

Contents lists available at ScienceDirect

# Global Ecology and Conservation



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

# Categorizing the songbird market through big data and machine learning in the context of Indonesia's online market

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## ARTICLE INFO

Keywords: Songbird Categorizing Machine learning Online market Wildlife trade

#### ABSTRACT

The songbird trade has been identified as a major threat to wild populations, and the bird market has now expanded to online platforms. The study explored the use of machine learning models as a monitoring framework; developed models for taxa identification; applied the best model to understand the current market situation (taxa composition, asking price, and location); and conducted a survey to understand the profile of sellers. The authors found that the machine learning models produced a high level of accuracy in distinguishing relevant ads and identified the songbirds' taxa. The Support Vector Machine (SVM) was selected as the best model and was used to predict the ad population. The model identified 284,118 songbirds from 247 taxa that were listed online from April 2020 to September 2021. The authors also found that 6.2% of ads listed threatened taxa based on the IUCN Red List. The survey results suggested that songbird sellers are mostly hobbyists or breeders looking for extra income from selling birds. As current studies of the songbird market are mostly conducted offline in the bird markets, transactions by non-bird traders or among hobbyists in the online market are remain underreported. Therefore, monitoring needs to be extended to the online market and to our knowledge, currently there is no applied system or platform is identified for monitoring online songbird market. The result from this study can help fill this gap. Information from the monitoring of the songbird online market in this study may assist stakeholders in formulating corrective action based on the current market situation.

# 1. Introduction

The wildlife trade is a multibillion-dollar business (Scheffers et al., 2019; Verissimo and Wan, 2019) and is known to be a major threat to species extinction, besides habitat loss (Collar et al., 1996; Collar and Juniper, 1991; Harris et al., 2017; Jepson et al., 2011; Jepson and Ladle, 2005; Nijman et al., 2018; Wright et al., 2001). It also raises concerns about the risk of disease and the introduction of invasive species (Smith et al., 2009). Among terrestrial vertebrates, birds are a major component of the wildlife trade (Scheffers et al., 2019). The keeping of songbirds has been part of local culture and tradition in many regions of Southeast Asia, and the trade involves millions of individual birds from hundreds of species annually (Lee et al., 2016). Indonesia is a major regional market with high demand for songbirds as pets and for songbird competitions, involving hundreds of bird species, including globally threatened ones (Chng et al., 2015; Chng and Eaton, 2016; Harris et al., 2017; Lee et al., 2016; Nijman, 2010). It was revealed in several studies

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https://doi.org/10.1016/j.gecco.2022.e02280

Received 4 May 2022; Received in revised form 21 August 2022; Accepted 2 September 2022

Available online 5 September 2022

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that the demand of caged birds in Indonesia, especially songbird species, linked to decrease of threatening species in nature. This phenomenomen called as Asian Songbird Crisis that led into various conservation initiatives for species in concern (Sykes, 2017). Most of the songbird trade is in the domestic market but also involves other countries in the region (Chng et al., 2015; Leupen et al., 2018). Indonesia is the largest importer and exporter of wild bird in Asia (Harris et al., 2017) and official export data shows that bird export value is increasing significantly in 2021 from 2016 that indicates that the trade volume to international market is growing (Ministry of Environment and Forestry, 2022). CITES database (https://trade.cites.org/) recorded that during 2012–2021, around 99% exported bird from Indonesia was in living form, although major species are not songbird species. On the other hand, the study on the seizure reports in Indonesia indicates that illegal trafficking of bird species to or from Indonesia is still ongoing, including songbird species (Indraswari et al., 2020).

The songbird trade is also evolving from physical marketplaces to online platforms (Harrison et al., 2016; Lee et al., 2016; Leupen et al., 2020; Shepherd et al., 2020). A recent household survey indicated that 12–21% of bird keepers use online platforms to buy songbirds (Marshall et al., 2020a). The songbird market's extension to online platforms, in which regulation for online trade is unclear (Iqbal, 2015), can potentially threaten any number of Indonesian species in the future due to uncontrolled trade (Bušina et al., 2018). Current studies and songbird market monitoring are conducted mostly in physical bird markets and in large cities (Chng et al., 2015, 2018; Chng and Eaton, 2016; Nijman et al., 2021; Rentschlar et al., 2018; Yohanna et al., 2021). As a result, the songbird trade outside physical bird markets is not captured in the observational data.

The expansion of the songbird market to online platforms also presents an opportunity to conduct big data analysis. This enables machine learning algorithms to uncover more fine-grained patterns and to make more timely and accurate predictions (Zhou et al., 2017). Raw information from advertisements cannot be directly linked to the songbird taxa, is unstructured and does not use standard language, for example most of bird names used in the advertisement are using slang or local names. Therefore, a further process in classifying songbird taxa was necessary. With the large volume of information that needs to be classified, machine learning tools can provide an automated classification with a high level of accuracy, as shown in other research, and are suitable for long-term monitoring to explore the supply chain and the actors involved (Di Minin et al., 2018, 2019; Fink et al., 2021; Jeawak et al., 2018; Stringham et al., 2021).

In this study, the authors explore an automated approach to classifying songbird species from online ads through the use of machine learning algorithms, applying the best selected model to understand the songbird online market and the characteristics of the bird sellers. Information on the composition and volume of species, and where they are traded, is highly valuable for conservation research and practice (Scheffers et al., 2019). An efficient and reliable monitoring framework is an important part of conservation strategies (Lee et al., 2016), and the model developed in this study can be a useful framework for monitoring the market, while helping reduce the risk of species extinction from the wildlife trade. Information on sellers' profiles can be used to target the appropriate audience when promoting sustainable wildlife trade (Marshall et al., 2020a; Verissimo et al., 2012). Thus, results from this study are relevant and could contribute to current conservation strategies.

# 2. Methods

#### 2.1. Data collection and preparation

We were collecting listings of songbird advertisement from an online marketplace in Indonesia that publicly available without further authentication or registration. The authors developed a Python-based web-scraping tool to collect all listing under bird category from the online marketplace. Information from the ads included titles that indicated the species, along with the asking prices and seller locations. For the model development, 35% of monthly ads from April 2020 to June 2021 were selected randomly. Pre-processing is an important component of a typical text-classification framework and may significantly improve the classification accuracy (Uysal and Gunal, 2014). To prepare clean text for the models, the authors converted text into lowercase and replaced the signs "+" and "&" with the word "and," and replaced all punctuation with a space. After looking at the dataset and finding a lot of words that were accidentally connected with punctuation from the models at the same time. The stop-word list for taxa classification models was also applied. As the words in the ads were written in *Bahasa* (Indonesian language) and were not standard – with a lot of abbreviations, misspellings and local terms relating to birds – the authors developed a stop-word list by generating a list of words from the ads and manually selecting those that were not related to the taxa names.

#### 2.2. Taxa classification model

For this study, songbirds are defined as passerine bird species and other birds that commonly participate in singing contests. These include Lovebirds (*Agapornis spp.*), various doves, and non-passerines that are known as master birds for competitive taxa, such as Kingfishers and Woodpeckers. However, in developing the machine learning model, the authors labelled and trained all listed birds to extend the model's ability, then filtered the ads using the songbird definition for further analysis.

Songbird taxa identification from the advertisements is comprised of two steps. In the first step, a model is developed to remove from the listing any nonrelevant ads, such as those relating to cages, feed and bird's accessories, as well as want-to-buy ads. The authors manually labelled the records into not relevant, wanted and relevant ads, using original text written in the title of the ads that have been pre-processed for this classification. The second step is taxa classification, which involves using only relevant ads from the first step and applying the stop-word list. In taxa identification, the record was labelled using the name lists from the Handbook of the

Birds of the World (HBW and BirdLife International, 2021) and the List of Indonesian Birds (Sukmantoro et al., 2007). The authors also labelled ad records that did not mention any taxa name as "Unknown" and removed from the training dataset those that had more than one taxon. As most taxa were listed using local names or trade names, the authors consulted local well-known songbird communities' websites, and compare the images from the listing with images from birdsoftheworld.org to identify the taxa scientific name. Taxonomy follows (del Hoyo and Collar, 2014, 2016).

For both steps, the authors used supervised machine-learning algorithms of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), the Naive Bayes classifier, the Random Forest technique, Support Vector Machines (SVM), and Linear Regression. All model development was performed in Python using the PyTorch (Paszke et al., 2019) and Scikit-learn library (Pedregosa et al., 2011).

#### 2.3. Model performance assessment

Labelled datasets were split into three with the following proportions: 80% for the training dataset, 10% validation dataset and 10% for the test dataset. The training dataset was used to train and make the model learn the patterns repeatedly, and continue to learn the features of the data. Validation processes evaluate the model performance during training and provide information that will be used to tune the model's hyperparameters and configurations. The model performance was later tested using the test dataset to provide unbiased final model performances. Splitting the dataset is important to prevent the model from overfitting and to accurately predict input that has not been introduced previously in the training and validation processes (Duda et al., 2000; Hastie et al., 2009). The number obtained from the test was used as an estimator of the true error of the learned predictor (Shalev-Shwartz and Ben-David, 2014). The authors used the Stratified Shuffle Split-Test Cross-Validation method. This is a combination of StratifiedKFold and ShuffleSplit that returns stratified randomized folds. Stratified splitting was used as the authors found imbalanced data distribution, and this method divides the dataset to maintain the proportion in each subset. Cross-validation is used to estimate the model performance in relation to the independent dataset when applied to the real world.

