Note on Methodology

UTILISING AFFORDABLE SMARTPHONES AND OPEN-SOURCE TIME-LAPSE PHOTOGRAPHY FOR POLLINATOR IMAGE COLLECTION AND ANNOTATION

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Abstract—Monitoring plant-pollinator interactions is crucial for understanding the factors influencing these relationships across space and time. Traditional methods in pollination ecology are resource-intensive, while time-lapse photography offers potential for non-destructive and automated complementary techniques. However, accurate identification of pollinators at finer taxonomic levels (i.e., genus or species) requires high enough image quality. This study assessed the feasibility of using a smartphone setup to capture time-lapse images of arthropods visiting flowers and evaluated whether these images offered sufficient resolution for arthropod identification by taxonomists. Smartphones were positioned above target flowers from various plant species in urban green areas around Leipzig and Halle, Germany. We present proportions of arthropod identifications (instances) at different taxonomic levels (order, family, genus, species) based on visible features in the images as interpreted by taxonomists. We document whether limitations stem from the automated setup (e.g., fixed positioning preventing capture of distinguishing features despite high image resolution) or from low image quality. Recommendations are provided to address these challenges. Our results indicate that 89.81% of all Hymenoptera instances were identified to family level, 84.56% of pollinator family instances to genus level, and only 25.35% to species level. We were less able to identify Dipterans to finer taxonomic levels, with nearly 50% of instances not identifiable to family level, and only 26.18% and 15.19% identified to genus and species levels. This was due to their small size and the more challenging features needed for identification (e.g., in the wing veins). Advancing smartphone technology, along with their accessibility, affordability, and user-friendliness, offers a promising option for coarse-level pollinator monitoring.

Keywords—Smartphones, plant-pollinator interactions, time-lapse photography, monitoring, arthropod identification, image observation

INTRODUCTION

The interactions between plants and their animal pollinators provide critical ecosystem services, by sustaining the reproduction of the majority of our food and wild plant species (Ollerton et al. 2011). It is thus critical to monitor plant-pollinator interactions and to understand the factors that cause these interactions to change across space and time. Since many species of pollinating insects cannot be identified on sight, most studies quantifying plant-pollinator interactions involve capturing insects observed visiting flowers and later identifying them using microscopy (e.g., Motivans Švara et al. 2021; Rakosy et al. 2022) or DNA barcoding (Creedy et al. 2020). While these methods are accurate and can provide museum specimens that are valuable for a wide variety of research purposes (Rakosy et al. 2023), they are time consuming, costly to scale, and require expert knowledge in insect taxonomy or barcoding. Further, these methods are destructive, requiring the killing of many insects in order to monitor biodiversity and interactions. With the

growing availability of video and photographic devices and artificial intelligence identification approaches, there is an opportunity for this field of science to move towards automated, non-destructive methods in pollinator research (Montero-Castaño et al. 2022).

Recent review studies show that there is great potential to automate the detection and identification of plant-pollinator interactions based on images and sound (Martineau et al. 2017; Barlow & O'Neill 2020; Pegoraro et al. 2020; Høye et al. 2021; Amarathunga et al. 2021; Kohlberg et al. 2024). We are working towards a future where pollinators visiting flowers can be rapidly monitored using an automated camera system (e.g., time lapse photography). In this system, artificial intelligence will be able to detect the presence of an insect in a photo (Stark et al. 2023; Sittinger et al. 2024) and classify it to the lowest possible taxonomic level (e.g., Spiesman et al. 2021).

The choice of camera system for automated monitoring is important, as both sharp images and high enough resolution are necessary to capture the distinguishing features needed for finer taxonomic identifications. Numerous camera systems are under investigation for monitoring pollinators. For example, camera systems include off-the-shelf digital products such as Apple iPod nanos (Lortie et al. 2012), fixed-lens cameras (Steen 2017), camera traps (Mcelveen & Meyer 2020; Naqvi et al. 2022), time-lapse cameras (Edwards et al. 2015; Smith et al. 2021; Alison et al. 2022; Nagai et al. 2022), and surveillance cameras (Steen & Thorsdatter Orvedal Aase 2011; Mertens et al. 2021), as well as recent programmable microcomputers such as NVIDIA Jetson Nano (Bjerge et al. 2022), Raspberry Pi (Ratnayake et al. 2021; Droissart et al. 2021; Bjerge, Alison, et al. 2023; Ratnayake, Amarathunga, et al. 2023), a Luxonis microcomputer-camera capable of edge AI coupled with a Raspberry Pi (Sittinger et al. 2024) and near-infrared sensors, like those offered by FaunaPhotonics (Rydhmer et al. 2022).

Among the multitude of camera systems, the use of smartphones and time-lapse photography to photograph diurnal arthropods visiting flowers is a simple and appealing option for several reasons, including affordability, ease of use, no supply shortages due to their high demand, the ability to simultaneously monitor other variables (e.g., sound, location, ambient light, atmospheric pressure, and temperature), and the ubiquity of smartphones that offers a broad scope and scale of monitoring (Lahoz-Monfort & Magrath 2021). Smartphones are already used in several citizen science initiatives aimed at monitoring pollinators, such as iNaturalist, Spipoll, ObsIdentify. For example, in Spipoll, citizen scientists are asked to watch and photograph all pollinators that visit a flower. iNaturalist allows citizens to identify organisms they see, including pollinators, by uploading images and using crowdsourced species identification. While these initiatives allow any camera system to be used, smartphones are a popular choice and the images captured by smartphones can often be identified to fine taxonomic grains (genus and species levels).

In citizen science initiatives that use smartphones, the citizen moves the camera to follow and focus on the insect and uploads only their best image. It is still an open question whether smartphones that are set for automated monitoring using time lapse, video, or motion-activated photography can capture images of pollinators that can be identified to finer taxonomic levels, such as genus or species. In a test using smartphones for motion-activated pollinator monitoring, Donovan et al. (2021) found their setup inefficient. Specifically, many of their images did not contain pollinators and appeared to have been triggered by wind and plant movement rather than by the insects themselves. Ratnayake et al. (2021) employed a Samsung Galaxy S8 smartphone camera placed on a tripod, positioned at a height of 0.6 m above a patch of *Scaevola* flowers, to capture videos of honeybee visitors. They reported high success with this method, however their focus was exclusively on a quantitative assessment of honeybee visits to a single plant species.

With this paper, we aim to assess the use of smartphones mounted above flowers to automatically capture images of arthropods visiting these flowers through time-lapse photography, requiring human intervention only at setup. We first give a detailed description of the observational setup and our approach to image selection and taxonomic identification. Second, we quantify the level of taxonomic identification that

is achievable from the images collected by having expert entomologists identify the arthropods to the lowest possible level, based on visible features and available taxonomic keys. We report the proportion of instances identified at different taxonomic levels (order, family, genus, and species), where each instance represents an arthropod marked with a bounding box in an image. Next, we discuss if the limited identification at finer taxonomic levels was due to the setup approach in general (i.e., observing distinguishing features is not possible even from a high-quality image) or due to low image quality (i.e. low resolution, out of focus). Then, we communicate some of the lessons learned and troubleshooting that were involved with using smartphones for pollination research. Finally, we discuss the next technological steps that would be necessary to allow for efficient automated pollinator monitoring, including developing AI that can detect and identify the arthropods in the images.

MATERIALS AND METHODS

Our study was conducted in the urban green areas at 30 sites in and around Leipzig and Halle, Germany (Appendix Tab. I). These field sites were chosen because they were active areas of research on pollinator biodiversity monitoring and plant-pollinator interaction studies. Within these field sites, individual plants in flower were selected for collecting images of their visiting pollinators (we use the term pollinator to define an arthropod which touched the reproductive parts of the flowers). The plants were chosen somewhat haphazardly at each site, based on the plant species that seemed to be getting a reasonable frequency of visits, as our goal was to maximise the number of images of visiting arthropods. We targeted flowers that were open and plants that hold their flowers straight up and avoided plant species that had drooping flowers, as these would be more difficult to photograph. In total, we monitored 33 different plant species (Appendix Tab. II). The fieldwork required a total of 280 hours to record time-lapse images of arthropods visiting flowers at the study sites. Images were collected from July through September 2021.

SMARTPHONE SETUP

To monitor visiting pollinators, we affixed a smartphone above the flower or inflorescence (setup example in Fig. 1). Our objective was to capture time-lapse images at one-second intervals, targeting a one-hour session duration for each observed flower. After each session, the smartphone was moved to another flower. Because the number and identity of plant-pollinator interactions vary during the day (Nagano 2023), images were captured from 8:00 AM to 5:00 PM (Appendix Fig. I). Observations were only conducted on sunny or mostly sunny days.

