Safety Science 139 (2021) 105273

Contents lists available at ScienceDirect

Safety Science

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

Factors affecting unmanned aerial vehicles' safety: A post-occurrence exploratory data analysis of drones' accidents and incidents in Australia

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ARTICLE INFO

Keywords:
Drone
Unmanned Aerial Vehicle (UAV)
Unmanned Aircraft System (UAS)
Remotely Piloted Aircraft System (RPAS)
Exploratory Factor Analysis (EFA)
Safety Procedures
Accident and Incident Prevention

ABSTRACT

Unmanned aerial vehicles (UAV) have made life easier in many ways, and their applications in civil practice are increasing rapidly. However, this benefit is not entirely risk-free, as unwanted accidents and incidents can cause serious harm and interrupt other aerial activities. In this paper, we investigate a dataset of UAV accidents and incidents in Australia and put up some precautionary exercises to reduce the risk of future events. To that end, univariate and bivariate distributions of past events are analysed, and the exploratory factor analysis technique is used to identify frequent accident and incident patterns. The findings show that equipment issues or/and lack of coordination between aerial activities are two of the accidents and incidents categories; therefore, necessitating regular safety inspections for UAVs and establishing an integrated monitoring system for aerial activities are expected to reduce the risk of accidents and incidents.

1. Introduction

Unmanned aerial vehicles or drones are shown beneficial to many non-military purposes including remote sensing (Nex and Remondino, 2014), maintenance (Ham et al., 2016), disaster management (Deruyck et al., 2016), safety (Irizarry et al., 2012), construction (Hubbard et al., 2015), mining (Lee and Choi, 2016), and agriculture (Tokekar et al., 2016). Following the cost effective application of drones in various disciplines, a surge in their utilization and market uptake is envisaged (Sachs, 2016, Gettinger, 2017). This trend underpins the importance of safety aspects of drone operation, calling for a comprehensive research in this area to develop appropriate safety measures and procedures.

The regulation of drone operation is a multifaceted issue, as imposing any form of restriction can negatively affect the market uptake of drones and hinder all its potential benefits for the society and the economy (Perritt and Sprague, 2016). Drones were initially assumed have similar operational and safety requirements as traditional aircrafts (Clothier and Walker, 2006), however, it gradually became evident that the two sectors are facing with different sources of risk and need separate treatments (Wild et al., 2017). Despite the isolated preliminary attempts by some nations, there is no universally acceptable standard to facilitate and regulate non-military drone operation. Besides, there is significant room for improvement in the current regulations. Further clarification is required regarding vital issues such as airworthiness certificate (Clothier et al., 2011, Cuerno-Rejado and Martínez-Val, 2011, Szabolcsi, 2014a), liabilities and insurance (Mathews, 2014, Sehrawat, 2018), pilot licensing (Jones, 2017) and reporting accidents and incidents (Wild et al., 2016).

One important barrier towards a comprehensive evidence-based approach to analyse drone operation is data scarcity and inconsistency in reporting style (Wild et al., 2016). In this study, we explore a small dataset on past drone accidents and incidents to provide more insight about the cause and the pattern of the observed cases. The dataset of this study is collected by Australian Transport Safety Bureau (ATSB). Consulting the existing safety manuals, the reported occurrence cases are categorised with respect to occurrence category, hazard category, phase of flight, colliding object, and operation type. The univariate and bivariate distributions of these categories are interrogated to identify common safety concerns. Moreover, se utilizes the exploratory factor analysis method to identify prevailing patterns in drone accidents and incidents. The findings of this practice are expected to help planners and policy makers to devise effective policies to regulate drone operations.

This paper is organised as follows. Section 3 discusses the process of refining the dataset of this study and section 4 discusses the utilized

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https://doi.org/10.1016/j.ssci.2021.105273
Received 26 October 2019; Received in revised form 10 March 2021; Accepted 22 March 2021
Available online 31 March 2021

methodology. Section 5 presents the modelling results, and section 6 provides the interpretation of the results. Finally, the findings of this study are summarised in section 7.