#### 2.4. Taxa composition, spatial distribution and asking prices of songbird ads in the online market

The best machine-learning model was used to classify all listings from the ad database. The authors used a longer observation period of 18 months from April 2020 to September 2021 for the total ad population to optimize their understanding of the songbird market. Each ad's location was extracted to capture the spatial distribution at provincial level. To remove outliers in the asking price, the authors applied a common method that uses the Z-score approach. Any Z-score greater than 3 or less than -3 were considered outliers and removed. For more understanding of the current threat to songbirds, the authors linked the name list to the recent IUCN Red List of Threatened Species (HBW and BirdLife International, 2021).

#### 2.5. Online seller characteristics and preferences

The authors selected respondents from the ad population using a simple random sampling technique. The process of selecting and contacting respondents continued until a predetermined number of surveys was reached in order to ensure a representative sample with a 5% margin of error at the 95% confidence level (Newing, 2010). Data were collected on demographic profiles and online market experience. Respondents who were selling native taxa were also asked about the songbird origin and their origin preferences. Respondents were contacted through the information provided in the online marketplace and were asked about their willingness to participate in the survey. Enumerators always received prior informed consent from respondents, and all data were anonymized.

#### 3. Results

#### 3.1. Taxa classification model

The authors manually labelled 104,957 listings and found 93% were relevant. All models showed a high level of accuracy in predicting relevant and nonrelevant ads. The models were able to classify these listings with a very high degree of accuracy, ranging from 97.1% to 99.2%. However, as the training data for relevant and nonrelevant ads were imbalanced, the authors also considered the

Table	1

Relevant and nonrelevant model	performances	(Step 1).
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Model	Accuracy	Precision	Recall	F1-score
SVM	0.992	0.902	0.872	0.887
Linear regression	0.989	0.647	0.636	0.642
ANN	0.988	0.650	0.629	0.639
GRU	0.988	0.637	0.643	0.640
Naive Bayesian	0.988	0.823	0.749	0.779
CNN	0.985	0.975	0.653	0.691
LSTM	0.978	0.596	0.645	0.618
Random forest	0.971	0.647	0.543	0.583

score from the precision, recall and F1-score to decide on the best model to use for the first step. The Support Vector Machines (SVM) model was found to be the outperformer and was selected as the best one for the first step. Even though SVM had a lower precision score than the Naive Bayesian classifier, the recall and F1-score of SVM was higher. This means the false positive number of SVM was lower than that of the Naive Bayesian and was better in identifying the false positive. The detailed performance of each model is shown in Table 1.

In the second step, the authors manually labelled 97,553 ads from 317 taxa and ran the model from 97,349 ads after removing the records with multiple taxa. As result, all the models performed very well for identifying taxa, with accuracy ranging from 95.6% to 97.5%. As in the first step, the SVM model proved to be the most accurate. A detailed performance of each model is shown in Table 2.

#### 3.2. Taxa composition, spatial distribution and asking prices

From the classification result on the total ad population, the authors found 326,201 records of relevant ads consisting of 284,118 songbirds and 24,608 non-songbird taxa based on the above-mentioned definition; 3351 ads from chickens and ducks; and 13,944 ads were unknown taxa. The details are provided in Appendix A. The authors identified 247 songbirds' taxa from 49 families, where 80% of taxa were native. The five most-listed taxa that represented 68% of ads were the Lovebird (*Agapornis spp.*) with 30.1%, followed by the White-rumped Shama (*Kittacincla malabarica*) with 14.7%, Canaries (*Serinus spp.*) with 14.7%, Zebra Dove (*Geopelia striata*) with 4.2%, and Oriental Magpie-robin (*Copsychus saularis*) with 4.1%. From the model result, we found 21 taxa is known as songbird competitive taxa and 63 taxa known as master bird.

The ads were recorded from 249 districts and 32 provinces in Indonesia. Java is the center of the songbird online trade, with more than 91% of ads coming from this island, followed by Sumatra with a share of 5.76%, Bali and Nusa Tenggara with 1.4%, Kalimantan with 1.5%, Sulawesi with 0.1%, and a very small number from the Maluku and Papua regions. On average, there were about 15,784  $\pm$  4006 ads listed monthly and the 2021 trend showed a decline from the year before. (Figs. 1–3).

From the results, the authors found that 18,073 ads – or about 6.2% of total songbird ads – listed threatened species from 14 taxa, including from non-native taxa. About 1.7% of ads listed vulnerable taxa (VU), while endangered taxa (EN) accounted for 0.9%, and critically endangered species (CR) were in 3.6% of ads. The Javan pied starling (CR) was the most listed threatened species, with 2.6% of ads, followed by the Javan myna (VU) with 1.1%, the Straw-headed Bulbul (CR) with 0.9%, Red Siskin (EN) with 0.7%, and Greater-green leafbird (VU) with 0.7% of ads. These five taxa represented 94% of the total threatened species listed in the online marketplace. The authors also found 3.5% of ads listing near-threatened species (NT).

The details for Fig. 4 are provided in Appendix B. The songbird with the highest asking price was the Straw-headed Bulbul (*Pycnonotus zeylanicus*) with a mean asking price of USD 709  $\pm$  362. But, in general, non-native taxa had higher mean asking prices such as (*Garrulax canorus*) with USD 305  $\pm$  159, the European Goldfinch (*Carduelis carduelis*) with USD 253  $\pm$  109, Hooded Siskin (*Spinus magellanicus*) with USD 250  $\pm$  131, and Black-throated Laughingthrush (*Garrulax chinensis*) with USD 249  $\pm$  92. From native taxa, there was the Bali Myna (*Leucopsar rothschildi*) with a mean asking price of USD 248  $\pm$  117, which was the second-highest mean asking price after the Straw-headed Bulbul. The songbirds with the lowest mean asking price were the Brown-throated Sunbird (*Anthreptes malacensis*) with USD 7  $\pm$  5 and Scaly-crowned Babbler (*Malacopteron cinereum*) with USD 7  $\pm$  2, both of which are native taxa.

### 3.3. Online seller characteristics and preferences

With a survey response rate of 14%, the authors surveyed 404 respondents. Based on the database population of 284,118 ads, the margin of error was about  $\pm$  5% with a 95% confidence level (Newing, 2010). Around 96% of respondents were male with ages ranging from 17 to 68 years old and the highest distribution in class age between 31 and 40 years old. Most respondents lived in urban communities and had a high-school education or higher (94%). Of all respondents, only 7% were bird traders, the term used for respondents whose main livelihood was selling birds. (Figs. 5–7).

Most respondents have quite a lot of experience selling songbirds through online platforms. About 51% of respondents had 2–5 years' experience, and 19% had been selling for more than 5 years. As much as 92% of respondents had at least some transaction success, with 58% claiming they often succeeded in selling and 18% saying they always succeeded in selling birds through the online platform. Overall, 95% of respondents said they had experience with buyers from the same city, and 60% from different cities on the same island. The authors also found that 6% of respondents had experience selling birds to another island and 1% of respondents

Table 2	
Taxa classification model performances (S	Step 2).

Model	Accuracy	Precision	Recall	F1-score
SVM	0.975	0.896	0.861	0.872
Linear regression	0.973	0.917	0.856	0.878
ANN	0.971	0.912	0.855	0.875
GRU	0.970	0.895	0.837	0.856
Naive Bayes	0.968	0.774	0.770	0.764
CNN	0.967	0.892	0.802	0.833
LSTM	0.966	0.858	0.835	0.842
Random forest	0.956	0.730	0.697	0.702

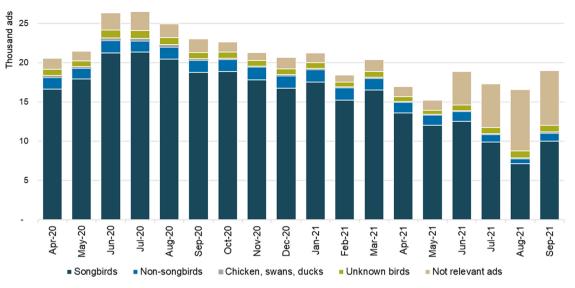
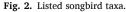


Fig. 1. Distribution of online market ads in the observation period.





selling overseas. Cash on delivery (COD) was the most common method (94%) used for transactions. The motivations for selling the birds included: (a) bird traders pursuing their main livelihood, (b) to earn extra income, (c) to make bird sales from breeding, (d) the desire for a change of bird, either to the same species or a different species, and (e) to reduce the number of birds the sellers owned. The

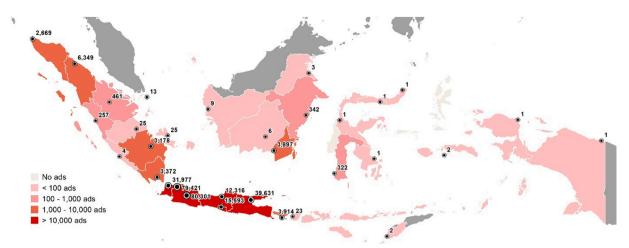


Fig. 3. Spatial distribution of songbird ads (by province).