The smartphones were securely mounted on tripods and powered through USB cables connected to power banks for a continuous flow of energy. We utilised power banks with an output of 5V and a range of 1-2.1mAh, resulting in a total cost of 130-200 EUR per setup unit (Tab. 1). We acquired six affordable Blackview A60 smartphones and received two donated, used smartphones, HomTom HT50 and HUAWEI

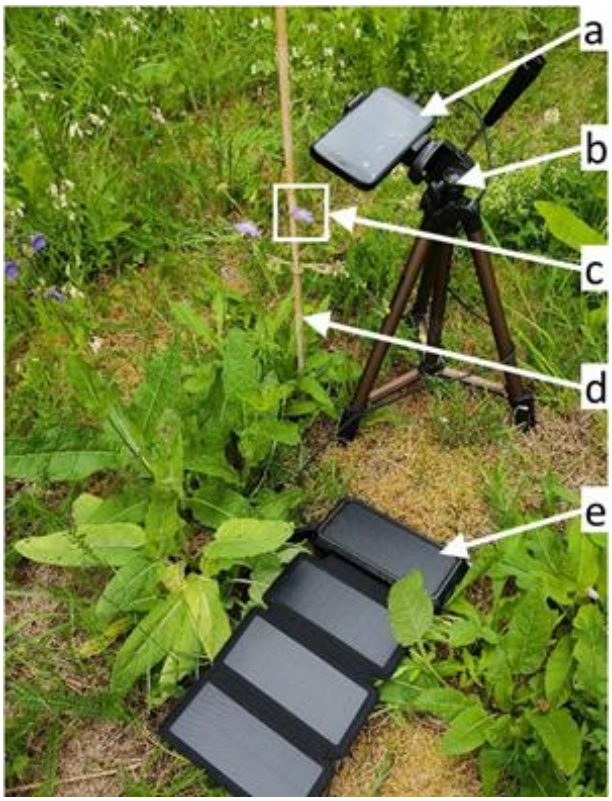

Figure 1. Example of the smartphone setup used for time-lapse photography, mounted on top of a target flower. a) smartphone, b) tripod, c) target flower, d) support stick used to stabilise the flower against wind movements, e) power bank.

Table 1. Example of affordable smartphone gear.

ID	Product	No. units	URL (last checked 2024-06-12)	Unit price (€, 2021)	Max. image resolution (width x height, pixels)
1	Blackview A60 smartphone	6	https://www.devicespecifications.com/en/model/d214501f	85	4160 x 3120
2	HomTom HT50 smartphone	1	https://www.devicespecifications.com/en/model/56af442f	Donated, used	3264 x 2448
3	HUAWEI WAS-LX1A smartphone	1	https://www.devicespecifications.com/en/model/8469421f	Donated, used	3968 x 2976
4*	Djroll Qi solar power bank 36000 mAh	2	https://www.amazon.com/dp/B08ZKK9GG3	40	
5*	Sweye solar power bank 26800 mAh	3	https://www.amazon.de/dp/B08CV3JV7C	22	
6*	Hermitshell Poweradd EnergyCell 10000 mAh	3	https://www.amazon.de/dp/B07T8N2B29	11	
7	Everesta aluminium tripod	8	https://www.amazon.de/dp/B0725GDDQX	23	
8	SanDisk micro SD card, 32 Gb	8	https://www.amazon.de/dp/B06XWMQ81P	9	

*) All three models of power banks were sufficient for supplying energy to the smartphones during the day. They were recharged along with the smartphones at the end of each field day.

WAS-LX1A and also included a small number of images in our study taken by a Canon EOS 200D DSLR camera with a 50mm lens (Tab. 3).

The smartphone gear setup was lightweight, weighing between 0.80 and 1.14 kg, with the power bank being the heaviest component, varying between 0.18 and 0.52 kg. We used the free Open Camera app (Harman 2023) for capturing the time-lapse images. The detailed protocol implemented for our field work can be found in Appendix VII.

To ensure consistent and high-quality recordings, we set a fixed focus at the start of each session on a target flower or portion of the flower or inflorescence which defined the region of interest (ROI). This was done by disabling the auto-focus feature in the Open Camera app, as it could result in images with a focus on the background rather than the target flower due to wind movements and/or arthropod activity (e.g., Bjerge, Frigaard, et al. 2023). To minimise wind movements, we secured the target flowers to a wooden stick using yarn. The smartphones were positioned at a distance of 15-20 cm from the centre of the target flower to frame as much of a single flower as possible, which is important given the small size of most pollinators. Due to the absence of a fixed duration recording feature in the Open Camera app, we employed a stopwatch for timing. After each one-hour interval, an alarm would sound, prompting us to manually stop the recording in the app. The Open Camera app was set to capture an image every second, and we manually created a unique folder for each recording session with the plant's name identified in the folder title. We used the Flora Incognita app (Mäder et al. 2021) to identify the focal plant species and this identification was verified by a botanist using the captured time-lapse images. The Open Camera app allows the user to set the image resolutions, depending on the smartphone model. The majority of the images in our dataset were set to be captured at a custom resolution of 1600 x 1200 pixels (below their maximal resolution – Tab. 1). We did not implement an experimental design to compare the smartphone models in terms of image resolution and quality. In line with best practices commonly acknowledged in camera trap research (e.g., Bjerge, Frigaard, et al. 2023; Sittinger et al. 2024), we configured the exposure to automatic mode. This approach, recommended to counteract issues of over- or underexposure, enables the camera to dynamically adjust to the changing lighting conditions, thus maintaining consistent image quality.

ARTHROPOD ANNOTATION AND IDENTIFICATION

For each unique folder corresponding to a time-lapse recording session for a target flower, we visually inspected each image to determine if it contained an arthropod. If an arthropod was present, we manually placed a tight bounding box around it and identified the arthropod to taxonomic order. For clarity, throughout this manuscript, we will use the term "instance" specifically to refer to any bounding box containing an arthropod. The data annotation phase required a cumulative total of 1,000 hours from four annotators. The free and open-source VGG Image Annotator (VIA) software (Dutta & Zisserman 2019) was utilised to view the images, draw bounding boxes, and enter the taxonomic order information. We annotated all arthropods present in each image, but did not assign a unique identifier to each individual. This software requires no installation, works across all common operating systems (Windows, Linux, or MacOS), and consists of a single HTML file that runs on most common web browsers (e.g., Google Chrome, Mozilla Firefox, etc.). To record annotation metadata for each bounding box, we created a custom JSON file template for VIA with a custom attribute table. A step-by-step annotation example and tutorial is provided on the GitHub repository[1] associated with this article.

Next, we converted the JSON data files into spreadsheet files using R and Python scripts available on our GitHub repository[2]. These spreadsheets contained the paths to images with arthropods, along with the pixel coordinates of the bounding boxes placed around the arthropods. We then merged the individual spreadsheets for each target flower into a single, comprehensive annotation spreadsheet. The decision to use spreadsheets was strategic due to their user-friendliness and simplicity. Additionally, we opted for spreadsheets because the VIA annotation tool currently lacks certain functionalities such as efficient filtering by multiple fields and the ability to easily drag and drop or copy-paste taxonomic information for consecutive frames (rows) of the same individual. To speed up the visualisation of each arthropod with its corresponding bounding box directly from the spreadsheets, we created the free and open source annotation tool 'boxcel' (Ștefan 2022).

Co-authors with entomological expertise visually inspected the images with arthropods and identified pollinators in the Hymenoptera and Diptera orders to the lowest taxonomic level possible. The identification of other flower visitors was limited to the order level only. If an arthropod was present across multiple consecutive frames, the identification was ultimately determined by the combined frames from which the expert could extract the maximum amount of information. These three co-authors cumulatively invested 720 hours in this effort. Their tasks also included familiarising themselves with the unique challenges of the image dataset, defining custom taxonomic categories, and developing tailored lists of visible features to aid identification. They also occasionally verified the placement of bounding boxes to ensure they were tightly fitted around the arthropods and checked the accuracy of previously recorded order labels. Time estimates are approximate and based on contract durations associated with this study.

We did not physically capture the insects for identity verification using methods such as microscopy or DNA analysis. Instead, we relied on keys often designed for microscopy, along with online visual guides, and thus acknowledge the potential for subjectivity in the identification process. The visible distinguishing features and the expert assessments are documented in Appendix Tables III and IV for Hymenoptera and Diptera, respectively, along with visual examples and references to taxonomic keys, online visual guides and other relevant sources used. In these tables, we provide details regarding identifications classified as either 'robust' or 'subjective'. Generally, 'robust' identifications were based on clear distinguishing characteristics consistently visible across the images and supported by detailed descriptions from various cited sources. In contrast, 'subjective' identifications relied on expert judgement due to less distinct features, drawing on the entomological experience of co-authors and their prior microscope-based

[1,2] https://github.com/valentinitnelav/pollinator-image-annotation

identification work. For example, while *Apis mellifera* is a common species observed in our study with distinct features, its identification is classified as 'subjective' because we cannot observe all the features required by a taxonomic key.