2. Literature review

In April 2014, at the Geraldton horse race competition in Western Australia, the filming drone lost the ground control and hit one of the competitors (Taillier, 2014). In the December of the same year, a filming drone, which was supposed to promote kiss-on-camera in a restaurant chain in the New York City, hit a photographer and cut her nose with its spinning blades. Ironically, the photographer was there to make a report from the drone operation (Allen, 2014). Four months later in March 2015, at the Melbourne Cricket Ground at the world cup cricket final, a drone, which was intended to provide an aerial perspective of the action for the television coverage, lost the ground control and collided with terrain (SANDILANDS, 2015). In April 2016, in Cape Town South Africa, a drone crashed through an office window and hit an office worker in his head (Borrello, 2016). These instances are a few examples of faulty operations that could inflict serious injuries. Moreover, there are ample reports on drones' faulty operation causing damage to the drone itself or its surrounding environment. Almost all the predictions for the future usage of drones unanimously envisage a rapidly growing trend for drones' applications, which necessitate a comprehensive plan and regulatory program to ensure safe and harmless operation of drones in the future. This study aims at exploring the past drone accidents and incidents to provide more insight about the cause and the pattern of the observed cases, which eventually can help planners and policy makers to devise effective policies to regulate drone operations.

Before starting the discussion, it is noteworthy to clarify the terminology around this versatile flying gadget. International Civil Aviation Organisation (ICAO) defines unmanned aerial vehicles (UAV) as aircrafts that operate without on-board pilot (Cary and Coyne, 2011). The term unmanned aircraft system (UAS) is used to refer to the system that makes a UAV work, i.e. the UAV, the person who is controlling it and the system in place connecting them. Note that UAV can refer to an autonomous unmanned aircraft as well. Remotely piloted aircraft (RPA) and remotely piloted aircraft system (RPAS) are two other terms equivalent to UAV and UAS respectively, but they do not include autonomous UAV. Finally, drone is a more common term used by people and media to refer to UAV and RPA. In this paper, we use UAV and drone interchangeably to refer to the unmanned aircraft and UAS to refer to the system.

In the last 10 years, rather than military purposes, a wide range of commercial applications for drones have been introduced, such as: remote sensing and 3D mapping (Nex and Remondino, 2014, Colomina and Molina, 2014), infrastructure maintenance (Ham et al., 2016, Máthé and Buşoniu, 2015), disaster management (D'Onfro, 2014, Deruyck et al., 2016, Quaritsch et al., 2010), real estate (Luppicini and So, 2016), safety (Irizarry et al., 2012), construction (Hubbard et al., 2015, Liu et al., 2014), mining (Lee and Choi, 2016), agriculture (Zhang and Kovacs, 2012, Tokekar et al., 2016) and cargo (Iwata and Matsumoto, 2013). One of the main reasons behind drones' numerous applications is the ability of mounting high-quality cameras or precise sensors on these flying machines, which provide a chance to reduce the cost of data gathering or accomplishing many desired tasks. In 2017 during Grenfell Tower fire, a drone assisted firefighters by providing high-resolution footage and determining the high-risk zones after the fire and assessing the structural damage (Margaritoff, 2017). In agriculture, monitoring crops in vast farms requires time and money but it could be automatically handled by UAVs (Veroustraete, 2015, Stehr, 2015, Malveaux et al., 2014). Inspection in remote areas that are currently undertaken with helicopter crew is another challenge that drones could ease the process as purchasing a semi-intelligent and programmable drone is cheaper than hiring helicopter crew for an hour. In infrastructure management and construction management fields, health monitoring, of infrastructures to establish current status of assets and determining defects, demand a considerable budget which can be considerably reduced with the help of UAS (Varghese et al., 2017, Kovacevic et al., 2016, Chan et al., 2015, Zakeri et al., 2016). In safety science, drones are utilized to collect trajectory of individual vehicle at high risk zones such as merging areas in highways to study the drivers behaviours (Gu et al., 2019) or similar data is used for lane changing risk analysis (Park et al., 2018).