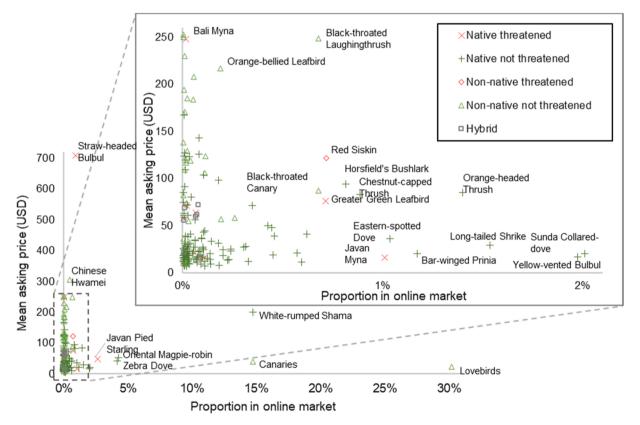
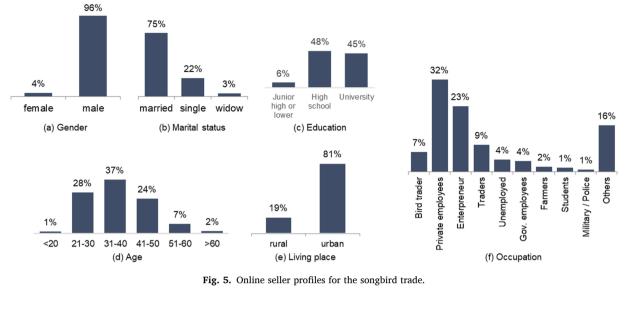


Fig. 4. Taxa compositions with distribution of mean asking prices in online market.

reasons for using online marketplace included: (a) to reach more potential customers, (b) to sell the birds relatively fast, and (c) the online market is simple and easy to use.

The authors asked the respondents selling native taxa songbirds about the listed songbirds' origin. About 79% said they were the captive-bred, 14% were wild-caught and the rest said they did not know where the birds came from. Around 71% of bird traders preferred to sell captive-bred songbirds, 11% preferred wild-caught ones, and 18% had no preference. As the non-trader respondents were hobbyists and breeders, the authors also asked about the origin they preferred. About 81% said they preferred captive-bred birds, 3% preferred wild-caught and 16% had no preference. Around 62% of respondents were breeders, most of whom bred non-native species, such as Lovebirds and Canaries, while 8% of respondents were also poachers. About 45% of respondents had participated in songbird singing competitions.







# 4. Discussion

The study demonstrated that machine learning is very effective in monitoring the songbird trade in the online market. Regular monitoring is crucial to understand market dynamics and species composition, and results from the study's model could provide such data in an automated manner. The model could accurately and quickly identify hundreds of songbird taxa listed in the online marketplace. However, this model is having limitation in predicting total number of listed individuals. The model can only predict one individual per ad record while the authors found there are ads that listing more than one individual per record. In the labelling process, the authors found less than 1% of ad records with more than one individual in an ad. The model prediction is also limited to the list of taxa provided in training datasets.

In general, the taxa composition in the online marketplace was relevant to taxa abundance of the caged bird inventory results from the recent study of Marshall et al. (2020b). Popular taxa, such as Lovebirds, Canaries, Zebra Doves, White-rumped Shama, and Oriental Magpie-robin dominate the online market. The domination of non-native taxa, such as Lovebirds and Canaries, was likely because they are known to be profitable and are easy to breed and sell (Marshall et al., 2020a). The survey also indicated most breeder respondents bred these two taxa. However, although species trend is relevant with existing caged bird inventories in Marshall et al. (2020b)., our results here may not reflect the actual condition in physical markets and we consider our result as complementary data to existing data from physical market survey.

The results confirmed that Java is the largest online songbird market which relevant with the fact that songbird trade at physical bird market in Java are more abundant and larger than any other places in Indonesia. The popularity of songbird trade in Java Island is also relevant with songbird-keeping culture and rise of songbird competition in Java. The trend of using online platforms to sell songbirds in Java is consistent with the results of Yahya and Sugiyanto (2020), showing that people who lived in Java, particularly in urban areas, were more likely to shop online. In the future, when the gap across regions narrows as the digital economy and tele-communications infrastructure develop, more songbird ads may be placed from outside Java. This also means the market for wild-caught birds – mostly supplied from regions outside Java, as indicated by studies from Bušina et al. (2018) and Rentschlar et al. (2018), – will be bigger and increase the threat to the wild population.

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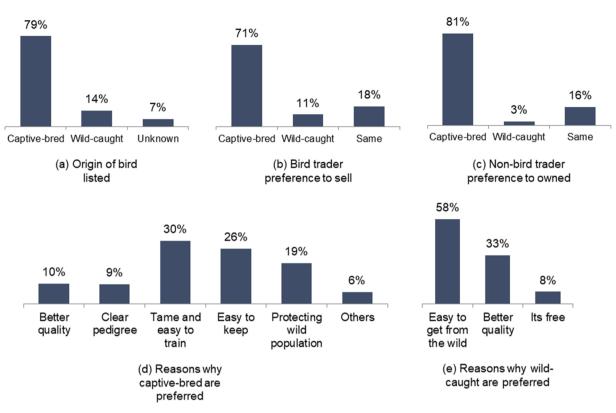


Fig. 7. Songbird origin, respondent preferences and reasons.

Overall, the asking price for each taxon was varied for many reasons. It sometimes included a cage, offered multiple individual birds in an ad, the songbirds' sex, and maturity. Rare conditions, like albinism and individual achievement, also made the asking price range can be very wide. Sub-species also create differences in the asking price, as found in Horsfield's Bushlark (*Mirafra javanica*) where *Mirafra javanica javanica* had a higher price than *Mirafra javanica parva*.

In economic theory, supply and demand influence the price, and taxa rarity will likely increase prices. The top list of songbirds with high asking prices is dominated by non-native taxa, except for Lovebirds and Canaries. Limited supply and import quotas for these taxa might lead to restricted stock in the market, as indicated by the low number of ads in the online market, and mean the asking prices from this group are high. For native taxa, the authors found that songbirds with high asking prices were threatened species and popular taxa for songbird competitions. However, the status of threatened species – which indicates a threat and low abundance in the wild population – is not always related to the asking price, as shown in the study. Several native threatened species had relatively low asking prices, such as the Ruby-throated Bulbul (VU) with USD  $14 \pm 10$ , Javan Myna (VU) with USD  $16 \pm 10$ , the Java Sparrow (EN) with USD  $16 \pm 10$ , and the Javan White-eye (EN) with USD  $21 \pm 17$ . This shows that the anthropogenic Allee effect (Courchamp et al., 2006), where the taxa rarity increases the economic value, did not affect all threatened songbird species. In this case, the songbird keeper's preference, that set the characteristic of supply in the online market, probably contributes more to determining the market prices rather than conservation status.

Songbird singing contests are considered one of the reasons for the increased of songbird trade and lead to the declining of wild population. The promotion of singing competitions between captive-bred birds has been recommended to reduce the demand for native species from wild-caught taxa, such as the White-rumped Shama (Burivalova et al., 2017). However, songbird competitions not only threaten the competitive taxa but also other non-competitive taxa that are used as master birds, which train the competitive taxa to imitate songs. The authors found a lot of ads mentioning this term. Master birds have less concern compared with the competitive taxa, and several master bird taxa are facing a serious threat of extinction in the wild – such as the Black-winged Starling (CR), Javan Green Magpie (CR), Java Sparrow (EN) and Ruby-throated Bulbul (VU) – or are known to have a seriously declining wild population, such as the Crested Shrikejay (NT) and the Yellow-throated Hanging-Parrot (NT).

The study shows online seller respondents are mainly middle-aged males who live in urban areas and had a high-school or university education. Most of them were hobbyists selling songbirds for some extra income and had been using online platforms for quite a long time. They often succeeded in selling songbirds and thought that the online marketplace was an effective and easy-to-use way to reach potential customers. The risk of fraud in using the online market was minimized by paying COD, whereby the buyer meets the seller directly before doing the transaction. But many of them also carried out online transactions based on trust. Few of them regularly conduct international trade with neighboring countries, such as Thailand and Malaysia. The study suggests that the major demographic group of songbird online sellers is also the major Internet user group in Indonesia. However, this condition is not reflecting

condition in physical bird market because there are sellers or hobbyist that not willing nor able to use online marketplace for selling bird. Nevertheless, raising awareness about the risk of songbird extinction and promoting sustainable songbird trade through online media will encourage the target audience to help reduce the risks from the wildlife trade.