Bombus species are common pollinators but are difficult to identify visually due to high morphological variation within species (e.g., across queens and workers) and sometimes similar colour patterns across species (Spiesman et al. 2021). For example, Carolan et al. (2012) showed that colour patterns and other morphological traits often fail to reliably distinguish cryptic species. Therefore, *Bombus* species expected in our study area and neighbouring regions (Germany and adjacent countries) were classified into morphospecies groups (Appendix Tab. III). Similarly, for Diptera, the visual similarity of certain families in our image dataset necessitated grouping them into clusters. Specifically, the families Calliphoridae and Muscidae were combined into a single cluster, and Sarcophagidae and Tachinidae were grouped into another. Additionally, with over 460 Syrphidae species potentially occurring in Germany (Ssymank et al. 2011), many genera exhibit superficial similarities that often rely on specific distinguishing features, which are unlikely to be discernible in our image dataset. To address this, Syrphidae species were grouped into broader clusters based on observable traits, such as mimicry, colour patterns, or shared morphologies (Appendix Tab. IV).

RESULTS AND DISCUSSION

We sampled 33 different plant species (see Appendix Tab. II) and annotated 213 unique folders, each corresponding to approximately one hour of time-lapse recordings, which resulted in a dataset of 460,056 images. Because we utilised a stopwatch for timing our recordings due to the limitations of the Open Camera app, some variation in recording durations occurred, with an average duration of 3,553 ± 372 seconds (mean ± S.D.) per target flower.

Our dataset of 460,056 images is sparse, with only 33,502 images (7.28%) containing at least one arthropod, resulting in a total of 35,194 instances (bounding boxes) (Tab. 2, Appendix Tab. II). The higher bounding box number was due to the presence of more than one arthropod in some images (e.g., Fig. 7C). The vast majority of images, 95.22%, contained only one arthropod, while 4.49% contained two arthropods, 0.28% contained three arthropods, and we only identified a single image containing four arthropods. The presence of multiple arthropods in the images did not significantly challenge the co-authors with taxonomic expertise during the identification process or cause data management issues as each arthropod was encapsulated within a bounding box assigned a box unique identifier. Most images containing arthropods (94.16%) were captured using the six Blackview A60 affordable smartphone models, with the majority (93.69%) taken at a resolution of 1600 x 1200 pixels, or 1.92 megapixels (Tab. 3).

Table 2 – Summary of annotated instances (bounding boxes, "No. box") for each taxonomic order in the dataset. The 11 bounding boxes without taxonomic order labels ("No Id.") correspond to 11 consecutive images of a very small flower visitor captured in blurred images.

Order	No. box	Percent %	% cumul. sum
Hymenoptera	20,987	59.63	59.63
Diptera	5,963	16.94	76.58
Coleoptera	3,254	9.25	85.82
Thysanoptera	2,965	8.42	94.25
Araneae	1,158	3.29	97.54
Hemiptera	812	2.31	99.84
Lepidoptera	44	0.13	99.97
No Id.	11	0.03	100
Total	35,194	100	

With the exception of one very small flower visitor for which only blurred images were captured, we identified all arthropods to order level. In total we observed seven different orders of arthropods visiting our flowers (Tab. 2 & Fig. 2). Around 60% of the annotated bounding boxes contained a Hymenopteran, while 17% were Dipterans, with the two groups comprising more than three quarters of the annotated boxes. We rarely observed Lepidopterans (0.03%).

IDENTIFYING HYMENOPTERA TO LOWER TAXONOMIC LEVELS

A total of 20,987 bounding boxes contained an insect instance from the order Hymenoptera (Tab. 2, Fig. 3A & Appendix Tab. V), with identification

Table 3 – Summary of annotated images per camera model.

Model	Image resolution (width x height, pixels)	No. images per model and resolution	%	No. images per model	%
Blackview A60	1600 x 1200	29,778	88.88	31,544	94.16
	1200 x 1600*	1,613	4.81		
	2048 x 1536	153	0.46		
HomTom HT50	1600 x 1200	711	2.12	1,052	3.14
	1152 x 864	203	0.61		
	2048 x 1536	138	0.41		
Canon EOS 200D**	2400 x 1600	654	1.95	654	1.95
HUAWEI WAS-LX1A	1280 x 720	252	0.75	252	0.75

*) Depending on the smartphone's orientation, the resolution may switch the width and height pixel values.

**) DSLR camera for trial purposes.

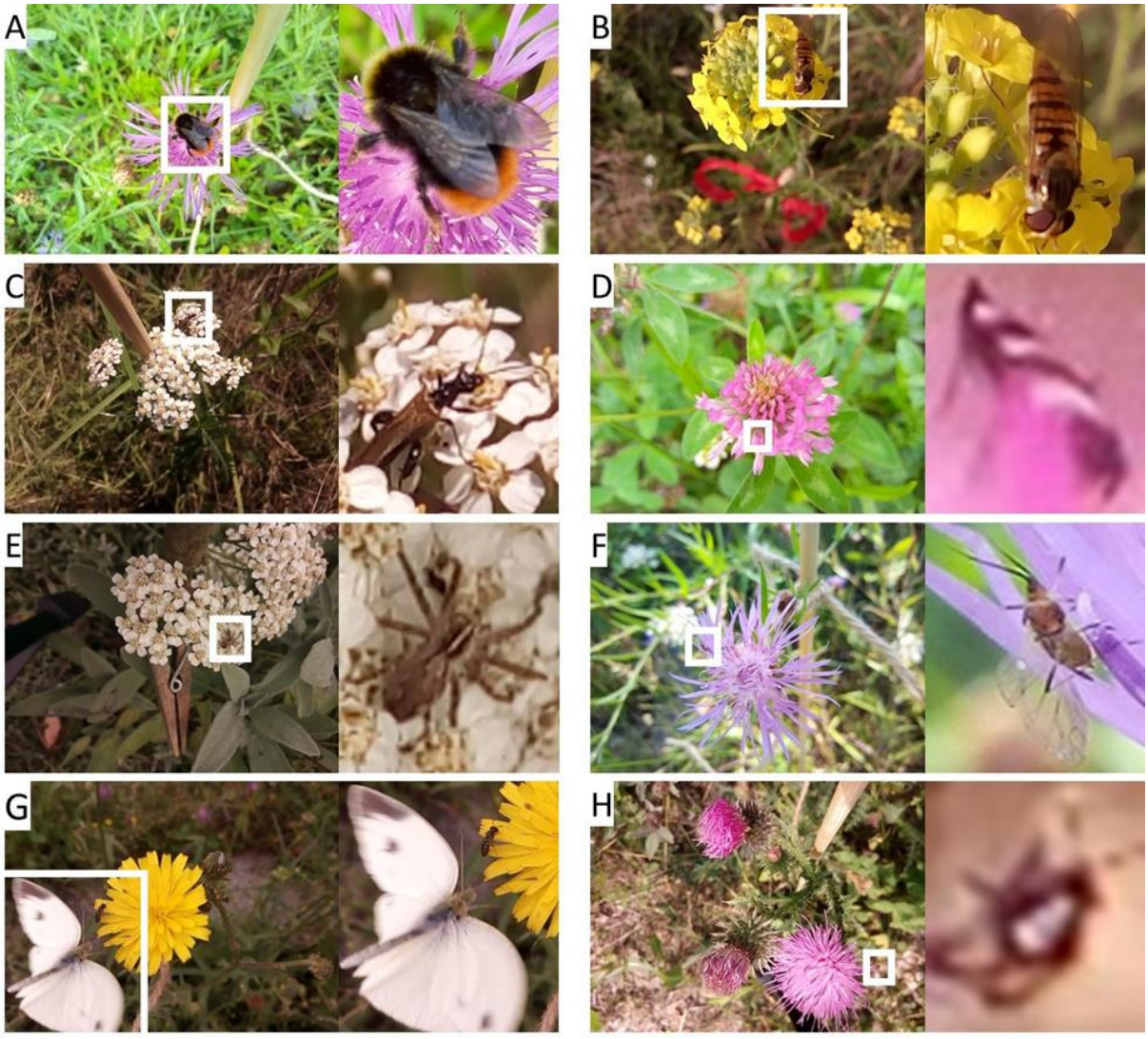

Figure 2. Examples of images with flower visitors from the seven observed orders with zoom on the respective bounding box for (A) Hymenoptera - *Bombus lapidarius* on flower of *Centaurea jacea*, (B) Diptera - *Episyrphus balteatus* on *Bunias orientalis*, (C) Coleoptera on *Achillea millefolium*, (D) Thysanoptera on *Trifolium pratense*, (E) Araneae on *Achillea millefolium*, (F) Hemiptera on *Centaurea jacea*, (G) Lepidoptera near *Picris hieracioides*, (H) No-Id, the order could not be identified.