The rapidly growing market of drones had a value of 27 billion US dollars in 2016 and was expected to reach a total value of 100 billion dollars between 2017 and 2020 (Sachs, 2016). This growth will provide a considerable number of job opportunities in businesses especially in construction, agriculture, insurance, and oil/gas. According to the Goldman Sachs Research report, it is expected that in 2020 around 8 million shipments will be handled by small drones (Sachs, 2016). At the moment over 800 million US dollars is spent for drones in the firefighting industry specifically for scene monitoring, search and rescue, post-fire assessment and jungle firefighting (Gettinger, 2017). A study in 2017 manifested that in the US more than 340 agencies including police, sheriff, fire, state government, and city councils are actively using drones (Gettinger, 2017). This figure shows over 500% increase in the number of agencies using drones in only two years (Gettinger, 2017).

In the United States, the number of registered drones is currently more than registered traditional manned aircraft (Administration, 2013). Despite the increasing number of registered drones, a commensurate body of research on the safety of drones has not been conducted. Most of the academic studies about drones are devoted to technical sides of this device including: GPS and antenna (Virone et al., 2014), flight control (Andrievsky and Fradkov, 2002), gyro and gimbal (Jędrasiak et al., 2013), navigation (Zhang et al., 2011), radar and communication (Gupta et al., 2016), mission payload modules (Yan et al., 2010), battery (Suzuki et al., 2012), and ground control (Walter et al., 2004).

While useful and with versatile applications, overlooking safety regulations around UAVs might result in disastrous outcomes. If no preventive and precautionary action is taken, safety becomes a major issue in the near future. Currently, the operation of small drones is limited to visual sight of the ground controller that decreases the potential applications of the small UAVs (Clarke, 2014a). There is a controversial dialogue around the legal enforcement for small UAVs to enforce some restriction on small drones' operations. This could provide a safer public environment; however, businesses analytics believe that these limits will lead to losing a considerable number of job opportunities in the market (Perritt and Sprague, 2016).

Australian Transport Safety Bureau (ATSB) recently has published a report about the growing safety concerns about the UASs (Bureau, 2017). This report reviews the reported collisions of small UAVs within 2012–2016. According to this report, most of the collision records occurred in 2016, around 40% of the collisions are related to ground control while only 10% of accidents caused by technical issues including engine breakdown. Considering the geographical distribution of the collisions indicates that most of the collisions happened in the major cities. However, this could be due to a bias in reporting collisions to ATSB in major cities. Due to the active industries in agriculture, construction, mining, and infrastructure maintenance in remote areas who claim for a large number of purchased drones, it is expected to have a more comparable number of reported accidents in the remote areas and metropolitan areas. This can be an indication that UAV users in the metropolitan areas are more likely to report drone accidents compared to the uses in rural regions.

In details, the drone safety concerns are including any incident or accident that UAVs are involved in. In this paper, the main causes of drones' collisions are investigated using a recent dataset collected by Australian Transport Safety Bureau (ATSB). Clothier and Walker (Clothier and Walker, 2006) believe that the required level of safety for drones is quite similar to traditional aircraft. They claim that although the drones and manned aircraft are designed to handle different tasks, both are exposed to similar sources of risks. However, Wild et al. (2017) consider the two sectors to be facing with different sources of risk and need separate treatments.

Large UAVs are similar to regular airplanes in terms of embedded navigations and communication technologies, but small drones are technologically different. Clarke (2014b) and Dalamagkidis et al (Dalamagkidis et al., 2008) studied the adoptability of existing aviation regulatory for small drones by focusing on public safety. Laarouchi et al. (2017) tried to identify the main cause of collision in their study and they showed that accidents are more frequent for small drones than large drones.

It has been found that safety is the main obstacle against integrating commercial drones in the National Airspace System (NAS) (Melnyk, 2013). Shelley (2016) investigates the potential harm of falling a drone on a human and criticises the existing regulations. Similarly, the weight for small drones is examined in other studies to define a threshold to prevent potential serious harm caused by small drones (Low, 2017, Koh et al., 2018a, Breunig et al., 2018, Koh et al., 2018b).