The survey results showed the songbirds listed were mostly captive-bred and were preferred for sale and ownership. The authors also found 19% of respondents said protecting the wild population from extinction was the reason why they preferred captive-bred songbirds. However, a low response rate in the survey can give rise to sampling bias. The authors also considered the possibility that contacted sellers who refused to be a respondent were reluctant to participate because they were selling wild-caught songbirds. Most online sellers who were willing to be respondents were selling captive-bred songbirds. Questions about sensitive information, such as songbird origin, may also cause reluctant respondents to rush through the survey as quickly as possible, leading to poor and inaccurate conclusions (Tourangeau et al., 2010).

Online platforms are expanding the songbird market. The authors found 93% of respondents were hobbyists or breeders who sold birds to earn extra income or to exchange their pet. Since most current studies of the songbird market were conducted in physical bird markets (Chng et al., 2015, 2018; Chng and Eaton, 2016; Nijman et al., 2021; Rentschlar et al., 2018; Yohanna et al., 2021), transactions by the non-bird traders or among hobbyists or breeders were missing from the observational data. The survey results on respondents' experience of successful transactions and how the respondent could reach buyers from other cities or even other countries suggest that the online marketplace has potential and will likely continue to grow. This means market monitoring also needs to be extended to the online market and, as far as the authors are aware, there no applied system or platform is identified for monitoring online songbird market to date. As the study indicates, since a lot of threatened taxa are listed, a monitoring platform is urgently needed. Realistically, Indonesia's bird trade is too economically and culturally important to be stopped completely (Marshall et al., 2020a, 2020b). Therefore, a robust and effective monitoring platform is needed to support a sustainable songbird trade, and this study has demonstrated a monitoring framework that can meet this need. However, data collection using web-scrapping should consider also the context of the privacy data policy in the source website and the country where the location of research is implemented. Privacy policy may restrict the disclosure of information, although the information is public and personally provide by people in the online platform.

#### 5. Conclusions

The authors' model has demonstrated that machine learning is viable to monitor the songbird online market. All the tested models showed a high level of accuracy in distinguishing relevant ads, and identified SVM as the best performing model. Based on the model prediction result from the ad population, the composition of songbird species in the online market is closely related to the caged bird abundance in the physical market. The trend is similar, but our results are not representing the number of trade in actual physical market. Beside the species composition, further analysis of advertisement data also able to provide information related to geographical condition, selling price, and seller information. These information is important as overview of online market condition for monitoring purposes. Since online platforms are a promising marketing channel for selling songbirds based on respondents' survey, a monitoring framework is needed to support the sustainable trade of songbirds. Coupled with big data analysis, the machine learning model in this study offers an effective way to regularly monitor the online songbird market and provides updated market data as input for stake-holders to assess existing conservation strategies and to formulate corrective action, if necessary.

# Funding

This output has been funded in whole or part by the UK Research and Innovation's Global Challenges Research Fund (UKRI GCRF) under the Trade, Development and the Environment Hub project (project number ES/S008160/1).

#### **Declaration of Competing Interest**

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

# Data Availability

Data will be made available on request.

#### Appendix A. Full list of taxa listed in online marketplace

No	Common Name	Scientific Name	IUCN Status	Num of listed	% of listed
1	Lovebirds*	Agapornis spp.	Х	85,740	30.18
2	White-rumped Shama	Kittacincla malabarica	LC	41,877	14.74
3	Canaries*	Serinus spp.	Х	41,868	14.74

# (continued)

lo	Common Name	Scientific Name	IUCN Status	Num of listed	% of liste
ļ	Oriental Magpie-robin	Copsychus saularis	LC	12,029	4.23
	Zebra Dove	Geopelia striata	LC	11,795	4.15
	Javan Pied Starling	Gracupica jalla	CR	7424	2.61
	Sunda Collared-dove	Streptopelia bitorquata	LC	5715	2.01
	Yellow-vented Bulbul	Pycnonotus goiavier	LC	5617	1.98
	Long-tailed Shrike	Lanius schach	LC	4364	1.54
)	Orange-headed Thrush	Geokichla citrina	LC	3983	1.40
1	Bar-winged Prinia	Prinia familiaris	NT	3334	1.17
2	Eastern Spotted Dove	Spilopelia chinensis	LC	2943	1.04
3	Javan Myna	Acridotheres javanicus	VU	2870	1.01
4	Straw-headed Bulbul	Pycnonotus zeylanicus	CR	2654	0.93
5	Chestnut-capped Thrush	Geokichla interpres	NT	2520	0.89
5	Horsfield's Bushlark	Mirafra javanica	LC	2321	0.82
7	Red Siskin*	Spinus cucullatus	EN	2038	0.72
8	Greater Green Leafbird	Chloropsis sonnerati	VU	2035	0.72
9	Black-throated Canary*	Crithagra atrogularis	LC	1933	0.68
0	Black-throated Laughingthrush*	Garrulax chinensis	LC	1932	0.68
l	Brown-cheeked Bulbul	Alophoixus bres	LC	1767	0.62
2	Sooty-headed Bulbul	Pycnonotus aurigaster	LC	1691	0.60
3	Black-throated Prinia	Prinia atrogularis	LC	1624	0.57
4	Black-naped Oriole	Oriolus chinensis	LC	1303	0.46
5	Chinese Hwamei*	Garrulax canorus	LC	1288	0.45
5	Common Iora	Aegithina tiphia	LC	1287	0.45
7	Olive-winged Bulbul	Pycnonotus plumosus	LC	1271	0.45
8	Hill Blue-flycatcher	Cyornis banyumas	LC	1211	0.43
9	Starlings	Sturnus spp.	X	989	0.35
0	Ashy Tailorbird Timor Zebra Finch	Orthotomus ruficeps	LC	938	0.33
1		Taeniopygia guttata	LC	896	0.32
2	Common Myna	Acridotheres tristis	LC	868	0.31
3	White-rumped Seedeater*	Crithagra leucopygia Garrulax mitratus	LC NT	744 686	0.26 0.24
4 5	Chestnut-capped Laughingthrush		LC	682	0.24
	Purple-throated Sunbird Great Tit	Leptocoma sperata	LC	661	0.24
6 7	Plain Prinia	Parus major	LC		
7 8	White-rumped Munia	Prinia inornata Lonchura striata	LC	639 578	0.22 0.20
9	Asian Glossy Starling	Aplonis panayensis	LC	575	0.20
0	Yellow-fronted Canary*	Crithagra mozambica	LC	544	0.20
1	Orange-bellied Leafbird*	Chloropsis hardwickii	LC	542	0.19
2	Scarlet-headed Flowerpecker	Dicaeum trochileum	LC	522	0.19
3	Bare-throated Whistler	Pachycephala nudigula	LC	511	0.18
3 4	Fulvous-chested Jungle-flycatcher	Cyornis olivaceus	LC	509	0.18
5	Pied Bushchat	Saxicola caprata	LC	406	0.13
5	Common Tailorbird	Orthotomus sutorius	LC	403	0.14
7	Eurasian Tree Sparrow	Passer montanus	LC	389	0.14
, 8	Orange-spotted Bulbul	Pycnonotus bimaculatus	NT	386	0.14
9	Asian Golden Weaver	Ploceus hypoxanthus	NT	353	0.14
)	Laughingthrushes*	Garrulax spp.	X	322	0.12
1	Gouldian Finch*	Chloebia gouldiae	NT	318	0.11
2	Brown-throated Sunbird	Geokichla dohertyi	LC	314	0.11
3	Chestnut-backed Thrush	Anthreptes malacensis	NT	314	0.11
, 1	Javan Fulvetta	Alcippe pyrrhoptera	LC	314	0.11
5	Java Sparrow	Lonchura oryzivora	EN	305	0.11
5	Asian Fairy-bluebird	Irena puella	LC	302	0.11
7	Blue-and-white Flycatcher	Cyanoptila cyanomelana	LC	296	0.10
8	Hooded Pitohui	Pitohui dichrous	LC	296	0.10
) )	Lesser Green Leafbird	Chloropsis cyanopogon	NT	293	0.10
)	Oriental White-eye	Zosterops palpebrosus	LC	289	0.10
Ĺ	Grosbeak Starling	Scissirostrum dubium	LC	288	0.10
2	Sunda Laughingthrush	Garrulax palliatus	NT	274	0.10
3	Blue-masked Leafbird	Chloropsis venusta	NT	268	0.09
4	Streaked Bulbul	Ixos malaccensis	NT	264	0.09
5	White-headed Munia	Lonchura maja	LC	264	0.09
5	Ruby-throated Bulbul	Pycnonotus dispar	VU	260	0.09
7	Hybrid Eastern-spotted Dove x Sunda Collared-dove	,	x	250	0.09
3	Javan Leafbird	Chloropsis cochinchinensis	NT	241	0.08
) )	Hooded Butcherbird	Cracticus cassicus	LC	235	0.08
0	Crested Jay	Platylophus galericulatus	NT	231	0.08
1	Oriental Reed-warbler	Acrocephalus orientalis	LC	221	0.08
	Hybrid Red Siskin x Island Canary	· · · · ·	NR	216	0.08
2	Trybrid Red Siskin x Island Ganary				