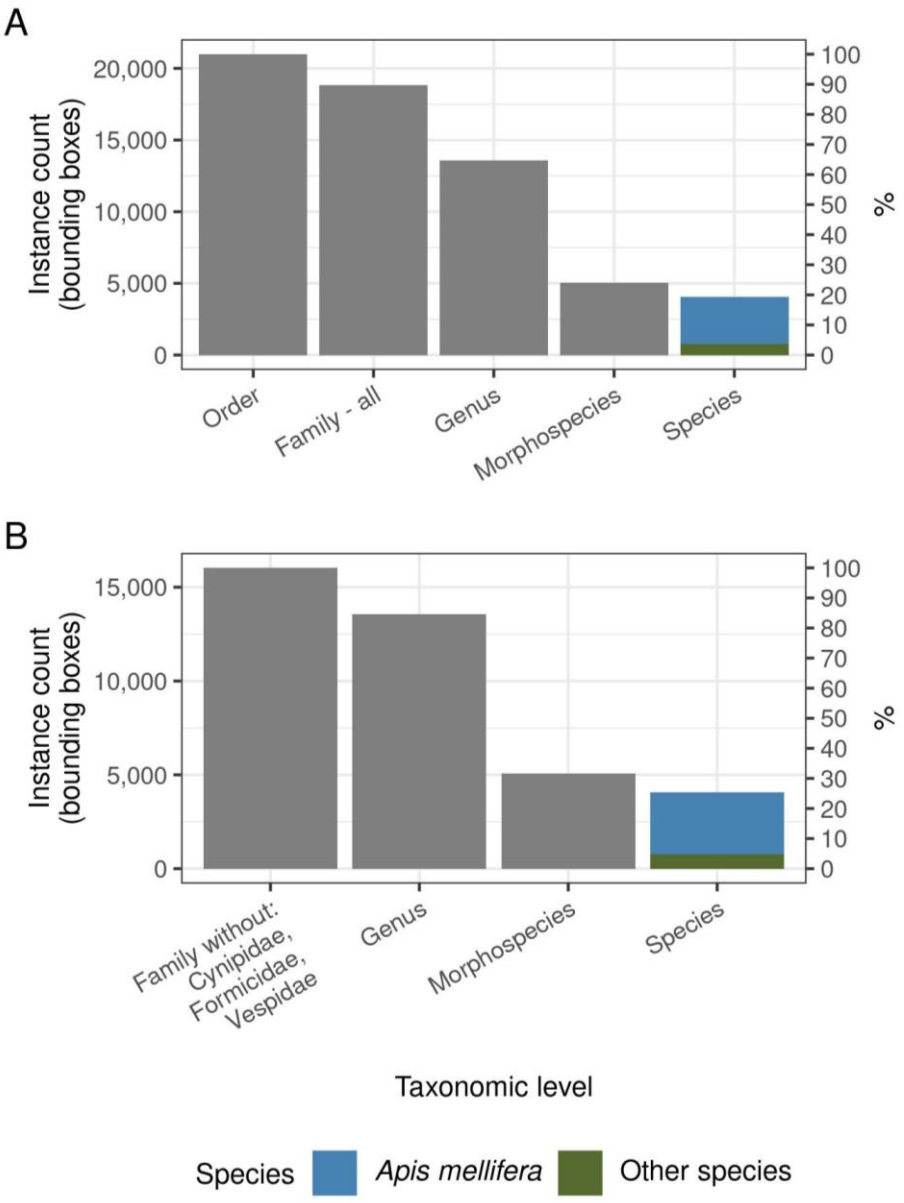

Figure 3. Bar plot illustrating the number and percent of instances (bounding boxes) at different taxonomic levels for the flower visitors in the order Hymenoptera (see also Appendix Tab. V). The primary y-axis (left) shows the count of instances, while the secondary y-axis (right) displays the corresponding percentage for each taxonomic level, relative to the total number of instances in the 'Order' level (panel A), and to the total number of instances at the pollinator family level (panel B, excluding the families Cynipidae, Formicidae, and Vespidae). This visualisation highlights the distribution and completeness of taxonomic information we could achieve within the Hymenoptera dataset, noting that for the families Cynipidae, Formicidae, and Vespidae, no further identification to lower taxonomic levels (genus, species) was attempted due to their unlikely role as pollinators. *Apis mellifera* comprised 15.76% of the total instances labelled as Hymenoptera.

details and corresponding cropped image examples provided in Appendix Tab. III. Of these, 18,849 (89.81%) could be identified to one of ten families (Appendix Tab. V). There are a variety of reasons why some instances could not be identified to the family level (Fig. 4). First, insects were outside the region of interest (ROI, Fig. 4A); in our case the ROI is typically a focal flower, an inflorescence, or a part of an inflorescence. Insects that were in the background rather than the ROI of the images were typically out of focus, obscured by surrounding vegetation, or appeared too small for further identification. For the purposes of many projects in pollination ecology, visitors on the focal flowers or inflorescence are the target of observations, and the ability to identify background insects that are outside this ROI would not be necessary. Second, identifying features of some insects that were inside the ROI were physically obscured from view in every image in which they occurred (Fig. 4B). These insects were in clear focus, but were either partly cut out of the image due to movement of the flower after the camera was set up, obscured by the surrounding vegetation, or positioned at an angle such that only part of the insect was ever visible. Hereafter, these cases are simply referred to as "obscured". Third, some insects within the ROI were too blurry to allow the discernment of the identifying features in every image in which they

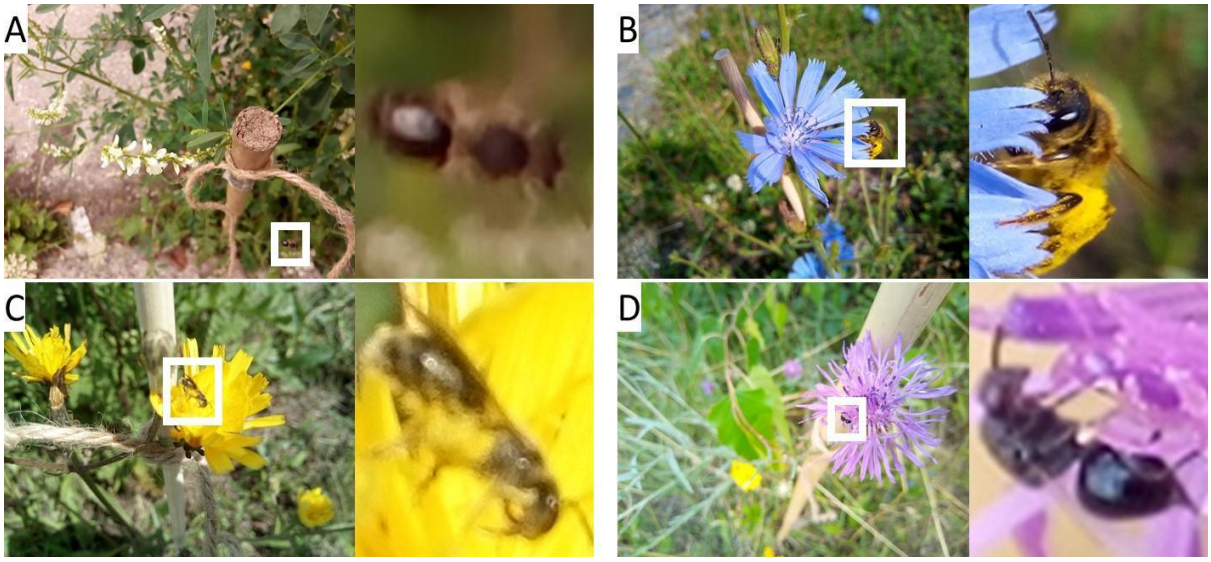

Figure 4. Examples of Hymenoptera insects that could not be identified to the family taxonomic level: (A) insect outside the region of interest (ROI), (B) insect within the ROI but all identifying features are physically obscured, (C) insect within the ROI but too blurry to identify, (D) tiny wasp.

occurred (Fig. 4C). This occurred when the insect was too small to be seen in high resolution from the set depth of field, when the depth of field was too narrow and only focused on the surface of the flower but not the visiting insects, or when the insect was moving when the photo was taken. Hereafter, these cases are referred to as "too blurry." Fourth, many instances were of a few individuals of tiny wasps that were only a handful of pixels in length (Fig. 4D). Because these tiny wasps remained on the same flower for several minutes at a time, we had hundreds of images of each individual. These tiny wasps were unlikely to be contributing to the pollination of the focal flowers and likely play a larger role in the ecosystem as parasitoids (Quicke 1997). The challenges of identifying very small insects are discussed further in the sections "Identifying Diptera to lower taxonomic levels" and "Lessons learned and ideas for future development". Of the 2,138 (10.19%) bounding boxes with insect instances that could be identified to order Hymenoptera but not further identified to family, 397 (18.57%) were outside the region of interest, 11 (0.51%) were obscured, 76 (3.55%) were too blurry, and 1,654 (77.36%) were tiny wasps.

