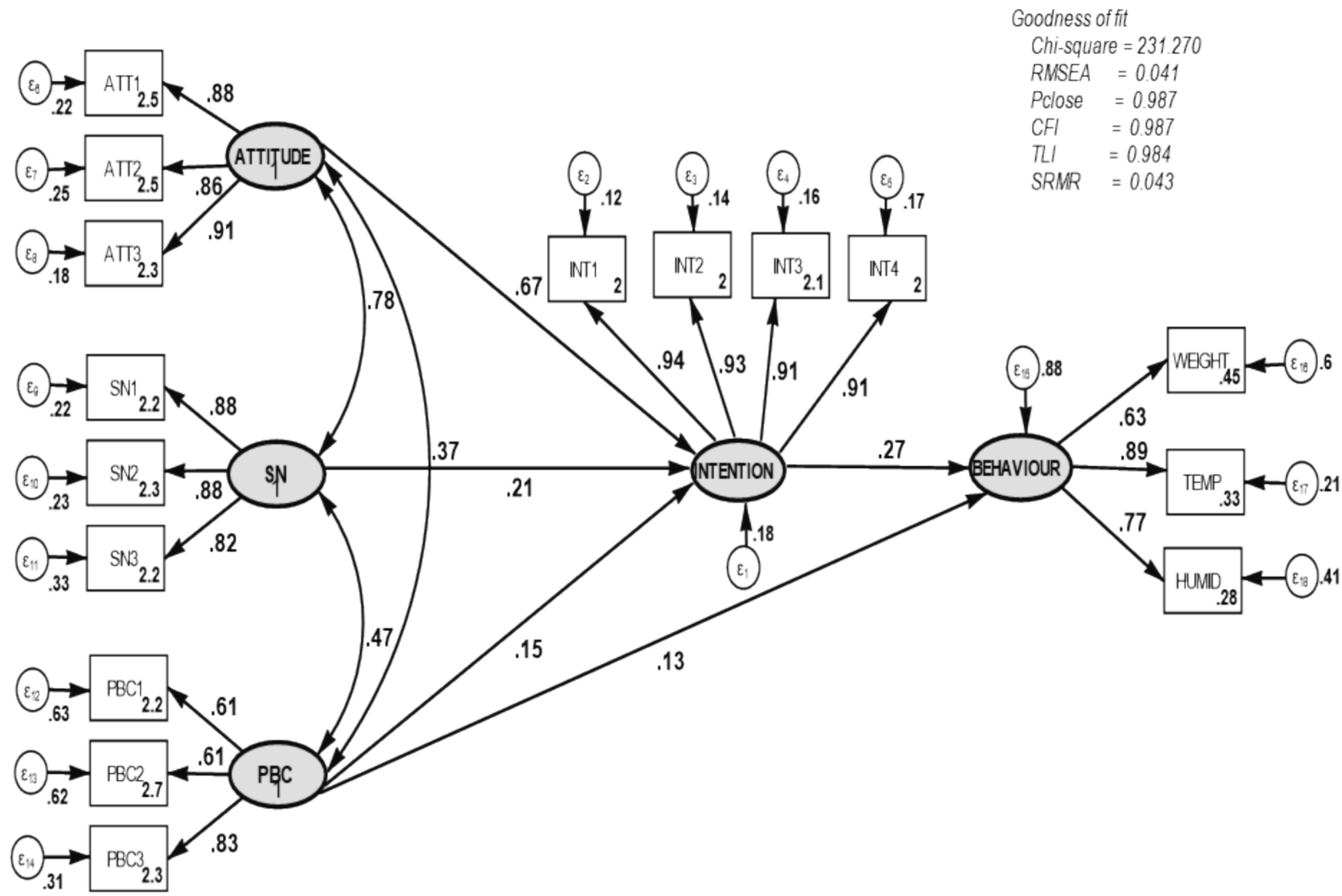

Fig. 3. Theory of Planned Behaviour structural equations model result: determinants of the adoption of digital beehive monitoring technology in European beekeeping, total sample (n = 844) (ATT = Attitude; SN = Social Norms; PBC = Perceived Behavioural Control; INT = Behavioural Intention; TEMP = temperature; HUMID = humidity).