# (continued)

No	Common Name	Scientific Name	IUCN Status	Num of listed	% of list
74	Scarlet Minivet	Pericrocotus flammeus	LC	210	0.07
75	Black-headed Bulbul	Brachypodius atriceps	LC	206	0.07
76	Hybrid Black-throated Canary x White-rumped Seedeater		NR	203	0.07
7	Javan Grey-throated White-eye	Heleia javanica	LC	203	0.07
8	Javan Munia	Lonchura leucogastroides	LC	194	0.07
'9	Hybrid Black-throated Canary x Island Canary		NR	186	0.07
0	Black-winged Myna	Acridotheres melanopterus	CR	185	0.07
1	Racquet-tailed Treepie	Crypsirina temia	LC	182	0.06
2	Orange-banded Thrush	Geokichla peronii	NT	181	0.06
3	Blue Whistling-thrush	Myophonus caeruleus	LC	180	0.06
4	Chestnut-crested Yuhina	Yuhina everetti	LC	180	0.06
5	Purple-backed Starling	Agropsar sturninus	LC	177	0.06
6	Javan White-eye	Zosterops flavus	EN	173	0.06
7	Black-collared Starling*	Gracupica nigricollis	LC	163	0.06
8	Lesser Shortwing	Brachypteryx leucophris	LC	163	0.06
9	Drongos	Dicrurus spp.	Х	162	0.06
0	Velvet-fronted Nuthatch	Sitta frontalis	LC	152	0.05
1	Spot-throated Babbler*	Pellorneum albiventre	LC	151	0.05
2	White-breasted Woodswallow	Artamus leucoryn	LC	143	0.05
3	Silver-eared Mesia	Leiothrix argentauris	LC	127	0.04
4	Red-billed Leiothrix*	Leiothrix lutea	LC	118	0.04
5	Lesser Racquet-tailed Drongo	Dicrurus remifer	LC	110	0.04
6	Mangrove Blue-flycatcher	Cyornis rufigastra	LC	103	0.04
7	Scaly-crowned Honeyeater	Lichmera lombokia	LC	99	0.03
8	Ashy Drongo	Dicrurus leucophaeus	LC	96	0.03
9	Red Avadavat	Amandava amandava	LC	96	0.03
00	Chestnut-capped Babbler	Timalia pileata	LC	94	0.03
01	House Crow	Corvus splendens	LC	93	0.03
02	Zitting Cisticola	Cisticola juncidis	LC	86	0.03
03	Finches*	-	Х	85	0.03
04	Long-tailed Sibia	Heterophasia picaoides	LC	83	0.03
05	Mugimaki Flycatcher	Ficedula mugimaki	LC	83	0.03
06	Hair-crested Drongo	Dicrurus hottentottus	LC	81	0.03
07	Streaked Weaver	Ploceus manyar	LC	81	0.03
.08	Javan Bulbul	Ixos virescens	LC	80	0.03
09	Woodpeckers		X	79	0.03
10	Thick-billed White-eye	Heleia crassirostris	LC	77	0.03
11	Helmeted Friarbird	Philemon buceroides	LC	75	0.03
12	Pin-tailed Parrotfinch	Erythrura prasina	LC	75	0.03
13	Horsfield's Babbler	Malacocincla sepiaria	LC	73 71	0.03
14	Indigo Flycatcher	Eumyias indigo	LC	69	0.02
14	Sulawesi Myna	Basilornis celebensis	LC	68	0.02
16	Calandra Lark*		LC	67	0.02
		Melanocorypha calandra			
17	Blue Nuthatch	Sitta azurea	LC	66	0.02
18	Common Flameback	Dinopium javanense	LC	66	0.02
19	Oriental Skylark*	Alauda gulgula	LC	66	0.02
20	Sunda Pygmy Woodpecker	Picoides moluccensis	LC	66	0.02
21	Black Drongo	Dicrurus macrocercus	LC	64	0.02
22	Chestnut-backed Scimitar-babbler	Pomatorhinus montanus	LC	64	0.02
23	Ruby-cheeked Sunbird	Chalcoparia singalensis	LC	61	0.02
24	Crested Myna*	Acridotheres cristatellus	LC	60	0.02
25	Scaly-crowned Babbler	Malacopteron cinereum	LC	59	0.02
26	Javan Green Magpie	Cissa thalassina	CR	58	0.02
.27	White-bibbed Babbler	Stachyris thoracica	LC	58	0.02
28	Ashy Bulbul	Hemixos flavala	LC	57	0.02
29	Mountain Warbler*	Phylloscopus trivirgatus	LC	57	0.02
30	Orange-bellied Flowerpecker	Dicaeum trigonostigma	LC	55	0.02
31	Bali Myna	Leucopsar rothschildi	CR	50	0.02
32	Long-tailed Paradise-whydah*	Vidua paradisaea	LC	50	0.02
33	Siberian Thrush	Geokichla sibirica	LC	47	0.02
34	Lemon-breasted Canary*	Crithagra citrinipectus	LC	46	0.02
35	Yellow-bellied Prinia	Prinia flaviventris	LC	44	0.02
36	Brown Prinia	Prinia polychroa	LC	43	0.02
37	Golden Whistler	Pachycephala pectoralis	LC	42	0.01
38	Sunda Blue Robin	Myiomela diana	LC	40	0.01
39	Timor Figbird	Sphecotheres viridis	LC	39	0.01
40	Javan Oriole	Oriolus cruentus	LC	38	0.01
.41	Olive-backed Sunbird	Cinnyris jugularis	LC	37	0.01
• •			LC	37	0.01
42	White-crested Laughingthrush	Garrulax leucolophus			

# (continued)

No	Common Name	Scientific Name	IUCN Status	Num of listed	% of list
144	Little Pied Flycatcher	Ficedula westermanni	LC	35	0.01
L45	Golden-bellied Gerygone	Gerygone sulphurea	LC	34	0.01
46	Oriental Dollarbird	Eurystomus orientalis	LC	34	0.01
47	Scaly-breasted Munia	Lonchura punctulata	LC	34	0.01
48	Chestnut Munia*	Lonchura atricapilla	LC	32	0.01
49	Crested White-eye	Heleia dohertyi	LC	32	0.01
50	Sunda Pied Fantail	Rhipidura javanica	LC	32	0.01
51	Fulvous-breasted Woodpecker	Dendrocopos macei	LC	31	0.01
52	Grey-cheeked Tit-babbler	Mixornis flavicollis	LC	31	0.01
53	Pied Triller	Lalage nigra	LC	31	0.01
54	White-breasted Babbler	Stachyris grammiceps	NT	31	0.01
55	Mangrove Whistler	Pachycephala cinerea	LC	30	0.01
56	Golden-headed Cisticola	Cisticola exilis	LC	29	0.01
57	Large Wren-babbler	Turdinus macrodactylus	NT	29	0.01
58	Little Spiderhunter	Arachnothera longirostra	LC	29	0.01
59	Hybrid Black-throated Canary x Yellow-fronted Seedeater		Х	28	0.01
50	Long-tailed Finch*	Poephila acuticauda	LC	27	0.01
51	Streaky-breasted Spiderhunter	Arachnothera affinis	LC	27	0.01
52	Common Hill Myna	Gracula religiosa	LC	26	0.01
53	Eurasian Skylark*	Alauda arvensis	LC	26	0.01
54	Superb Starling*	Lamprotornis superbus	LC	26	0.01
65	Crimson Sunbird	Aethopyga siparaja	LC	25	0.01
56	Eyebrowed Thrush	Turdus obscurus	LC	23	0.01
57	Grey-bellied Bulbul	Pycnonotus cyaniventris	NT	22	0.01
68	Javan Shortwing	Brachypteryx montana	LC	21	0.01
69	Southern White-necked Myna	Streptocitta albicollis	LC	21	0.01
70	Yellow-bellied Warbler	Abroscopus superciliaris	LC	21	0.01
71	Brahminy Starling*	Sturnia pagodarum	LC	20	0.01
72	Golden Myna	Mino anais	LC	20	0.01
73	Hybrid White-rumped Seedeater x Yellow-fronted Seedeater	Millo uluis	NR	20	0.01
74	Red-breasted Parakeet	Psittacula alexandri	NT	20	0.01
75			LC	19	0.01
	Large Cuckooshrike Bulbuls	Coracina javensis			
76		Pycnototus spp.	NR	18	0.01
77	Mountain White-eye	Zosterops montanus	X	18	0.01
78	Rufous-tailed Tailorbird	Orthotomus sericeus	LC	17	0.01
79	Siberian Blue Robin	Larvivora cyane	LC	17	0.01
80	Yellow-rumped Flycatcher	Ficedula zanthopygia	LC	17	0.01
81	European Goldfinch*	Carduelis carduelis	LC	16	0.01
82	Pallas's Grasshopper-warbler	Locustella certhiola	LC	16	0.01
83	Rosy Starling*	Pastor roseus	LC	16	0.01
84	Hybrid Rock Dove x Sunda Collared-dove		X	15	0.01
85	Striated Grassbird	Megalurus palustris	LC	15	0.01
86	Village Indigobird*	Vidua chalybeata	LC	15	0.01
87	Black-bellied Crimson Finch	Neochmia phaeton	LC	14	0.00
88	Blue-eared Kingfisher	Alcedo meninting	LC	14	0.00
89	Mountain Tailorbird	Phyllergates cucullatus	LC	14	0.00
90	Chestnut-fronted Shrike-babbler	Pteruthius aenobarbus	LC	13	0.00
91	Crescent-chested Babbler	Cyanoderma melanothorax	LC	13	0.00
92	Dusky Munia	Lonchura fuscans	LC	13	0.00
93	Hooded Siskin*	Spinus magellanicus	LC	13	0.00
94	Bank Myna*	Acridotheres ginginianus	LC	12	0.00
95	Varied Honeyeater	Gavicalis versicolor	LC	12	0.00
96	Sumatran Laughingthrush	Garrulax bicolor	EN	11	0.00
97	Javan Broadbill	Eurylaimus javanicus	NT	10	0.00
98	Black Mannikin	Lonchura stygia	NT	9	0.00
99	Black-winged Flycatcher-shrike	Hemipus hirundinaceus	LC	9	0.00
00	Crimson-breasted Flowerpecker	Prionochilus percussus	LC	9	0.00
01	Mongolian Lark*	Melanocorypha mongolica	LC	9	0.00
02	Rufous-browed Babbler	Pellorneum capistratum	LC	8	0.00
03	Javan Cochoa	Cochoa azurea	VU	7	0.00
04	Arctic Warbler	Phylloscopus borealis	LC	7	0.00
05	Blue-capped Cordon-bleu*	Uraeginthus cyanocephalus	LC	7	0.00
06	Scarlet-breasted Flowerpecker	Prionochilus thoracicus	NT	6	0.00
07	Grey-crowned Mannikin	Lonchura nevermanni	LC	6	0.00
08	Hairy-backed Bulbul	Tricholestes criniger	LC	6	0.00
09	Kingfishers	Alcedo spp.	X	6	0.00
10	Lineated Barbet	Psilopogon lineatus	LC	6	0.00
10		Gymnorhina tibicen	LC	5	0.00
1.1	Australian Magpie	aynnionnina twicen	ъс		
12	Blue-faced Honeyeater	Entomyzon cyanotis	LC	5	0.00