In the following paragraphs, we present the identification results for instances of insects from the Hymenoptera families in alphabetical order, consistent with the organisation of Appendix Tab. V.

Of the 608 (2.90%) bounding boxes with insect instances identified to the family Andrenidae, 253 could be further identified to the genus *Andrena* (Fig. 5). Over 100 species of *Andrena* are present in Germany and determination to the species level is often challenging even using microscopic traits, rendering identification from smartphone images mostly impossible. Of the Andrenidae instances that could not be identified to genus, one was

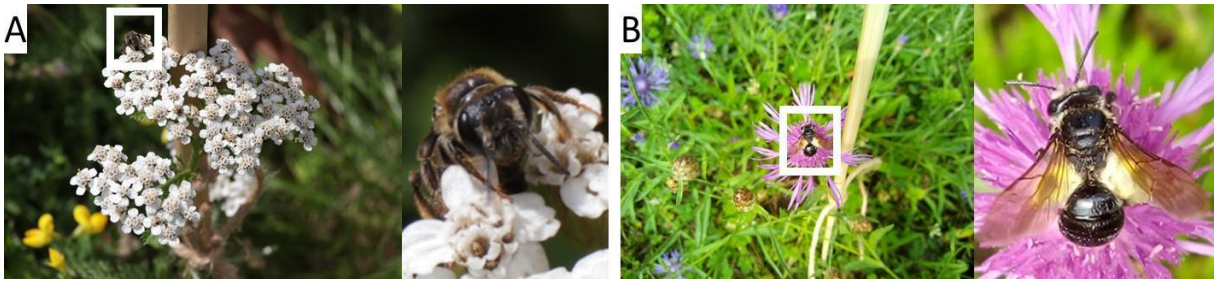

Figure 5. Examples of individuals from the *Andrena* genus: (A) showcasing distinctive facial foveae, (B) emphasising the presence of two submarginal cells, visible in the right wing's venation.

outside the ROI, 28 were obscured, and 326 were too blurry.

All 8,485 (40.43%) instances identified as Apidae were further classified to genus: *Bombus* (5,178) and *Apis* (3,307). For the genus *Apis*, all instances were of the Western honeybee, *Apis mellifera* (e.g., Fig. 6A). For the genus *Bombus*, 5,063 instances could be identified to five morphospecies (Fig. 6B-F), 115 instances were obscured (Fig. 6G), and seven could be identified as *Bombus lapidaries* (Fig. 2A).

Of the 404 (1.93%) instances identified to the family Colletidae, all could be identified further to two genera that occur in Germany: *Colletes* (two instances) and *Hylaeus* (402 instances). There are nearly 40 species of *Hylaeus* that occur in Germany and differentiation between species depends on minute differences in the maculations that are not visible in the field images.

A total of 390 (1.86%) instances were identified to the family Cynipidae (gall wasps). Lower-level identification of these instances was not attempted, as we focus on pollinators rather than parasitoids (Whitfield 1998).

The family Formicidae (ants) comprised 2,426 (11.56%) of the identified instances. Lower-level identification was not attempted due to our focus on pollinating insect groups. Ants are rarely

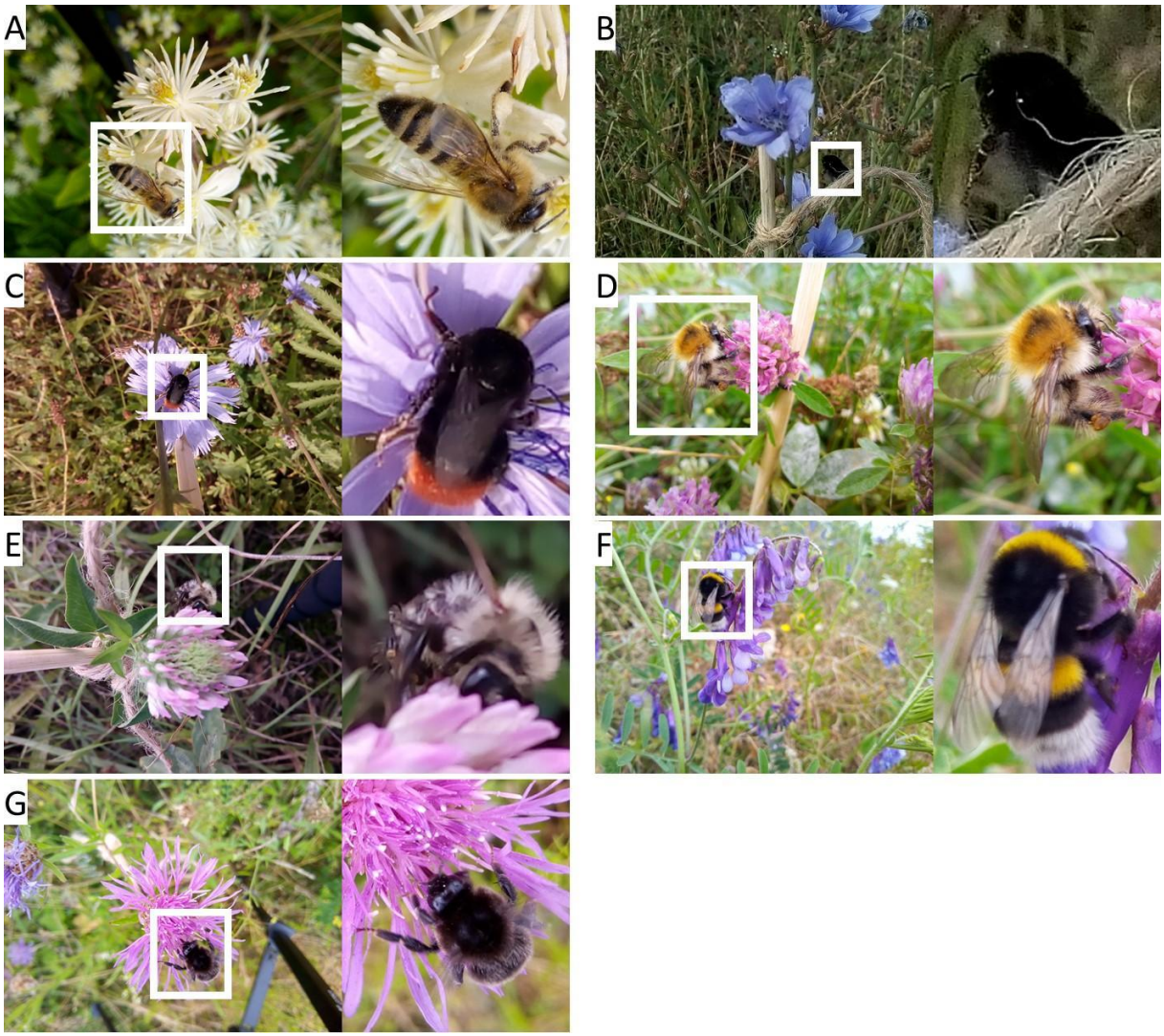

Figure 6. Examples of individuals from the Apidae family: (A) with all characteristic features of *Apis mellifera* - golden-brown coloration, corbiculae ("pollen baskets"), striped abdomen, and banana-shaped marginal cell, (B) example of *Bombus* "black" morphospecies group, (C) *Bombus* "red-tailed" morphospecies group, (D) *Bombus* "red and yellow" morphospecies group, (E) *Bombus* "striped" morphospecies group, (F) *Bombus* "white-tailed" morphospecies group, (G) *Bombus* individual which could not be assigned to a morphospecies group.

Figure 7. Examples of individuals from the Halictidae family: (A) with strongly curved basal wing vein characteristic of the family Halictidae, (B) with abdominal furrow, characteristic of females in the genera *Halictus* and *Lasioglossum*, (C) with apical banding of the tergites in *Halictus* male (lower individual) and female (upper individual), (D) with basal banding of the tergites in *Lasioglossum*.

pollinators in temperate grassland ecosystems, and more often disrupt pollination by damaging flowers or changing the foraging behaviour of pollinators (Wills & Landis 2018).