Table 3
Theory of Planned Behaviour (TPB): structural equation model (SEM) results (Table 3a), and Perceived Behavioural Control (PBC) – Behavioural Intention – Behaviour path mediation test using bootstrapping (Table 3b) (n = 844).

(a) Structural equation model (SEM)	β	S.E.	t	p
Attitude (ATT) → Intention (INT)	0.666	0.032	20.720	<0.001
Social norms (SN) → Intention (INT)	0.206	0.037	5.570	<0.001
Perceived Behavioural Control (PBC) → Intention (INT)	0.145	0.025	5.870	<0.001
Intention (INT) → Behaviour	0.273	0.042	6.440	<0.001
Perceived Behavioural Control (PBC) → Behaviour	0.126	0.048	2.650	0.008

(b) Path mediation test	Bootstrapping		95% bias-corrected CI		p
	Indirect effect (β)	Boot S.E	Boot LLCI	Boot ULCI	
PBC → INT → Behaviour	0.040	0.009	0.022	0.058	<0.001

must be satisfied for the behaviour to take place.

3.5.3. SEM by beekeeper type

As suggested by the results of the logistic regression, the relative importance of Attitude, Subjective Norm, and Perceived Behavioural Control in predicting Behavioural Intention and the use of DBMT may vary depending on the type of beekeeper (notably hobbyists vs. professionals) and the beekeeper's social embeddedness in the beekeeping community. Therefore, we tried to understand eventual differences in the interest in adopting DBMT among purely hobbyist beekeepers versus professional beekeepers, and among beekeepers who assume a managerial role in a beekeepers association versus those who do not. The latter analysis did not reveal major meaningful differences in the strength of effects in the TPB-model (Table 4). Attitude had consistently the strongest effect on Behavioural Intention to use DBMT. The only meaningful – albeit rather minor difference is observed for the role of PBC in the model for purely hobbyists versus professionals, indicating that PBC has a lower effect in shaping the intention and adoption of DBMT among hobbyist beekeepers, versus a much stronger effect among professionals. Possible explanations and implications are discussed in the discussion section.

4. Discussion and conclusion

The evolution during the past decade of digital farming (Agriculture 4.0), as with digital beekeeping (Apiculture 4.0) as presented in this study has been remarkable. Apiculture 4.0 is enabled through the automated collection, integration and analysis of data from beehives and external monitoring (e.g., sensors or landscape and weather data). This new paradigm requires a shift from traditional (beekeeping) practices to management that is enhanced by digital systems, with benefits that enable cost reductions, enhance profitability and foster the environmental-social-economic sustainability of agriculture (Maffezzoli et al., 2022). Most research contributions have focused on the enabling technologies, the main application domains and/or on the actual benefits from the adoption of Agriculture 4.0. The same technologies are increasingly available for implementation in the beekeeping sector as well. The adoption of digital beehive monitoring technologies offers

Table 4
Theory of Planned Behaviour (TPB): structural equation model (SEM) results for purely hobbyist vs. professional beekeepers and for beekeepers who assume vs. not assume a management role in a beekeepers association.

Type of beekeeper*	Purely hobbyist beekeepers (n = 396)				Professional beekeepers (n = 160)			
	β	S.E.	t	p-value	β	S.E.	t	p-value
Attitude (ATT) → Intention (INT)	0.727	0.052	13.900	<0.001	0.721	0.065	11.180	<0.001
Social norms (SN) → Intention (INT)	0.141	0.059	2.410	0.016	0.131	0.083	1.580	0.114
Perceived Behavioural Control (PBC) → Intention (INT)	0.084	0.039	2.130	0.033	0.223	0.054	4.160	<0.001
Intention (INT) → Behaviour	0.315	0.061	5.170	<0.001	0.161	0.113	1.420	0.155
Perceived Behavioural Control (PBC) → Behaviour	0.063	0.071	0.890	0.372	0.225	0.119	1.900	0.057
Assuming a management role in a beekeepers association	**Yes (n = 215)**				**No (n = 629)**			
	β	**S.E.**	**t**	**p-value**	**β**	**S.E.**	**t**	**p-value**
Attitude (ATT) → Intention (INT)	0.655	0.077	8.460	<0.001	0.668	0.035	19.080	<0.001
Social norms (SN) → Intention (INT)	0.214	0.082	2.620	0.009	0.206	0.042	4.890	<0.001
Perceived Behavioural Control (PBC) → Intention (INT)	0.132	0.047	2.780	0.005	0.150	0.029	5.070	<0.001
Intention (INT) → Behaviour	0.261	0.079	3.300	0.001	0.297	0.050	5.890	<0.001
Perceived Behavioural Control (PBC) → Behaviour	0.152	0.087	1.750	0.080	0.096	0.057	1.680	0.094