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No	Common Name	Scientific Name	IUCN Status	Num of listed	% of listed
214	Red-whiskered Bulbul*	Pycnonotus jocosus	LC	5	0.00
215	Scaly Thrush	Zoothera dauma	LC	5	0.00
216	Puff-backed Bulbul	Euptilotus eutilotus	NT	4	0.00
217	Chestnut-cheeked Starling*	Agropsar philippensis	LC	4	0.00
218	Common Nightingale*	Luscinia megarhynchos	LC	4	0.00
219	Greater Bird-of-paradise	Paradisaea apoda	LC	4	0.00
220	Long-tailed Broadbill	Psarisomus dalhousiae	LC	4	0.00
221	White-eared Bulbul*	Pycnonotus leucotis	LC	4	0.00
222	Sumatran Cochoa	Cochoa beccarii	VU	3	0.00
223	Black-and-white Bulbul	Microtarsus melanoleucos	NT	3	0.00
224	Indian Paradise-flycatcher	Terpsiphone paradisi	LC	3	0.00
225	Island Thrush	Turdus poliocephalus	LC	3	0.00
226	Olive-backed Oriole	Oriolus sagittatus	LC	3	0.00
227	White-bellied Canary*	Crithagra dorsostriata	LC	3	0.00
228	White-spotted Mannikin	Lonchura leucosticta	LC	3	0.00
229	White-chested Babbler	Trichastoma rostratum	NT	2	0.00
230	Black-naped Monarch	Hypothymis azurea	LC	2	0.00
231	Cream-browed White-eye	Heleia superciliaris	LC	2	0.00
232	Long-tailed Glossy Starling*	Lamprotornis caudatus	LC	2	0.00
233	Red-vented Bulbul*	Pycnonotus cafer	LC	2	0.00
234	Yellow-spectacled White-eye	Heleia wallacei	LC	2	0.00
235	Zebra Waxbill*	Amandava subflava	LC	2	0.00
236	Spotted Crocias	Laniellus albonotatus	NT	1	0.00
237	Scaly-breasted Bulbul	Pycnonotus squamatus	NT	1	0.00
238	Asian Brown Flycatcher	Muscicapa dauurica	LC	1	0.00
239	Diamond Firetail*	Stagonopleura guttata	LC	1	0.00
240	Eurasian Jay*	Garrulus glandarius	LC	1	0.00
241	Fire-tufted Barbet	Psilopogon pyrolophus	LC	1	0.00
242	Green-fronted White-eye	Zosterops minor	LC	1	0.00
243	Reichenow's Seedeater*	Crithagra reichenowi	LC	1	0.00
244	Siberian Rubythroat*	Calliope calliope	LC	1	0.00
245	Streak-headed White-eye	Heleia squamiceps	LC	1	0.00
246	Sultan Tit	Melanochlora sultanea	LC	1	0.00
247	Tahiti Swallow	Hirundo tahitica	LC	1	0.00
248	Violet-backed Starling*	Cinnyricinclus leucogaster	LC	1	0.00
249	White-flanked Sunbird	Aethopyga eximia	LC	1	0.00
250	Yellow-throated Hanging-parrot	Loriculus pusillus	NT	1	0.00

\*Indicates non-native taxa

x Indicates identify in family, genera level or hybrid species, and IUCN status not applicable

# Appendix B. Full list taxa with mean asking prices

No	Common Name	Scientific Name	Price (USD)			
			Min	Max	Mean	SD
1	Lovebirds*	Agapornis spp.	2	126	23	21
2	White-rumped Shama	Kittacincla malabarica	17	909	201	131
3	Canaries*	Serinus spp.	2	206	40	31
4	Oriental Magpie-robin	Copsychus saularis	3	210	52	26
5	Zebra Dove	Geopelia striata	2	290	41	41
6	Javan Pied Starling	Gracupica jalla	3	196	49	20
7	Sunda Collared-dove	Streptopelia bitorquata	2	91	20	14
8	Yellow-vented Bulbul	Pycnonotus goiavier	2	71	17	13
9	Long-tailed Shrike	Lanius schach	2	122	29	18
10	Orange-headed Thrush	Geokichla citrina	2	350	85	57
11	Bar-winged Prinia	Prinia familiaris	2	87	20	13
12	Eastern Spotted Dove	Spilopelia chinensis	2	206	36	41
13	Javan Myna	Acridotheres javanicus	2	77	16	10
14	Straw-headed Bulbul	Pycnonotus zeylanicus	77	2.797	709	362
15	Chestnut-capped Thrush	Geokichla interpres	13	332	83	49
16	Horsfield's Bushlark	Mirafra javanica	8	559	94	99
17	Red Siskin*	Spinus cucullatus	2	524	122	77
18	Greater Green Leafbird	Chloropsis sonnerati	7	301	76	39
19	Black-throated Canary*	Crithagra atrogularis	3	350	87	45
20	Black-throated Laughingthrush*	Garrulax chinensis	4	944	249	92
21	Brown-cheeked Bulbul	Alophoixus bres	5	189	41	19
22	Sooty-headed Bulbul	Pycnonotus aurigaster	2	56	11	7