Altogether, 6,153 (29.32%) instances were identified to the family Halictidae (Fig. 7). A total of 2,959 (14.10%) instances were labelled as belonging to the genus *Halictus* and 1,102 (5.25%) to the genus *Lasioglossum*. Further identification within these genera is complicated by the large number of species, but a few species were somewhat distinctive (see also Appendix Tab. III & V): *Halictus scabiosae* (287 instances), *Halictus subauratus* (422 instances) and males of *Lasioglossum calceatum* (28 instances). A total of 2,092 (9.97%) instances labelled as Halictidae could not be identified to genus. Of these, 678 were outside the ROI, 142 were obscured, and 1,272 were too blurry.

Of the 195 (0.93%) instances identified to the family Megachilidae, 13 were identified as *Anthidium manicatum* (Fig. 8A), 150 were identified as *Megachile* and four were identified as *Osmia* (Fig. 8B,C, Appendix Tab. III). The remaining 28 instances could not be identified to the genus level: 14 were outside the ROI and 14 were too blurry for finer identification.

A total count of 181 (0.86%) instances were identified to the family Melittidae. There are no

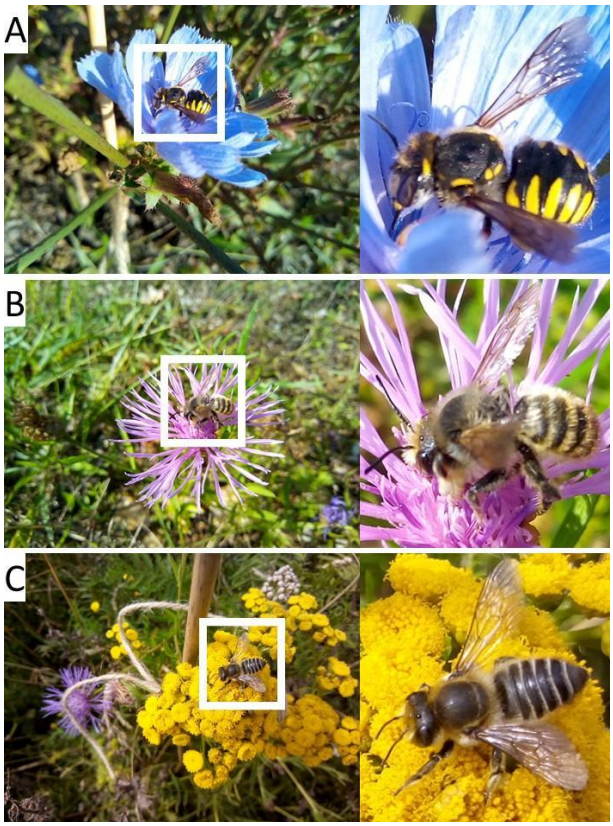

Figure 8. Examples of individuals from the Megachilidae family: (A) *Anthidium manicatum*, (B) showing abdominal position of *Osmia* genus, (C) showing abdominal position of *Megachile* genus.

Figure 9. Examples of individuals from the Melittidae family: (A) of *Dasypoda* genus and its characteristically long leg hairs, (B) of *Macropis* genus and its characteristic tibial hairs.

unique traits that unite the family Melittidae, and thus all bounding boxes were assigned to one of two genera: *Dasypoda* (three instances, Fig. 9A) and *Macropis* (178 instances, Fig. 9B). Identification to the species level in both genera requires close examination of the hairs on the legs and abdomen, which is not possible from our images.

Two larger wasps were also observed. One individual (five instances) belonged to the family Pompilidae and was a member of the genus *Episyron*. The other individual (two instances) belonged to the family Vespidae. We did not attempt to further identify this individual.

For the purposes of pollination ecology, it is desirable to identify insects to at least genus level, as this provides structural information on the plant-pollinator network that is similar to the species level (Rodrigues & Boscolo 2020). The ability of sampling with smartphones to capture images that enabled this level of identification was high. Of the 18,849 (89.81%) instances with flower visitors identified to families within the order Hymenoptera, we did not attempt to identify 2,818 (14.95%) further because they are unlikely to be pollinators (families Cynipidae, Formicidae, Vespidae). Of those 16,031 (76.39%) instances from pollinating families for which further identification was attempted, we identified 13,556 (84.56 %) to genus and 4,064 (25.35%) to species (Fig. 3B). Of the 2,475 instances from pollinating families that could not be identified to genus, 693 (28.00%) were outside the ROI, and thus would not have been the target for observations in pollination ecology (i.e., they are not visiting the focal flower we are observing). 171 (6.91%) were obscured, and thus even more expensive camera systems would not have enabled a closer identification. Finally, 1,611 (65.09%) were blurry. The blurry cases reflect the possible limitations of sampling with affordable smartphones, as more expensive camera systems might have better been able to capture sharper photos of small or fast-moving insects visiting the ROI.

Identifying Diptera to lower taxonomic levels

Distinguishing between Diptera families from images requires a clear view of characters of the wing veins in combination with other distinctive features such as body shape, patterning and/or colour. However, wing venation was not typically visible in our images. Therefore, identification to the family level posed significant challenges, and identification to finer levels (genus and species) proved even more demanding or impossible.

A total of 5,963 bounding boxes contained an insect instance from the order Diptera (Tab. 2, Fig. 10 & Appendix Tab. VI), with identification details and corresponding cropped image examples provided in Appendix Tab. IV. Of these, 3,066 (51.42%) could be identified to one of the six families or family-clusters: Anthomyiidae, Calliphoridae/Muscidae, Chyromyidae, Sarcophagidae/Tachinidae, Syrphidae and Tachinidae (Appendix Tab. VI). Further identification to genus level was possible for only 1,561 (26.18%) instances, and to species level for just 906 (15.19%).

Of the insect instances found in the bounding boxes that were labelled as Diptera, nearly half (2,761 instances, or 46.30%) were subsequently identified as Syrphidae. This was the only family for which species-level identification was possible, with the three identified species illustrated in Fig. 11 and their instance counts presented in Appendix Tab. VI. A total of 1,210 (20.29%) instances were assigned to Syrphid morphological groups. Only seven instances marked as Syrphidae could not be identified to the morphological group level - two were outside the ROI, three displayed incomplete views of the insect (obscured), and two featured insects in flight (too blurry).

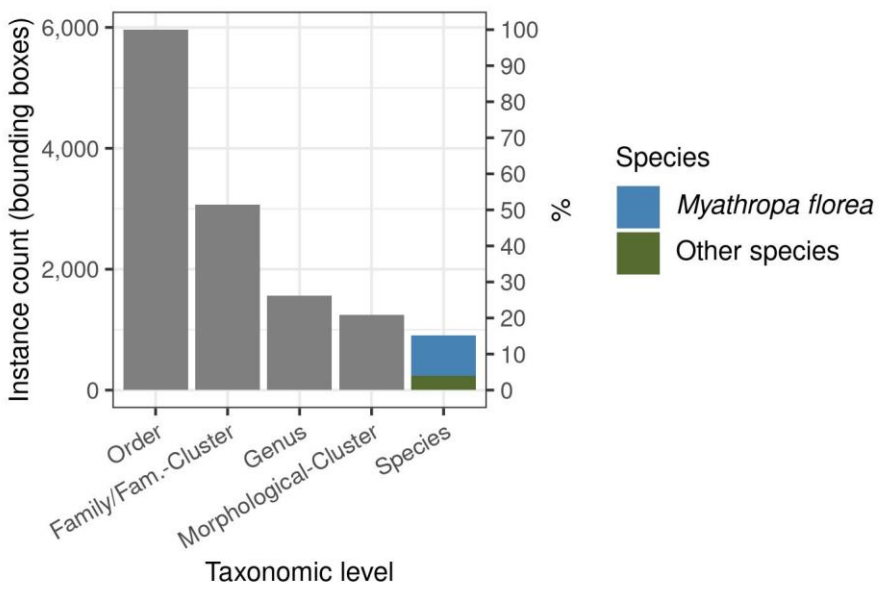

Figure 10. Bar plot illustrating the number and percent of instances (bounding boxes) at different taxonomic levels for the flower visitors in the order Diptera (see also Appendix Tab. VI). The primary y-axis (left) shows the count of instances, while the secondary y-axis (right) displays the corresponding percentage for each taxonomic level relative to the total number of instances in the 'Order' level. This visualisation highlights the distribution and completeness of taxonomic information within the Diptera dataset. *Myathropa florea* comprises 11.25% of the total instances labelled as Diptera.