* Beekeepers who self-classified as neither 'purely hobbyist' nor 'professional' were left out of this analysis.

considerable potential to assist the apicultural sector to cope with the substantial challenges facing beekeeping in Europe and beyond (Willcox et al., 2023). Whereas digital innovations have been flagged as having the potential to contribute to more sustainable and resilient agriculture in general, the potential unequal distribution of their benefits imposes particular challenges (Finger, 2023). This underscores the relevance of investigating the interest, uptake and expected benefits amongst a diversity of target groups for technology adoption. The present study has focused on European beekeepers' behaviour towards and interest in digitalisation. This study addresses one of the key areas of agricultural economics' and innovations' research need, notably on "farmer's behaviour towards digitalisation" as identified by Finger (2023: 1300), and one of the priority research questions within the theme "understanding benefits and uptake of data and technologies" as identified by Ingram et al. (2022: 7).

This study revealed that the proportion of European beekeepers currently using some kind of digital monitoring in their apiaries is still relatively low (20.9 %). For beekeepers using this technology it is in most cases limited to the monitoring of a single parameter (mostly hive weight) and only implemented on a limited number of hives. Our analysis revealed a decreasing share of the number of hives being digitally monitored with increasing size of the beekeeping operation. This suggests that beekeepers with larger numbers of beehives select 'model' or 'indicator' hives for monitoring, e.g., one or a few hives per apiary or location rather than equipping every single hive with the technology, which is a logical choice from a cost efficiency point of view. Among the 'rather or fully professional' beekeepers in our study sample, the adoption rate amounted more than 40 %. This number corresponds with a study by Vardakas et al. (2023) who reported a 45 % adoption rate of some form of 'precision apiculture system' among beekeepers in France, Germany and Greece, while confirming that weighing scales were the most commonly used. According to Centola et al. (2018) as cited in Shepherd et al. (2020), the critical mass of technology adoption needed to create a 'social tipping point' is about 25 % of the relevant population. The concept of a social tipping point refers to a point in a dynamic socio-environmental system where a small change in actors' behaviour triggers an abrupt irreversible change in the system (Juhola et al., 2022). In the context of technology adoption, it refers to a situation where a minority group of innovators and early adopters of a technology initiate a cascading change of social behaviour, which speeds up further adoption of the technology. The data of our survey suggest that such a social tipping point is not yet reached for the European beekeeping sector as a whole (ranging from hobbyists to professionals). Nevertheless, we suggest this 'social tipping point' is possibly within sight, with around one fifth of the beekeepers in the total study sample having implemented some kind of digital hive monitoring. Among professional beekeepers, this cascading point is already reached with an adoption rate of more than 40 %. However, it should be noted that the proportions of adoption as measured in this study (and others alike using similar online data collection methods) may be somewhat inflated as compared to the overall population of beekeepers because of the use of an online data collection method in our survey. This may have induced some bias towards more ICT-literate beekeepers in the study sample, which eventually associates with more openness to and a higher likelihood of using digital innovations. The absolute share of beekeepers adopting or intending to adopt DBMT described above can reasonably be debated as merely being a snapshot, time-dependent and not apt for extrapolation beyond the characteristics of the study sample. Notwithstanding this, the finding that the social tipping point is in sight or already surpassed in specific groups (e.g. professional beekeepers) underscores the relevance, timeliness and topicality of the present research.