According to the regulations, a manned aircraft requires an airworthiness certificate to be permitted to fly. Airworthiness is a standardized certificate that ensures an aircraft is safe to fly. In the literature there is a considerable amount of research devoted to how to determine the airworthiness of a UAV (such as (Haddon and Whittaker, 2003, Clothier et al., 2011, Allouche, 2001, Hodson, 2008, Cuerno-Rejado and Martínez-Val, 2011, Szabolcsi, 2014b Szabolcsi, 2014a). In mid-2013, this concern was legislated by FAA for UASs and Optionally Piloted Aircrafts (OPAs) (Administration, 2013). Moreover, after a few suspicious drone activities (Schmidt and Shear, 2015, OGURA, 2015), a fundamental discussion has been formed about the security concerns of UAVs and how aviation legislation could control the commercial drone industry while not limiting their growing applications (Maddox and Stuckenberg, 2015, Finn and Wright, 2012). Besides, in the literature, there are many papers focused on the safety of military UAVs (such as (Neubauer et al., 2007, Giese et al., 2013, Weibel and Hansman, 2006)).

In this paper, we focus on the collision of commercial UAVs to extract prevailing patterns in the observed accidents and incidents which can help with developing effective legislation and regulation for UAV operations. We believe, on one hand, there is a big technological difference between military and commercial drones, and on the other hand, the functionality and purpose of small drones is drastically different from the manned aircraft. Therefore, neither the safety procedure for military drones, nor the existing regulations and procedures for manned aircraft cannot be simply adapted to off-the-shelf consumer drones. The distinctive performance and applications of commercial drones necessitate a tailor-made and comprehensive legislation around drone operations. The comprehensive legislation is meant to reduce the rate of accidents by providing appropriate safety procedures, and more importantly, should clarify responsibilities and liabilities in case of accidents. The latter one is essential for the business to grow, as without a clear vision about risks and rewards, insurance and financial firms are reluctant to participate in the market. Currently in Australia, the civil and aviation safety authority (CASA) strongly recommend organisations to consider third party personal and property insurance or UAV insurance as a part of their business, however, there is no regulatory requirement from CASA. Types of insurance are applicable to drone users: HULL and operation insurance. HULL insurance covers the damage or loss to the UAV, and operation insurance covers any damage to third party.

3. Data

There is no accurate data available on UAV usage in Australia (Bureau, 2017). Australian Transport Safety Bureau reports the number of registered UAV with CASA is around 1000 by 2017. However, not all the UAVs require registration for their operation.

The dataset of this study is obtained from the Australian Transport Safety Bureau (ATSB). The main aim of ATSB is improving safety and public confidence for all modes of transport, including aviation. The dataset includes 138 records of accidents and incidents for UAS under civil operation from June 2000 to June 2018 across Australia. It is noteworthy to mention that these accidents are only the ones that have been reported to ATSB. It is plausible to assume it is more likely for sever accidents to be reported, which means the less sever accidents are underrepresented in this study. The original dataset includes the date and location of the occurrence, the details of the UAV and a short summary about the occurrence. Based on the severity of the occurrence, the records are classified in three levels of *accident*, *serious incident* and *incident*, where accidents are the most severe collisions and incidents the least sever ones.

3.1. Data classification

To conduct a quantitative exploratory analysis, we converted the descriptive summary about the accidents and incidents into quantitative variables which describe the occurrence attributes. Since there is no standard or manual to offer a unified set of variables for UAS safety analysis, we adopted a list of attributes from the standards in aviation or previous studies and made modifications when necessary. The main reference in this section is CAST/ICAO Common Taxonomy Team (CICTT, 2011), which has developed common taxonomies and definitions for aviation accident and incident reporting (CICTT, 2011) and the study of Wild et al. (Wild et al., 2017). We could identify seven categorical variables to explain the severity of the occurrence. One of the variables incidents the severity of incidents and accidents, and one of the variables indicates the state where the incidents and accidents are recorded. The details of the remaining five variables are presented in the following subsections. To distinguish between the variables and the levels (possible outcomes for a variable) in this paper, we use quotation marks when referring to “variables” and italic style when referring to their *levels*.