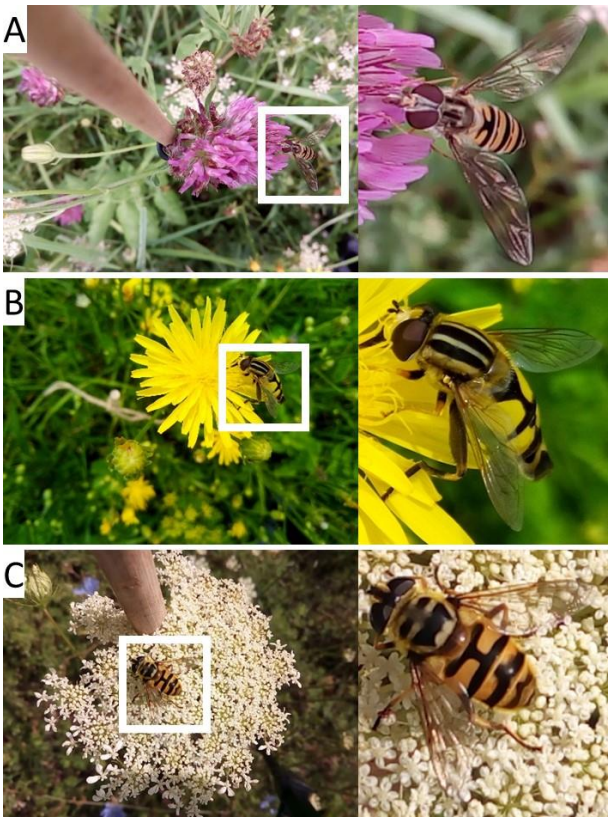

Figure 11. Examples of Syrphidae identified to species level: (A) *Episyrphus balteatus*, (B) *Helophilus trivittatus* , (C) *Myathropa florea*.

The remaining 2,897 (48.58%) instances could not be identified to the family/family-cluster level (e.g., Fig. 12). Of these, in most cases the insect was too small and zooming in to see identifying features resulted in blurry, pixelated images. This occurred when we attempted to capture an entire inflorescence as a ROI, which resulted in blurry images of the small flies that visited flowers within that inflorescence (Fig. 12A). Similarly, if the phone was positioned too distant from the target flower, the images of small flies were blurry (Fig. 12B). Moreover, some of these flies were so tiny that identifying features could not be seen even when the camera was fairly close to and focused on the target flower (Fig. 12C). We note that 697 (24.06%) of these instances were from one time-lapse photoset of one very tiny fly individual (Fig. 12C). Finally, 182 instances (6.28%) were outside the region of interest (ROI), so were not in the focus of the camera (Fig. 12D).

Using a camera lens with more powerful optical zoom is a possible solution to these challenges, although it is important to note that there was a depth of field issue for such small flies. Increasing the optical zoom can further decrease the depth of field, making it even more challenging to maintain focus on small, moving insects across the complex three-dimensional structure of the target flowers. Although some identifying features may have been visible if the fly was at the correct focal depth, achieving this focus is difficult given the size of the flies.

Lessons learned and ideas for future development

Overall, we found that smartphones that are set for automated monitoring using time lapse photography can capture images of pollinators

Figure 12. Examples of Diptera insects that could not be identified to the family or family-cluster taxonomic level: (A) the insect appears too small when attempting to capture the entire large inflorescence, (B) if the phone was too far from the flower, the insect appeared small and the identifying features are not visible, (C) Even if the phone is close to the flower and the insect is within the ROI, its features may not be visible due to its tiny size, (D) The insect is out of focus and outside the ROI.

that can be identified at the order level, with identification becoming more challenging at finer taxonomic levels. Our ability to identify Hymenoptera from images was significantly better than in the case of most Diptera. The most common arthropod flower visitors were in the order Hymenoptera (59.63% of total instances, Tab. 2). Of the bounding boxes containing bee instances, 84.56% could be identified to genus level when excluding unlikely pollinator families (Cynipidae, Formicidae, and Vespidae), for which further identification was not attempted (Fig. 3B). Only 25.35% of Hymenoptera instances from pollinator families could be identified to the species level, the majority of which were *Apis mellifera* (Fig. 3). Identifying Dipterans proved to be more challenging. Due to factors such as their smaller size and intricate identification features, particularly in their wing veins, only 26.18% of fly instances could be classified to the genus level, and just 15.19% to the species level, the majority of which were *Myathropa florea* (Fig. 10). The extensive fieldwork and data annotation involved substantial time investments. Therefore, at this point, collecting data on plant-pollinator interactions using time-lapse photography and employing taxonomists to identify the arthropods in the images is not a time-saving approach. However, we see this research as an important first step towards greater automation. The next steps involve developing an arthropod detector and classifier to enhance automation and efficiency. To achieve this, a comprehensive, annotated dataset is essential, which we have now created with this study. Currently, we are not aware of any general-purpose arthropod detector and classifier suitable for automatically annotating our complex image dataset.

The meticulous process of placing bounding boxes around arthropod instances in our images was time-consuming but strategic. This process aided our taxonomists in quickly identifying the arthropods to lower taxonomic levels than just the order, saving time otherwise spent searching for them. While a simpler key-point approach (i.e., placing a simple dot in the centre of the arthropod) could have been faster, bounding boxes will facilitate the future development of both an arthropod detector (e.g., Bjerge, Alison, et al. 2023; Stark et al. 2023; Sittinger et al. 2024), and an arthropod classifier (e.g., Spiesman et al. 2021; Bhuiyan et al. 2022; Ratnayake, Yasin, et al. 2023; Bjerge, Geissmann, et al. 2023; Sittinger et al. 2024) using the cropped images within the bounding boxes. While these existing classifiers are highly effective within their specific scope, often limited to a genus or a particular species, our project captures a broader diversity of taxa. Classifiers are also deployed online as prototypes or

demonstrations (e.g., BeeMachine[2], iNaturalist Computer Vision Demo[3]) or through smartphone apps (e.g., Seek by iNaturalist[4], ObsIdentify by Observation.org[5]). However, these systems require that images be uploaded individually, which is impractical for bulk processing of tens of thousands of images, as is the case with our datasets. Moreover, Beery et al. (2018) have shown that such AI models do not usually generalize to new image datasets taken with different cameras or to new locations. Therefore, our future aim is to create a custom arthropod detector, optimised for edge device cameras (e.g., Sittinger et al. 2024) and a custom classifier. Training models to detect and classify arthropods requires a varied image dataset, so that the model will perform well under different field conditions, including diverse flower backgrounds, pollinator taxa, and lighting. Understanding the limitations associated with classifying our field images from this study has practical implications for defining realistic classes and setting appropriate expectations for the pollinator classifier that will process future cropped field images.

In the course of our fieldwork, we encountered several practical challenges that offered valuable lessons and highlighted areas for potential innovation. The following paragraphs outline these key observations.

One practical consideration is the security of our equipment. We acknowledge that camera trap theft and vandalism can be significant issues (e.g., Meek et al. 2019). However, due to our constant presence in the field, we did not experience any theft with our setup. Our workflow involves deploying smartphones during the day and retrieving them in the evening for charging. Locating a target flower and setting up a smartphone on a tripod takes only a few minutes. We didn't specifically test the upper limit, but it is feasible for a user to sequentially set up multiple smartphones, relocating them as each hour-long recording session ends, and continue this process throughout the day, allowing for necessary breaks. If needed, recording sessions could extend beyond an hour, allowing extra time for any other field work. Additionally, if theft remains a concern, research suggests that personal messages left on devices may reduce theft and vandalism (Clarin et al. 2014).

We did not experience any battery issues in the field. We used the phones for several hours each day, and we ensured that they were recharged at the end of each day. If energy consumption becomes an issue, the implementation of solar panels for smartphones as a solution has been recommended by Donovan et al. (2021).

Some of our smartphones shut down during extreme heat. Similarly, it has been reported that there is also a risk that they might not charge under high humidity conditions (pers. comm. Robert Tropek, Charles University, Prague). To mitigate the heat issue, we used white casings that reflect light (a simple solution we employed involved using a piece of paper). This issue may also arise in microcomputers, where heatsinks and coolers are essential to maintain the device at operational temperatures (e.g., Sittinger et al. 2024). Nevertheless, surveillance cameras designed for outdoor use appear to be more resilient to such conditions, though they are typically more expensive than smartphones (pers. comm. Robert Tropek, Charles University, Prague). Another potential solution could involve using casings, similar to those suggested by Donovan et al. (2021). These casings would not only protect the devices but also incorporate features for reflecting and dissipating heat, or even include coolers or heat sinks on the surface of the smartphones. Additionally, incorporating silica gels within these specialised cases offers an extra benefit, as they absorb moisture (e.g., Sittinger et al. 2024).