Perhaps more importantly, for enabling and promoting the adoption of beneficial technology and transitioning to Apiculture 4.0, are our analyses revealing diversity among beekeepers and determinants of intention and adoption behaviour. Logistic regression analysis indicated that the adoption of digital hive monitoring differs significantly between EU regions, type of beekeeper (professional vs. hobbyist, and associated size of the beekeeping operation), number of years of experience as a beekeeper, and social embeddedness through an active involvement in the board of beekeepers' associations. The findings of this study herewith coincide with several previous studies in other domains of agriculture where it was shown that technology adoption is more likely among larger commercial farms (Shepherd et al., 2020). Also in the participatory workshops organised by Ingram et al. (2022), there was general agreement that larger commercial farms would benefit most from digitalisation, and that this would characterise future trends as production systems become more specialised. The five-times higher likelihood of adopting DBMT among professional (i.e., larger and more commercially oriented) beekeepers as compared to hobbyists also aligns with previous studies.

The challenges associated with technology adoption may be experienced differently by different beekeepers operating in different contexts e.g., environmental or working conditions. For example, with respect to sensors, the challenges concern their ability to function in rugged conditions and meeting power requirements in situations where battery changes cannot easily be performed (Shepherd et al., 2020). These challenges also apply to beekeeping since beehives are often located in remote or rural areas with limited power supply and where they may be exposed to harsh weather conditions. This may explain why the adoption of DBMT is lower in Northern European countries where cold weather conditions may impact battery life. Furthermore, battery changes may be difficult to implement if a beehive (which can weigh up to 100 kg and requires minimal disturbance in certain periods of the year) must be removed from the scale or platform that carries the main electronic components. Developers and providers of DBMT solutions will need take into account these realities for widespread adoption. Furthermore, rural areas have been flagged as among the most excluded from fast and reliable broadband developments, such as the Internet of Things. For this reason, Shepherd et al. (2020: 5085) noted connectivity issues as “perhaps the single largest technical challenge that will limit the uptake of digital agriculture”. Similarly, with beehives mostly located in rural areas, connectivity is a considerable challenge that DBMT solutions will need to contend with. Furthermore, Vardakas et al. (2023) reported a positive correlation between the use of digital monitoring technology and distance of the apiary from the beekeeper’s place of residence; a factor our study did not explicitly account for. Our analysis revealed a higher likelihood of adopting DBMT among beekeepers who migrate their bees for honey production, which is a management practice implying longer distances between the beekeeper’s place of residence and apiary location. This underscores the significance of the ‘connectivity challenge’ for the implementation and adoption of DBMT ‘remote monitoring’ solutions, where power and internet network connectivity are essential. In line with Geels and Ayoub (2023) who studied the dynamics of social tipping points in the context of climate change mitigation, further techno-economic improvements, actor reorientations, and policy support will be essential, together with extension services, communication and targeted marketing efforts by involved stakeholders.