3.1.1. Occurrence category

CICTT, defines “occurrence category” to classify the cause of accidents or incidents at a high level (CICTT, 2011). There are more than 30 categories defined by CICTT for this variable; however, many of them are specifically defined for operations involving large size aircraft conducting commercial air transport. We excluded irrelevant categories, modified the related ones, and added some new categories to explain the UAS accident and incidents of this study.

- *Awareness*. Refers to all accidents and incidents that pilot’s loss of awareness about the location of UAV has led to the occurrence.
- *Bird*. This category is adapted from CICTT and refers to bird strikes.
- *Collision*. This category includes collision to any obstacle and barrier except for birds. CICTT has a category called “collision with obstacle (s) during take-off and landing (CTOL)”, but as the operation altitude for UAV is not as high as the commercial aircrafts, we modified this category to include collisions during hovering and cruise as well.
- *Near occurrence*. Includes all the near collisions between two UAVs or between a UAV and other aerial vehicles and objects such as manned aircrafts and parachutes. It also includes cases when a UAV interrupts or is sighted in the proximity of another UAV, or manned aircraft (ATSB, 2017). This category is a modified version of “airprox/ TCAS alert/ loss of separation/near midair collisions/midair collisions (MAC)” in CCITT (CICTT, 2011).
- *Navigation*. Refers to all the cases, where the navigation of UAS is the cause of accident or incident. This category is a sub-category of “air traffic management or communications, navigation, or surveillance service issues” (ATM) by CICTT.
- *System component failure – non-power plant (SCF-NP)*. The definition of this variable in CICTT includes a clause about unmanned aircraft: *“includes failure or malfunction of ground-based, transmission, or*

aircraft-based communication systems or components –or– datalink systems or components". We used the same definition here.
- *System component failure – power plant (SCF-PP)*. This category is also adapted from CICTT and it includes failures or malfunctions related to the battery and power plant controls of the UAS.
- *Loss of ground control (LGC)*. Includes all the cases where losing the control of UAV is the cause of accident or incident. Note that, CICTT has two categories called "loss of control – ground" and "loss of control – inflight" but the definition of these variables is different from LGC. Loss of ground control occurs due to three major reasons: equipment failure where either the UAV or the controller does not respond properly, increasing the distance between the UAV and the controller, and electro-magnetic interference which can affect the communications.
- *Turbulence*. Directly extracted from CICTT, refers to encounters with turbulence.

3.1.2. Hazard category

"Hazard category" is also defined by CICTT to identify the cause of accidents or incidents (CICTT, 2014). CICTT considers four hazard categories and we used the same categories to summarise the UAS accidents and incidents in this study. However, we altered the definition and usage of them as discussed below.

- *Environmental*. This label is used when the cause of occurrence is a factor of the environment, such as severe weather events. This label is also used for the cases where bird strike is the cause of occurrence.
- *Technical*. This category refers to the cases where technical deficiencies have caused the accident or incident.
- *Organisational*. This category is defined by CICTT to identify the cases where operational policies, procedures, and organisational regulations are the cause of occurrence. We used this label to the cases where lack of coordination between UAS operators and other organisations.
- *Human*. This category encompasses physical, medical, cognitive and psychological functioning of involved humans.

3.1.3. Phase of flight

CICTT defines twelve categories for the phase of flights to specify the phase of operation of accidents and incidents (CICTT, 2013). Except for *take-off* and *landing*, the rest of the categories are not suitable for UAS operations. Therefore, we added a phase called *cruise* which is defined as follows.

- *Take-off*. From detaching from the ground, or pilot's hands, until reaching the operational altitude.
- *Landing*. from reducing altitude for landing purpose until UAV touches the ground. This phase includes non-conventional landing methods such as using parachute.
- *Cruise*. All the phases that cannot be labeled as *take-off* or *landing*. This includes cruising, hovering and changing altitude while completing the pre-assigned tasks.