# (continued)

No	Common Name	Scientific Name	Price (USD)			
			Min	Max	Mean	SI
23	Black-throated Prinia	Prinia atrogularis	2	98	21	16
24	Black-naped Oriole	Oriolus chinensis	3	157	39	22
25	Chinese Hwamei*	Garrulax canorus	26	1.189	305	15
26	Common Iora	Aegithina tiphia	2	70	19	13
27	Olive-winged Bulbul	Pycnonotus plumosus	2	196	48	22
28	Hill Blue-flycatcher	Cyornis banyumas	3	182	50	28
29	Starlings	Sturnus spp.	2	336	71	69
30	Ashy Tailorbird	Orthotomus ruficeps	2 2	66 106	12	7 19
31 32	Timor Zebra Finch Common Myna	Taeniopygia guttata Acridotheres tristis	2	126 122	28 27	16
32 33	White-rumped Seedeater*	Crithagra leucopygia	9	210	58	25
33 34	Chestnut-capped Laughingthrush	Garrulax mitratus	7	84	25	1
35	Purple-throated Sunbird	Leptocoma sperata	3	91	23	14
36	Great Tit	Parus major	2	42	14	7
37	Plain Prinia	Prinia inornata	2	49	13	8
38	White-rumped Munia	Lonchura striata	2	105	24	18
39	Asian Glossy Starling	Aplonis panayensis	2	91	18	12
40	Yellow-fronted Canary*	Crithagra mozambica	7	210	57	22
41	Orange-bellied Leafbird*	Chloropsis hardwickii	28	839	217	87
42	Scarlet-headed Flowerpecker	Dicaeum trochileum	2	35	8	4
13	Bare-throated Whistler	Pachycephala nudigula	14	315	98	4
44	Fulvous-chested Jungle-flycatcher	Cyornis olivaceus	3	119	31	2
45	Pied Bushchat	Saxicola caprata	3	122	33	10
46	Common Tailorbird	Orthotomus sutorius	2	38	9	5
47	Eurasian Tree Sparrow	Passer montanus	2	70	20	10
48	Orange-spotted Bulbul	Pycnonotus bimaculatus	3	59	14	6
49	Asian Golden Weaver	Ploceus hypoxanthus	2	59	15	12
50	Laughingthrushes*	Garrulax spp.	9	490	124	10
51	Gouldian Finch*	Chloebia gouldiae	9	385	106	53
52	Brown-throated Sunbird	Geokichla dohertyi	2	28	7	5
53	Chestnut-backed Thrush	Anthreptes malacensis	6	175	44	20
54	Javan Fulvetta	Alcippe pyrrhoptera	2	49	12	7
55	Java Sparrow	Lonchura oryzivora	2	56	16	10
56	Asian Fairy-bluebird	Irena puella	9	133	43	19
57	Blue-and-white Flycatcher	Cyanoptila cyanomelana	3	52	24	8
58	Hooded Pitohui	Pitohui dichrous	31	245	104	45
59	Lesser Green Leafbird	Chloropsis cyanopogon	2	105	27	13
60	Oriental White-eye	Zosterops palpebrosus	3	59	17	10
61	Grosbeak Starling	Scissirostrum dubium	8	105	26	13
62	Sunda Laughingthrush	Garrulax palliatus	7	140	36	16
63	Blue-masked Leafbird	Chloropsis venusta	6	105	37	14
64	Streaked Bulbul	Ixos malaccensis	4	59	19	9
65	White-headed Munia	Lonchura maja	2	35	9	7
66	Ruby-throated Bulbul	Pycnonotus dispar	2	52	14	10
67	Hybrid Eastern Spotted Dove x Sunda Collared-dove		3	66	16	10
68	Javan Leafbird	Chloropsis cochinchinensis	3	94	23	11
69	Hooded Butcherbird	Cracticus cassicus	17	420	143	60
70	Crested Jay	Platylophus galericulatus	14	420	126	49
71	Oriental Reed-warbler	Acrocephalus orientalis	2	105	22	12
72	Hybrid Red Siskin x Island Canary		7	196	72	33
73	Pale Blue-flycatcher	Cyornis unicolor	3	59	17	9
74	Scarlet Minivet	Pericrocotus flammeus	2	42	15	7
75	Black-headed Bulbul	Brachypodius atriceps	2	49	11	7
76	Hybrid Black-throated Canary x White-rumped Seedeater		23	182	62	2
77	Javan Grey-throated White-eye	Heleia javanica	2	45	11	7
78	Javan Munia	Lonchura leucogastroides	2	70	14	1:
79	Hybrid Black-throated Canary x Island Canary		14	182	60	29
30	Black-winged Myna	Acridotheres melanopterus	2	245	64	38
31	Racquet-tailed Treepie	Crypsirina temia	5	140	34	2
82	Orange-banded Thrush	Geokichla peronii	17	210	56	31
83	Blue Whistling-thrush	Myophonus caeruleus	4	94	27	14
84	Chestnut-crested Yuhina	Yuhina everetti	2	105	35	13
85	Purple-backed Starling	Agropsar sturninus	3	59	14	10
86	Javan White-eye	Zosterops flavus	3	91	21	17
87	Black-collared Starling*	Gracupica nigricollis	70	524	208	7:
88	Lesser Shortwing	Brachypteryx leucophris	3	59	14	9
89	Drongos	Dicrurus spp.	5	105	27	13
90	Velvet-fronted Nuthatch	Sitta frontalis	7	59	22	10

# (continued)

No	Common Name	Scientific Name	Price (USD)				
			Min	Max	Mean	SI	
91	Spot-throated Babbler*	Pellorneum albiventre	9	490	184	95	
92	White-breasted Woodswallow	Artamus leucoryn	4	70	20	12	
93	Silver-eared Mesia	Leiothrix argentauris	10	315	80	4	
94	Red-billed Leiothrix*	Leiothrix lutea	31	350	119	6	
95	Lesser Racquet-tailed Drongo	Dicrurus remifer	3	140	41	2	
96	Mangrove Blue-flycatcher	Cyornis rufigastra	10	105	31	1	
97	Scaly-crowned Honeyeater	Lichmera lombokia	2	105	22	1	
98	Ashy Drongo	Dicrurus leucophaeus	7	70	23	1	
99	Red Avadavat	Amandava amandava	2	49	15	7	
100	Chestnut-capped Babbler	Timalia pileata	2 24	31	9	5 7	
101 102	House Crow	Corvus splendens	24	490 35	123 10	7	
102	Zitting Cisticola Finches*	Cisticola juncidis	3	210	55	5	
103	Long-tailed Sibia	Heterophasia picaoides	7	115	30	2	
104	Mugimaki Flycatcher	Ficedula mugimaki	5	38	18	9	
105	Hair-crested Drongo	Dicrurus hottentottus	9	117	38	2	
106	Streaked Weaver	Ploceus manyar	2	35	38 15	8	
107	Javan Bulbul	Ixos virescens	3	33 42	13	8	
108	Woodpeckers	1403 111 500115	5	42	25	1	
1109	Thick-billed White-eye	Heleia crassirostris	4	63	25 19	1	
110	Helmeted Friarbird	Philemon buceroides	4	140	61	3	
111	Pin-tailed Parrotfinch	Erythrura prasina	2	140 45	12	3 8	
112	Horsfield's Babbler	Malacocincla sepiaria	2	45 31	12	6	
115 114	Indigo Flycatcher	Eumyias indigo	2	31	10	6	
114	Sulawesi Myna	Basilornis celebensis	3	38 140	72	2	
115	Calandra Lark*	Melanocorypha calandra	5 56	350	129	6	
110	Blue Nuthatch	Sitta azurea	5	56	129	1	
117	Common Flameback	Dinopium javanense	5 4	50 70	19 30	1	
118 119	Oriental Skylark*	Alauda gulgula	4 35	668	30 185	1	
120	Sunda Pygmy Woodpecker	Picoides moluccensis	35 5	52	185	1	
120 121	Black Drongo	Dicrurus macrocercus	5 6	52 94	19 28	1	
121	Chestnut-backed Scimitar-babbler	Pomatorhinus montanus	4	94 42	28 15	7	
122	Ruby-cheeked Sunbird	Chalcoparia singalensis	4	42 66	23	1	
123 124	Crested Myna*	Acridotheres cristatellus	3 23	315	23 74	5	
124 125	Scaly-crowned Babbler	Malacopteron cinereum	23 4	315 21	74 7	2	
125 126	Javan Green Magpie	Cissa thalassina	4 35	21 126	7 71	2	
126 127	White-bibbed Babbler	Stachyris thoracica	35 3	49	71 14	8	
127	Ashy Bulbul	Hemixos flavala	3 7	49	21	8	
128 129	Mountain Warbler*	Phylloscopus trivirgatus	3	45 26	21 10	8 4	
129	Orange-bellied Flowerpecker	Dicaeum trigonostigma	3 2	20 59	10	4	
130	Bali Myna	Leucopsar rothschildi	2 112	59 601	248	1	
131	Long-tailed Paradise-whydah*	Vidua paradisaea	42	315	248 120	6	
132 133	Siberian Thrush	Geokichla sibirica	42 3	315 56	120 19	1	
133 134	Lemon-breasted Canary*	Geokicnia sibirica Crithagra citrinipectus	3 56	56 301	19 117	3	
134	Yellow-bellied Prinia	Prinia flaviventris	2	42	117	9	
135 136	Brown Prinia	Prinia polychroa	2	42 35	10	9	
136 137	Golden Whistler	Pachycephala pectoralis	3 7	35 56	13 29	1	
137	Sunda Blue Robin	Myiomela diana	7	50 52	29 17	8	
138	Timor Figbird	Sphecotheres viridis	7 24	52 210	17	8 4	
139 140	Javan Oriole	Oriolus cruentus	24 10	210 87	39	4	
140 141	Olive-backed Sunbird	Cinnyris jugularis	2	87 52	39 16	1	
141	White-crested Laughingthrush	Garrulax leucolophus	35	350	109	7	
142 143	Black Laughingthrush	Garrulax leucolophus Garrulax lugubris	35 14	350 56	27	1	
143 144	Little Pied Flycatcher	Ficedula westermanni	14 3	50 42	10	8	
144 145	Golden-bellied Gerygone	Gerygone sulphurea	3	42 42	10	0 1	
145 146	Oriental Dollarbird	<b>1</b> 0 1	3 9	42 147	15 91	3	
		Eurystomus orientalis Lonchura punctulata	3	147 14	8	3	
147 148	Scaly-breasted Munia Chestnut Munia*	Lonchura punctulata Lonchura atricapilla	3 2	14 20	8 9	3	
	Chestnut Munia*	÷					
149	Crested White-eye	Heleia dohertyi Bhinidura izvanica	6	70 45	18	1	
150	Sunda Pied Fantail	Rhipidura javanica	3	45	14	8	
151	Fulvous-breasted Woodpecker	Dendrocopos macei	5	63	16	1	
152	Grey-cheeked Tit-babbler	Mixornis flavicollis	3	26	8	6	
153	Pied Triller	Lalage nigra	2	35	9	6	
154	White-breasted Babbler	Stachyris grammiceps	5	35	15	7	
155	Mangrove Whistler	Pachycephala cinerea	6	27	21	5	
156	Golden-headed Cisticola Large Wren-babbler	Cisticola exilis Turdinus macrodactylus	6 2	49 42	31 18	1	
157						8	