Ingram et al. (2022) flagged the role of enabling conditions and relationships between constituent actors as being missing thus far in adopting digital technologies and transitioning to Agriculture 4.0. This observation echoes studies showing the importance of agricultural knowledge and advice networks, respectively, in increasing the utility of digital agricultural technologies and the need to consider the role of so-called meso-scale actors. The latter has also been referred as the requirement for a more networked and collaborative understanding of adoption. These research needs have been addressed in the present study through studying the role of social norms (SN, as a proxy for the role of networks and peers) and perceived behavioural control (PBC, as a proxy for the role of knowledge, skills, and means). Although, personal attitudes are the predominant driver of behavioural intention (for hobbyist and professional beekeepers alike), the significant contribution of SN confirms the importance of other people’s opinions in driving the adoption of DBMT. This result stresses the role of the social environment and beekeepers’ social embeddedness in driving technology adoption. When distinguishing between hobbyist and professional beekeepers, it was found that SN (i.e., other’s opinions) matters especially for DBMT adoption among hobbyist beekeepers whose adoption rate is still below the so-called social tipping point. The social tipping point for technology adoption has been surpassed among professional beekeepers, which may imply that social influences have eventually become less relevant among this group. Meanwhile, PBC (i.e., self-efficacy) emerges as a stronger driver among professional beekeepers for whom facilitating conditions are clearly more important than social norms. The findings indicate that different enabling factors are at stake for hobbyists versus professionals, which has major implications for speeding up DBMT adoption. Dissemination of favourable experiences, e.g. by innovators and early adopters, may play a key role in speeding up DBMT adoption especially among hobbyists. Those disseminators may indeed be professional beekeepers who share their experiences with hobbyists. In addition, beekeepers’ associations and networks can provide mechanisms for influencing adoption with newsletter articles and use of social media highlighting beneficial technological developments, ‘success stories’ as experienced by fellow beekeepers. The role of social norms in the TPB-model underscores the importance and potential of a cascading change of social behaviour in the adoption of DBMT, which can be especially important among hobbyist beekeepers who constitute the majority of European beekeepers, both in terms of sheer number and managed beehives. Professional beekeepers can eventually function as an important reference group for hobbyists as far as their drivers and motives for beekeeping match.

With respect to the uptake of digital technologies, the Ingram et al. (2022) workshop participants also agreed that, although demographic and farm factors are influential determinants, there are many other critical factors, such as trust, habits, skills and infrastructure, which deserve urgent research attention. Some of these factors have been addressed in the present study through their incorporation in the PBC component of the TPB model. PBC refers to an individual’s perception of their ability to perform a behaviour, which has also been referred as self-efficacy. If the perceived behaviour in question is one that the individual believes to have limited (volitional) control over, such as a behaviour that requires significant resources, skills, expertise or external support, then PBC may even have a negative effect on intention to use DBMT. The findings of this study indicate that PBC has a positive although relatively weak contribution to intention and behaviour in our beekeeper sample, which suggests that cost, technical know-how or availability are neither seen as major barriers nor drivers to DBMT adoption. However, DBMT adoption among professional beekeepers is more influenced by PBC (compared to hobbyists), suggesting facilitating conditions such as low cost, adequate technical know-how and technology availability are important, which logically corresponds with professional beekeepers’ stronger business orientation towards beekeeping. Our study indicates that adoption rates are already higher amongst professional beekeepers, nevertheless the continued development of beneficial digital technologies must focus on the practical implications and realisable benefits that can enhance beekeeping management practices also among professionals. Ultimately, DBMT solutions will need to deliver by effectively enabling beekeepers, particularly those who derive their livelihood from beekeeping, to maintain healthy, productive and sustainable honey bee colonies. Shepherd et al. (2020), noted that the mere availability of a technology may not be a primary driver for the uptake itself, while adoption is expected to depend mostly on evidence that digitalisation can provide desired benefits. The latter is indeed reflected in the dominant role of Attitude as a predictor of future adoption in our TPB model, in that DBMT solutions are perceived to be beneficial based on beekeepers’ convictions and/or experiences over time.

Finally, it should be acknowledged that this study faces some limitations. A first limitation stems from the applied participant recruitment and data collection procedure, which were online and implying that participation was based on self-selection. As a result, the survey sample might be biased towards beekeepers with some degree of ICT-literacy (as already mentioned) and a strong involvement in the research topic. This imposes limits on the generalisation of study findings beyond the characteristics of the study sample. Second, the collected data are based on self-reports and self-assessments, which may be prone to social desirability bias. The latter warrants caution especially in the treatment and interpretation of single variables. Efforts have been made to address limitations resulting from the collection of self-reported data through multistage questionnaire pilot-testing, the use of multiple-item rather than singe-item measures (specifically in the case of the TPB-statements), randomisation of question items within questions and of questions within survey sections, and guaranteeing anonymous and aggregated data analysis and reporting.