3.1.4. Colliding object

This category is added in this study to identify common obstacles causing UAV accidents and incidents. The following categories are defined based on the dataset of this study; thereby, it may not be comprehensive for UAS occurrence analysis.

- *Terrain*
- *Water*
- *Tree*
- *Other solid objects*
- *Bird*
- *Human*

3.1.5. Operation type

This variable clarifies the type of activity during which an accident or incident is occurred. Similar to "colliding object", this category is derived based on the available dataset of this study. The reported activities are listed below:

- *Survey*
- *Training*
- *Test*
- *Agriculture*
- *Emergency medical service (EMS)*
- *Rescue*

4. Methodology

The processed dataset includes seven categorical variables that can potentially explain the severity of incidents and accidents. To conduct a quantitative analysis, the categorical are converted into multiple binary variables, resulting in 38 explanatory variables. This study uses the exploratory factor analysis (EFA) method to reduce the dimensionality of observed variables and represent them in a more tractable form with a fewer number of latent variables (Tryfos, 1998). More importantly, EFA can uncover potential underlying structures in the data. Identifying these structures is essential in developing standard taxonomy for data recording, as well as developing safety measures and procedures. EFA investigates whether the observed variables $\boldsymbol{x} = (x_1, \cdots x_p)$ can be summarized by a set of unobserved factors (aka latent variables) $\boldsymbol{f} = \left(f_1, \cdots, f_q\right)$. To obtain a parsimonious description of the variables, q is expected to be considerably smaller than p. The underlying relationship between observed variables and latent variables is assumed to be a stochastic as formulated in equation (1) (Bartholomew, 1980). In this equation, $g(\boldsymbol{x})$ and $h(\boldsymbol{f})$ are the joint distribution functions of the observed and latent variables respectively, and $\pi(\boldsymbol{x}|\boldsymbol{f})$ is the conditional probability function of $\boldsymbol{x}$ given $\boldsymbol{f}$. The integral is defined over $\mathscr{R}$ which is the range space of the latent variables.

$$g(\boldsymbol{x}) = \int_R \pi(\boldsymbol{x}|\boldsymbol{f})h(\boldsymbol{f})d\boldsymbol{f} \tag{1}$$

In order to make the analysis simpler and the interpretation easier, in many applied EFA studies (Shalizi, 2013) a few simplifying assumptions are made about the relationship between observed and latent variables. First, the factors are assumed to be independent $\left(cov\left(f_i, f_j\right) = 0, \forall i \neq j\right)$. This assumption reduces the dimension of the integral in equation (1). Note that the independent assumption only applies to the factors and not the observed variables. Second, the relationship between observed variables and factors are assumed to be linear. Under these assumptions, for an available set of n observation with p attributes, equation (2) illustrates the relationship between observed values and latent factors. In this equation, $X_{n\times p}$ is the standardised matrix of observed variables. In this matrix, the n observations are stacked on top of each other. The standardised version of data indicates that the variables are scaled to have a variance of one and the expected value of zero. The $F_{n\times q}$ in this equation denotes the matrix of factor scores (value of factors corresponding to each observed instances). The factors are assumed to be independent across variables and observations (rows and columns). $\Phi_{q\times p}$ is the matrix of factor loadings, and $\boldsymbol{\varepsilon}_{n\times p}$ is the matrix of error terms, which represents the stochasticity. The expected value for each variable is zero, $(E(\varepsilon_j) = 0, j = 1, \cdots, p)$, but there is no assumption for the variance of residuals, so the error terms can have unequal variances $(var(\varepsilon_j) = \sigma_j, j = 1, \cdots, p)$.

$$X = F\Phi + \varepsilon \tag{2}$$

Assuming the number of factors (q) is known, the aim is to estimate the loadings (Φ). The rationale behind the estimation process is obtaining a set of factor scores and loadings that preserve the observed covariance matrix for the columns of X, in the reduced dimension space. The covariance matrix of X is determined by equation (3), where ψ in this equation is the covariance matrix of error terms. In this equation, which holds true for the population, the covariance matrix ν is not dependent on factor scores.