# (continued)

No	Common Name	Scientific Name	Price (USD)				
			Min	Max	Mean	SI	
59	Hybrid Black-throated Canary x Yellow-fronted Seedeater		31	161	69	32	
50	Long-tailed Finch*	Poephila acuticauda	45	175	109	29	
51	Streaky-breasted Spiderhunter	Arachnothera affinis	3	42	16	1	
52	Common Hill Myna	Gracula religiosa	52	350	127	6	
63 64	Eurasian Skylark*	Alauda arvensis	105	594	230	1	
64 65	Superb Starling*	Lamprotornis superbus	91 5	455	171 15	8 1	
65 66	Crimson Sunbird Eyebrowed Thrush	Aethopyga siparaja Turdus obscurus	5 10	52 35	15	6	
67	Grey-bellied Bulbul	Pycnonotus cyaniventris	2	38	20	9	
.68	Javan Shortwing	Brachypteryx montana	7	49	19	9	
69	Southern White-necked Myna	Streptocitta albicollis	, 59	294	167	6	
70	Yellow-bellied Warbler	Abroscopus superciliaris	2	28	8	6	
71	Brahminy Starling*	Sturnia pagodarum	24	490	194	1	
72	Golden Myna	Mino anais	14	315	124	7	
73	Hybrid White-rumped Seedeater x Yellow-fronted Seedeater		17	105	56	2	
74	Red-breasted Parakeet	Psittacula alexandri	28	126	61	2	
75	Large Cuckooshrike	Coracina javensis	9	42	24	6	
76	Bulbuls	Pycnototus spp.	14	122	59	2	
77	Mountain White-eye	Zosterops montanus	3	28	13	6	
78	Rufous-tailed Tailorbird	Orthotomus sericeus	3	31	11	6	
79	Siberian Blue Robin	Larvivora cyane	38	98	63	2	
80	Yellow-rumped Flycatcher	Ficedula zanthopygia	8	21	11	2	
81	European Goldfinch*	Carduelis carduelis	86	385	253	1	
82	Pallas's Grasshopper-warbler	Locustella certhiola	3	42	18	1	
83	Rosy Starling*	Pastor roseus	42	126	82	3	
84	Hybrid Rock Dove x Rock Dove	<b></b>	12	35	22	6	
85	Striated Grassbird	Megalurus palustris	5	49	15	9	
86	Village Indigobird*	Vidua chalybeata	52	350	138	7	
87	Black-bellied Crimson Finch	Neochmia phaeton	7	35	26	6 8	
88 89	Blue-eared Kingfisher Mountain Tailorbird	Alcedo meninting Phyllergates cucullatus	3 5	35 17	16 13	8 4	
90	Chestnut-fronted Shrike-babbler	Pteruthius aenobarbus	3	28	13	7	
91	Crescent-chested Babbler	Cyanoderma melanothorax	2	28	13	9	
92	Dusky Munia	Lonchura fuscans	31	140	75	2	
93	Hooded Siskin*	Spinus magellanicus	94	559	250	1	
94	Bank Myna*	Acridotheres ginginianus	14	77	36	1	
95	Varied Honeyeater	Gavicalis versicolor	23	140	85	3	
96	Sumatran Laughingthrush	Garrulax bicolor	24	105	58	2	
97	Javan Broadbill	Eurylaimus javanicus	N/A	N/A	N/A	Ν	
98	Black Mannikin	Lonchura stygia	N/A	N/A	N/A	Ν	
99	Black-winged Flycatcher-shrike	Hemipus hirundinaceus	N/A	N/A	N/A	Ν	
00	Crimson-breasted Flowerpecker	Prionochilus percussus	N/A	N/A	N/A	Ν	
01	Mongolian Lark*	Melanocorypha mongolica	N/A	N/A	N/A	Ν	
02	Rufous-browed Babbler	Pellorneum capistratum	N/A	N/A	N/A	N	
03	Javan Cochoa	Cochoa azurea	N/A	N/A	N/A	N	
04	Arctic Warbler	Phylloscopus borealis	N/A	N/A	N/A	N	
05	Blue-capped Cordon-bleu*	Uraeginthus cyanocephalus	N/A	N/A	N/A	Ν	
06	Scarlet-breasted Flowerpecker	Prionochilus thoracicus	N/A	N/A	N/A	N	
07	Grey-crowned Mannikin	Lonchura nevermanni	N/A	N/A	N/A	N	
08	Hairy-backed Bulbul	Tricholestes criniger	N/A	N/A	N/A	N	
09	Kingfishers	Alcedo spp.	N/A	N/A	N/A	N	
10	Lineated Barbet	Psilopogon lineatus	N/A	N/A	N/A	N	
11	Australian Magpie	Gymnorhina tibicen	N/A	N/A	N/A	N	
12	Blue-faced Honeyeater	Entomyzon cyanotis	N/A	N/A	N/A	N	
13	Five-coloured Munia	Lonchura quinticolor	N/A	N/A	N/A	N	
14	Red-whiskered Bulbul*	Pycnonotus jocosus	N/A	N/A	N/A	N	
15	Scaly Thrush	Zoothera dauma	N/A	N/A	N/A	N	
16	Puff-backed Bulbul Chaptaut abacked Starling*	Euptilotus eutilotus	N/A	N/A	N/A	N	
17	Chestnut-cheeked Starling* Common Nightingale*	Agropsar philippensis	N/A	N/A N/A	N/A	N	
18 10	0 0	Luscinia megarhynchos Daradicaea apoda	N/A	N/A	N/A	N	
19 20	Greater Bird-of-paradise	Paradisaea apoda Psarisomus dalhousiae	N/A	N/A	N/A	N	
20 21	Long-tailed Broadbill White-eared Bulbul*	Psarisomus dalhousiae	N/A N/A	N/A N/A	N/A	N	
21 22		Pycnonotus leucotis	N/A	N/A N/A	N/A	N	
22 23	Sumatran Cochoa Black-and-white Bulbul	Cochoa beccarii Microtarsus melanoleucos	N/A N/A	N/A N/A	N/A N/A	N	
23 24	Indian Paradise-flycatcher	Microtarsus melanoleucos Terpsiphone paradisi	N/A N/A	N/A N/A	N/A N/A	N N	
24 25	Island Thrush	Terpsiphone paradisi Turdus poliocephalus	N/A N/A	N/A N/A	N/A N/A	N	
			IN/A	IN/A		IN	

#### (continued)

No	Common Name	Scientific Name	Price (USD)			
			Min	Max	Mean	SD
227	White-bellied Canary*	Crithagra dorsostriata	N/A	N/A	N/A	N/A
228	White-spotted Mannikin	Lonchura leucosticta	N/A	N/A	N/A	N/A
229	White-chested Babbler	Trichastoma rostratum	N/A	N/A	N/A	N/A
230	Black-naped Monarch	Hypothymis azurea	N/A	N/A	N/A	N/A
231	Cream-browed White-eye	Heleia superciliaris	N/A	N/A	N/A	N/A
232	Long-tailed Glossy Starling*	Lamprotornis caudatus	N/A	N/A	N/A	N/A
233	Red-vented Bulbul*	Pycnonotus cafer	N/A	N/A	N/A	N/A
234	Yellow-spectacled White-eye	Heleia wallacei	N/A	N/A	N/A	N/A
235	Zebra Waxbill*	Amandava subflava	N/A	N/A	N/A	N/A
236	Spotted Crocias	Laniellus albonotatus	N/A	N/A	N/A	N/A
237	Scaly-breasted Bulbul	Pycnonotus squamatus	N/A	N/A	N/A	N/A
238	Asian Brown Flycatcher	Muscicapa dauurica	N/A	N/A	N/A	N/A
239	Diamond Firetail*	Stagonopleura guttata	N/A	N/A	N/A	N/A
240	Eurasian Jay*	Garrulus glandarius	N/A	N/A	N/A	N/A
241	Fire-tufted Barbet	Psilopogon pyrolophus	N/A	N/A	N/A	N/A
242	Green-fronted White-eye	Zosterops minor	N/A	N/A	N/A	N/A
243	Reichenow's Seedeater*	Crithagra reichenowi	N/A	N/A	N/A	N/A
244	Siberian Rubythroat*	Calliope calliope	N/A	N/A	N/A	N/A
245	Streak-headed White-eye	Heleia squamiceps	N/A	N/A	N/A	N/A
246	Sultan Tit	Melanochlora sultanea	N/A	N/A	N/A	N/A
247	Tahiti Swallow	Hirundo tahitica	N/A	N/A	N/A	N/A
248	Violet-backed Starling*	Cinnyricinclus leucogaster	N/A	N/A	N/A	N/A
249	White-flanked Sunbird	Aethopyga eximia	N/A	N/A	N/A	N/A
250	Yellow-throated Hanging-parrot	Loriculus pusillus	N/A	N/A	N/A	N/A

\*Indicates non-native taxa

USD 1 = IDR 14.500

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