Building upon primary cross-sectional data collected from a pan-European sample of beekeepers, this study provided insight in current use, benefits sought and determinants of intention to adopt DBMT. The analyses discerned differences between hobbyist and professional beekeepers, those engaged in beekeeping associations, and across European regions. While beekeepers’ personal attitudes consistently emerged as the primary driver of behavioural intention, social norms among hobbyists and perceived behavioural control amongst professionals exhibited a more pronounced effects. These results offer valuable insights into the dynamics for enabling and influencing technology adoption within distinct segments of the beekeeping community. A better understanding of beekeeper characteristics, usage patterns, and determinants enhances the discourse on healthy and sustainable beekeeping practices and the potential role of Apiculture 4.0 therein. This study suggests a 'social tipping point' for transitioning Apiculture 4.0 is possibly within sight, however for this to be realised key social and practical enabling conditions (e.g., dissemination of 'success stories', reliable connectivity, cost efficiency, effectiveness in improved beehive management) still need to be addressed.

CRediT authorship contribution statement

Wim Verbeke: Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Mariam Amadou Diallo:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Coby van Dooremalen:** Writing – review & editing, Methodology, Conceptualization. **Marten Schoonman:** Writing – review & editing, Methodology, Conceptualization. **James H. Williams:** Writing – review & editing, Methodology, Conceptualization. **Marie Van Espen:** Writing – review & editing, Visualization, Data curation. **Marijke D'Haese:** Writing – review & editing, Supervision. **Dirk C. de Graaf:** Writing – review & editing, Supervision, Resources.

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.

Acknowledgements

This study has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No. 817622 (project B-GOOD). Project consortium partners and beekeepers' associations who assisted in the recruitment beekeepers are gratefully acknowledged. Dana Freshley (Ghent University) is gratefully acknowledged for her help with data collection and curation.

Data availability

Data will be made available on request.

References

Acock, A.C., 2013. Discovering structural equation modeling using Stata. Stata Press Books.

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.

Ajzen, I., 2002. Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1. J. Appl. Soc. Psychol. 32, 665–683.

Araújo, S.O., Peres, R.S., Barata, J., Lidon, F., Ramalho, J.C., 2021. Characterising the agriculture 4.0 landscape—emerging trends, challenges and opportunities. Agronomy 11, 667.

Arribas, F.A., Hortelano, M.R., 2023. An Internet of Living Things based device for a better understanding of the state of the honey bee population in the hive during the winter months. Comput. Electron.in Agriculture 212, 108026.

Aydin, S., Aydin, M.N., 2022. Design and implementation of a smart beehive and its monitoring system using microservices in the context of IoT and open data. Comput. Electron. Agric. 196, 106897.

Bagozzi, R.P., Yi, Y., 2012. Specification, evaluation, and interpretation of structural equation models. J. Acad. Mark. Sci. 40, 8–34.

Bencsik, M., McVeigh, A., Tsakonas, C., Kumar, T., Chamberlain, L., Newton, M.I., 2023. A monitoring system for carbon dioxide in honey bee hives: an indicator of colony health. Sensors 23, 3588.

Bilik, S., Zmcik, T., Kratochvila, L., Ricanek, D., Richter, M., Zambanini, S., Horak, K., 2024. Machine learning and computer vision techniques in continuous beehive monitoring applications: a survey. Comput. Electron. Agric. 2017, 108560.

Braga, A.R., Gomes, D.G., Freitas, B.M., Cazier, J.A., 2020a. A cluster-classification method for accurate mining of seasonal honey bee patterns. Eco. Inform. 59, 101107.

Braga, A.R., Gomes, D.G., Rogers, R., Hassler, E.E., Freitas, B.M., Cazier, J.A., 2020b. A method for mining combined data from in-hive sensors, weather and apiary inspections to forecast the health status of honey bee colonies. Comput. Electron. Agric. 169, 105161.

Cecchi, S., Spinsante, S., Terenzi, A., Orcioni, S., 2020. A smart sensor-based measurement system for advanced bee hive monitoring. Sensors 20, 2726.

Centola, D., Becker, J., Brackbill, D., Baronchelli, A., 2018. Experimental evidence for tipping points in social convention. Science 360, 1116–1119.