$$\nu = \psi + \phi^T \phi \tag{3}$$

4.1. Method of parameter estimation

Several methods are available for estimating the parameters of the model. In this study, we use the maximum likelihood method, and for that purpose, we need to make an additional assumption on the distribution of the factors. The usual assumption is that $f_i\ \mathscr{N}(0,1)$ and factors are independent with each other and across observations (Shalizi, 2013). Under these assumptions, the variables will be normally distributed with the covariance matrix of ν. The likelihood for a multinomial normal probability distribution is as shown in equation (4). This pertains to a single observation in the sample and in order to obtain the likelihood function we need to wrap around all the observations. Also, the common practice in the maximum likelihood estimation method is to use the logarithm of the likelihood function to obtain parameter estimates. Equation (5) shows the log-likelihood function for estimating the parameters of the model. In this equation, the covariance matrix is replaced from equation (3). In this equation $\hat{\nu}$ is the covariance matrix for the observed sample, and tr(.) is trace of a matrix.

$$\mathscr{L} = (2\pi)^{-p/2}|\nu|^{-1/2}\exp\left\{-\frac{1}{2}X_i^{'}\nu^{-1}X_i\right\} \tag{4}$$

$$\mathscr{L}\mathscr{L} = -\frac{np}{2}log2\pi - \frac{n}{2}\log|\psi + \phi^T\phi| - \frac{n}{2}tr\left((\psi + \phi^T\phi)^{-1}\hat{\nu}\right) \tag{5}$$

4.2. Rotation

The estimated loadings in CFA are not unique (Shalizi, 2013). Factor analysis projects observed data from a p dimensional space into a q dimensional sub-space. Infinite solutions are possible because setting up the coordinate system for the factors is quite arbitrary. Therefore, by rotating the axis of factors' coordinate system, and adjusting the factor loadings accordingly, a new set of factor scores and loadings is obtained that its performance in preserving the covariance of observed variables is identical to the original set of factor scores and factor loadings (Shalizi, 2013).

Often, when the original estimated loadings are not easy to interpret, by rotating the axis, a new version of loadings is generated which can be more easily interpreted. One of the commonly used rotation methods is *varimax* which maximizes the variance of the squared loadings for each factor. Applying the varimax method helps in detecting factors that are related to a fewer number of variables. This method helps to segregate the contribution of latent factors in explaining the observed variables (Tryfos, 1998).

4.3. Categorical variables

The discussion above was based on the assumption that all the variables are ratio variables. When the observed data includes categorical variables, which is the case of this study, further consideration is required in the factor analysis; otherwise the results will be incorrect or potentially very biased (Starkweather, 2014). As discussed above, estimating factor loadings is dependent on the observed covariate matrix and Pearson correlation matrix, which is defined for numerical data, is no more suitable. In this study all the variables are categorical. To tackle this issue, appropriate binary variables are defined, and factor analysis is proceeded by Polyserial correlation matrix (Starkweather, 2014).

4.4. Number of factors

Usually the number of factors and their nature are not known in advance. According to Revelle and Rocklin (Revelle and Rocklin, 1979) the methods to determine the number of factors can be categorised into three groups. The first method is the use of theoretical arguments, where the number of factors is decided based on the interpretability of the results. The second method is psychometric rules of thumb such as scree test or using the threshold of 1 for the eigenvalues of the correlation matrix. The third category is a statistical approach which tries to find a parsimonious set of necessary factors to describe the observed data (Revelle and Rocklin, 1979). For the dataset of this study, only for the cases with less than 8 factors the eigenvalues are above 1, and as this is a manageable number of factors, we examined all the cases from 8 factors to 1 and compared the results based on their interpretability. It is a common practice in EFA that modelers develop several models with a various number of factors to obtain a reliable model which supports the underling theories and is intuitive in interpretation (Tryfos, 1998).