While it is tempting to increase the image resolution to the maximum offered by the smartphone model (e.g., Tab. 1), it is not advisable because storing a larger amount of data can become impractical for data transfer and logistics without providing additional taxonomic details, particularly if the focus is not sharp enough. Most images in our dataset (95.81%) were taken at a resolution of 1600 x 1200 pixels (Tab. 3). Generally, we envision that resolution ranges from 1000 x 1000 to 1200 x 1200 pixels (1 to 1.44 megapixels) is sufficient for capturing essential arthropod traits,

[2] https://beemachine.ai/
[3] https://www.inaturalist.org/computer_vision_demo
[4] https://www.inaturalist.org/pages/seek_app
[5] https://observation.org/apps/obsidentify/

provided that the arthropod is in focus and the smartphones are set no further than the recommended distance of 15-20 cm from the target flower.

The Open Camera app provides various custom features essential for our fieldwork, such as custom resolution, manual focus, custom time steps, automatic exposure, file format, image compression, and custom image folder naming. However, despite its versatility, Open Camera lacks the ability to define a rectangular region of interest (ROI). We were unable to find any open-source app for Android OS that combines this feature with the other requirements. Therefore, there is the necessity for an app feature that can capture images based on a predefined rectangular ROI that can be set at the beginning of the time-lapse session. This ROI should be adjusted to frame only the target flower or inflorescence, possibly including a buffer to account for wind movements, and minimise background noise. Establishing such a ROI ensures that the camera focuses on visiting arthropods, while also maximising their occupancy in the image, thereby facilitating localisation and identification.

Employing two distinct lenses per smartphone could be advantageous: one for capturing close-up images, providing greater detail for smaller arthropods (e.g., smaller than 2 cm); and another with a field of view or ROI configured to accommodate larger insects (e.g., larger than 2 cm). This approach can help ensure comprehensive image collection across a range of arthropod sizes. Furthermore, when selecting a smartphone for pollinator monitoring, we suggest to prioritise larger optical magnification (i.e., longer focal lengths) over high resolution sensors. The use of recent smartphone models, which are often equipped with 2X optical zoom lenses, is suggested. Digital zoom is not advisable due to the resulting information loss. An optical zoom allows for a reduction in background noise in the frame without the need to get too close to the flower, which may disturb the visitors.

There is also the potential in employing multiple smartphones per target flower to capture images of pollinators from different angles. However, such an approach would significantly increase the monitoring costs per flower. While we have not specifically tested this method, we believe the additional expense may not be fully justified by the benefits unless different types of lenses are being used. Using a single smartphone already enables capturing useful time-lapse images of pollinators from diverse angles as they move across the surface of the target flower. In instances where identification is challenging, such as with Dipterans, the most informative angle for identification has been one that allows observation of wing venation, typically from above and with minimal sunlight reflection. However, capturing images where wing venation is clearly visible posed a particular challenge, especially for small Dipteran individuals. Therefore, we envisage that more significant benefits might be derived from employing lenses with optical zoom on a second smartphone per target flower.

Data transfer directly from phones via USB cables was slow, prone to interruptions, and carries a risk of data loss. Such loss can occur when users mistakenly believe the data has already been downloaded and proceed to delete it from the phone to prepare for the next day. However, this issue is not unique to smartphones and can affect any camera system, unless streaming to a server is utilised where internet coverage is available in the field. To expedite data transfer, an alternative approach involved removing the micro SD card from the smartphone and uploading the data directly using a computer's microSD card reader. However, this method necessitated frequent opening and closing of the phone, increasing the risk of breaking the protective casing or causing other damage due to the repeated exposure of fragile components to sharp tools. More recent phone models might allow easier access to the SD cards and/or faster download speeds.

Affordable smartphones are generally slower at capturing images compared to devices like Raspberry Pi units. Although we configured the Open Camera app to capture an image every second, in practice, due to overheating or processing power limitations, smartphones struggled to maintain this rate. Instead, they typically captured images at a time step of 1.6 ± 0.4 seconds (mean ± S.D.), equivalent to an average frame rate of approximately 0.63 frames per second (fps), with a S.D. range from 0.5 to 0.83 fps. In contrast, microcomputers can rapidly capture dozens of images per second (e.g., Droissart et al.

2021; Sittinger et al. 2024) without requiring significant processing power. Nonetheless, even at reduced frame rates of capturing an image every 1.5 or 2 seconds, we were typically able to capture multiple images of each visiting individual, enabling taxonomists to identify arthropods by observing them from various angles. Furthermore, capturing flower-visiting arthropods at these intervals could also help estimate their abundance, particularly if a standardised protocol is used, such as monitoring the same plant species for the same duration, positioning smartphones at a consistent distance, and assigning a unique identifier to each visitor. Bjerge et al. (2022) reported on tracking individual insects at a frame rate of 0.33 fps (approximately one frame every 3 seconds) using a camera based on a Jetson Nano microcomputer, suggesting that our frame rate is likely sufficient for abundance estimates, which could be validated in future studies. Additionally, it is worth noting that reducing the time step to capture several frames per second would quickly exhaust the storage capacity of the micro SD cards on the smartphones. For example, with an image resolution of 1200 x 1200 pixels and assuming a JPG file format that allows 1 MB per frame, capturing at 2 frames per second could easily generate between 7 and 8 GB in just one hour.

Due to the time-lapse approach employed in capturing images, around 93% of the images in our dataset did not contain arthropods. It is customary to observe such results with time-lapse camera systems. For instance, Ruczyński et al. (2020), noted that over 90% of their captured photographs were devoid of arthropods. Ideally, a custom trigger for pollinators would help reduce the volume of stored data. However, several challenges exist, such as arthropods not emitting heat, often being too small to trigger motion sensors, or sensors being activated by wind movement. There are ongoing efforts to develop AI triggers for pollinators, which involve real-time AI pipelines (edge AI) powered by nano-GPUs in the field (e.g., Bjerge et al. 2022; Sittinger et al. 2024). Unfortunately, smartphones do not come yet with powerful GPUs like those found in Jetson Nano from NVIDIA (2019) or Coral microcomputers from Google (Coral 2020), which allow for edge AI (e.g., rapid arthropod detection on the device). However, fast on-device detection carries significant risks, as it may miss small species or any taxa that the AI was not trained on (Van Horn et al. 2018; van Klink et al. 2022). Another solution could involve processing images on the smartphone by running an AI model in the background (not in real-time) to discard images without pollinators. However, this may be too energy-intensive for longer recording sessions. Alternatively, images could be uploaded to a GPU server at the end of the fieldwork day, which offers superior detection and classification capabilities, though this would require a reliable internet connection.

With nearly all arthropods identified at the order level, our study suggests that the smartphone setup fixed above target flowers has the potential to be a useful tool for monitoring pollinators visiting flowers, particularly at coarse taxonomic levels. However, significant limitations remain for finer taxonomic identification. Hymenopterans that are known to pollinate could mostly be identified to the family level, with progressively reduced success at genus and species level. Dipteran identification works best when there are sharp photos of the wings, which was often not achieved with the smartphone setup. As a result, nearly 50% of the instances containing Diptera could not be identified to the family level. Thus, Dipterans could not be identified as well from images taken with the smartphone setup as Hymenopterans. Our identification process involved some subjectivity. Verification through methods such as microscopic examination or DNA analysis were not attempted in this study to test whether this subjectivity is problematic, and could be the topic of future research. In addition, future work that creates taxonomic keys based only on features that are visible from images is necessary to advance this field of study. Likewise, when finer taxonomic resolution is not possible from images, experts should group larger taxonomic groups into morphological clusters. Defining these categories provides a valuable framework for developing tailored AI classifiers for automated pollinator monitoring, considering the limitations of camera sensors in taxonomic identification. These categories and their identification process can be incrementally refined from coarse to finer taxonomic resolutions as imaging technology advances.

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AUTHOR CONTRIBUTION

Concept and design V.S., T.K.; Implementation: V.S.; Data collection and curation: V.S., A.W., J.C.C.; Species identification: A.W., J.C.C., D.R.; Analysis: V.S.; Writing: V.S. (lead author), T.K., A.W., J.C.C., D.R.; Edits and approval for publication: all authors. Funds acquisition: T.K., V.S.

DISCLOSURE STATEMENT

The authors declare no potential conflict of interest.

DATA AVAILABILITY STATEMENT

The image dataset associated with this research is available from the corresponding author upon reasonable request, owing to its substantial storage size. The remaining data for this study are published as supplementary material alongside the online version of this article. The image annotation data and the R code used for creating some of the figures and tables in this manuscript and appendices are available in our GitHub repository at: https://github.com/valentinitnelav/pollinator-image-annotation

APPENDICES

Additional supporting information may be found in the online version of this article:

Appendix Figure I. Frequency of images by hour of the day.

Appendix Table I. List of sites

Appendix Table II. Sampled plant species and number of annotated images.

Appendix Table III. Visible features for Hymenoptera.

Appendix Table IV. Visible features for Diptera.

Appendix Table V. Hymenoptera - counts of instances.

Appendix Table VI. Diptera - counts of instances.

Appendix VII. Fieldwork protocol.

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