Cheng, E.W.L., 2019. Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). Educ. Technol. Res. Dev. 67, 21–37.

de Graaf, D., Bencsik, M., De Smet, L., Neumann, P., Schoonman, M., Sousa, J.P., Topping, C., Verbeke, W., Williams, J., van Dooremalen, C., 2022. B-GOOD: giving beekeeping guidance by cOmputatiOnal-assisted decision making. Res. Ideas Outcomes 8, e84129.

Degenfellner, J., Templ, M., 2024. Modeling bee hive dynamics: assessing colony health using hive weight and environmental parameters. Comput. Electron. Agric. 218, 108742.

Finger, R., 2023. Digital innovations for sustainable and resilient agricultural systems. Eur. Rev. Agric. Econ. 50, 1277–1309.

Geels, F.W., Ayoub, M., 2023. A socio-technical transition perspective on positive tipping points in climate change mitigation: Analysing seven interacting feedback loops in offshore wind and electric vehicles acceleration. Technol. Forecast. Soc. Chang. 193, e122639.

Goulson, D., Nicholls, E., Botías, C., Rotheray, E.L., 2015. Bee declines driven by combined stress from parasites, pesticides, and lack of flowers. Science 347, 1255957.

Gray, A., Adjlane, N., Arab, A., Ballis, A., Brusbardis, V., Charrière, J.-D., Chlebo, R., Coffey, M.F., Cornelissen, B., Amaro da Costa, C., 2020. Honey bee colony winter loss rates for 35 countries participating in the COLOSS survey for winter 2018–2019, and the effects of a new queen on the risk of colony winter loss. J. Apic. Res. 59, 744–751.

Hadjur, H., Ammar, D., Lefèvre, L., 2022. Toward an intelligent and efficient beehive: A survey of precision beekeeping systems and services. Comput. Electron. Agric. 192, 106604.

Hair, J.F., Ringle, C.M., Sarstedt, M., 2013. Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. Long Range Plan. 46, 1–12.

Hassler, E., MacDonald, P., Cazier, J., Wilkes, J., 2021. The sting of adoption: The Technology Acceptance Model (TAM) with actual usage in a hazardous environment. J. Inform. Syst. Appl. Res. 14 (4), 13–20.

Ingram, J., Maye, D., Bailye, C., Barnes, A., Bear, C., Bell, M., Cutress, D., Davies, L., de Boon, A., Dinnie, L., 2022. What are the priority research questions for digital agriculture? Land Use Policy 114, 105962.

Jacques, A., Laurent, M., Consortium, E., Ribière-Chabert, M., Saussac, M., Bougeard, S., Budge, G.E., Hendrikx, P., Chauzat, M.-P., 2017. A pan-European epidemiological study reveals honey bee colony survival depends on beekeeper education and disease control. PLoS One 12, e0172591.

Juhola, S., Filatova, T., Hochrainer-Stigler, S., Mechler, R., Scheffran, J., Schweizer, P.-J., 2022. Social tipping points and adaptation limits in the context of systemic risk: Concepts, models and governance. Front. Clim. 4, e1009234.

Maffezzoli, F., Ardolino, M., Bacchetti, A., Perona, M., Renga, F., 2022. Agriculture 4.0: a systematic literature review on the paradigm, technologies and benefits. Futures.

Meikle, W.G., Holst, N., 2015. Application of continuous monitoring of honey bee colonies. Apidologie 46, 10–22.

Meikle, W.G., Weiss, M., Maes, P.W., Fitz, W., Snyder, L.A., Sheehan, T., Mott, B.M., Anderson, K.E., 2017. Internal hive temperature as a means of monitoring honey bee colony health in a migratory beekeeping operation before and during winter. Apidologie 48, 666–680.

Metlek, S., Kayaalp, K., 2021. Detection of bee diseases with a hybrid deep learning method. J. Fac. Eng. Archit. Gazi Univ. 36, 1715–1731.

Olate-Olave, V.R., Verde, M., Vallejos, L., Perez Raymonda, L., Cortese, M.C., Doorn, M., 2021. Bee Health and Productivity in Apis mellifera, a Consequence of Multiple Factors. Veterinary Sciences 8, 76.

Potts, S.G., Roberts, S.P.M., Dean, R., Marris, G., Brown, M.A., 2010. Declines of managed honey bees and beekeepers in Europe. J. Apic. Res. 49, 15.

Scheffer, M., Bolhuis, J.E., Borsboom, D., Buchman, T.G., Gijzel, S.M., Goulson, D., Kammenga, J.E., Kemp, B., van de Leemput, I.A., Levin, S., 2018. Quantifying resilience of humans and other animals. Proc. Natl. Acad. Sci. 115, 11883–11890.

Shepherd, M., Turner, J.A., Small, B., Wheeler, D., 2020. Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture' revolution. J. Sci. Food Agric. 100, 5083–5092.

Taber, K.S., 2018. The use of Cronbach's alpha when developing and reporting research instruments in science education. Res. Sci. Educ. 48, 1273–1296.

Thakkar, J.J., 2020. Structural equation modelling. Application for Research and Practice. Singapore: Springer.

Ulgezen, Z.N., van Dooremalen, C., van Langevelde, F., 2021. Understanding social resilience in honey bee colonies. Curr. Res. Insect Sci. 1, 100021.

van der Zee, R., Gray, A., Holzmann, C., Pisa, L., Brodschneider, R., Chlebo, R., Coffey, M.F., Kence, A., Kristiansen, P., Mutinelli, F., 2013. Standard survey methods for estimating colony losses and explanatory risk factors in Apis mellifera. J. Apicultural Res. 52, 1–36.

van Dooremalen, C., Cornelissen, B., Poleij-Hok-Ahin, C., Blacquière, T., 2018. Single and interactive effects of Varroa destructor, Nosema spp., and imidacloprid on honey bee colonies (Apis mellifera). Ecosphere 9, e02378.

van Dooremalen, C., Ulgezen, Z.N., Dall'Olio, R., Godeau, U., Duan, X., Sousa, J.P., Schäfer, M.O., Beaurepaire, A., van Gennip, P., Schoonman, M., et al., 2014.

Bridging the Gap between Field Experiments and Machine Learning: The EC H2020 B-GOOD Project as a Case Study towards Automated Predictive Health Monitoring of Honey Bee Colonies. Insects 15, 76.
van Dooremalen, C., van Langevelde, F., 2021. Can colony size of honey bees (Apis mellifera) be used as predictor for colony losses due to Varroa destructor during winter? Agriculture 11, 529.
Van Espen, M., Williams, J.H., Alves, F., Hung, Y., de Graaf, D.C., Verbeke, W., 2023. Beekeeping in Europe facing climate change: A mixed methods study on perceived impacts and the need to adapt according to stakeholders and beekeepers. Science of The Total Environment 164255.
Vanbergen, A.J., the I.P. Initiative, 2013. Threats to an ecosystem service: pressures on pollinators. Front. Ecol. Environ. 11, 251–259.
Vardakas, F., Mainardi, G., Minaud, E., Requier, F., Steffan-Dewenter, I., Hatjina, F., 2023. How ready are beekeepers for Precision Apiculture Systems (P.A.S.)? A survey in France, Germany and Greece. In: Roditakis, E., Andreadis, S. (Eds.), Book of Abstracts, XII European Congress of Entomology 2023, Heraklion: Hellenic Entomological Society, pp. 241.
Vellis, R.F.D., 2003. Scale development: Theory and applications. Sage Publications, Thousand Oaks, CA.
Willcox, B.K., Potts, S.G., Brown, M.J.F., Alix, A., Al Naggar, Y., et al., 2023. Emerging threats and opportunities to managed bee species in European agricultural systems: a horizon scan. Sci. Rep. 13, 18099.
Zacepins, A., Brusbardis, V., Meitalovs, J., Stalidzans, E., 2015. Challenges in the development of Precision Beekeeping. Biosyst. Eng. 130, 60–71.
Zaman, A., Dorin, A., 2023. A framework for better sensor-based beehive health monitoring. Comput. Electron. Agric. 210, 107906.