4.5. Sample size

The minimum required sample size to obtain reliable outcome from EFA has received considerable attention during the past few decades. This is mainly because many studies encounter small samples where increasing the sample size may not be possible. Gorsuch (1983) and KLINE (2014) suggest an absolute minimum of 100 for sample size in EFA. de Winter et al. (2009) studied the conditions in which EFA provides reliable results for sample sizes below 50. They confirmed that the ratio of number of variables on number of factors (p/q) is a strong factor analytic determinant, nonetheless it is not a comprehensive measure. They showed, the minimum required sample size for $\frac{p}{q} = 2$ can vary between 11 and 48 depending on the number of variables and factors. de Winter et al. (2009) concluded that the required condition to achieve stable estimates with sample sizes below 50 are high communality, high number of variables and small number of factors. Jung and Lee (2011) studied the impact of estimation method for small samples (below 50). In particular, they compared Maximum likelihood estimator, generalised least square error, and regularised EFA (REFA) and concluded REFA can return stable results even for cases with a singular sample covariance matrix and where the sample size is smaller than the number of observations. Pearson and Mundform (2010) studied the role of sample size for stable factor recovery with dichotomous variables and they showed that even a sample size of 100 is enough to achieve a reliable model with three factors with at least 24 variables when communalities are high, and variables have a symmetric distribution.

For the current study, we acknowledge that increasing the sample size can lead in more reliable outcomes, and we advocate for more formal and compelling processes to record RPAS accidents and incidents; however, according to the previous studies on EFA for small samples, it is safe to proceed with conducting EFA on the available 138 records of data.

5. Results

The analyses of this study are presented in two sections. First, the descriptive statistics of the data is discussed, and then the results of the exploratory factor analysis are presented.

5.1. Univariate and bivariate distribution analysis

After categorising the occurrence records of this study, the frequencies of variables are visualised to assist with exploring existing patterns in the data. There are seven categorical variables, including "accident category", and each category has multiple levels. As mentioned before, we use quotation marks when referring to "variables" and italic style when referring to their *levels*. Fig. 1 shows the distribution of the categorical variables. The *unknown* cases are omitted from these distributions to increase the readability of the figures and to avoid biasedness in the interpretation. The omitted cases are less than 10% of the records for all the variables except for "hazard category" and "colliding object". Only in 86 records out of the 138 accidents and incidents the "hazard category" was identifiable, which means 38% of the records are removed for this variable. Moreover, in 17% of the records, the object to which the UAV had collided was not clear, thereby removed from the distribution for "colliding object".

In the plots of Fig. 1, the frequency bars are broken down into *accident*, *serious incident* and *incident* which are the predefined levels of "category" and revealing the severity of the occurrence. The first plot in Fig. 1 pertains to "colliding object". According to this plot, in most cases, the UAV has directly collided into the *terrain*. Water is the next frequent item in a collision, but in this category, there is no case of incident or serious incident. This is because finding a UAV after it has sunk into water is somehow impossible and all the cases where the UAV is not retrieved are labelled as an accident.

As shown in the plot for "Hazard category", *equipment factor* is the most frequent category, and *human factors* is the least frequent one. After removing the 52 cases for which this variable was *unknown*, the hazard category for 61% of the accidents and incidents was equipment problems. In this plot, the share of *environmental issues*, *organisation issues*, and *human factor* are 18%, 10% and 9% respectively.

The breakdown of "occurrence category" shows that *loss of ground control (LGC)* with 31% is the most frequent category. It is followed by *non-power plant system component failure (SCF-NP)* with a percentage of 25%. After that comes *power plant system component failure (SCF-PP)* and *collision* with 10% and then the rest of occurrence categories are all below 10%.

Regarding the "operation type", most of the accidents and incidents in the dataset of this study (nearly 77%) were during *survey* which includes video recording, laser scanning, and image taking. After *survey*, all other operation categories have a percentage below 10.

The distribution plot for "phase of flight" shows that nearly 80% of accidents and incidents occurred while aircrafts are hovering or cruising, whereas only 8% of them happened during *take-off*.

Finally, the breakdown of records for the "states and territories" shows that *Queensland* and *Western Australia* with 34% and 25% of accidents and incidents are the first two states with the highest number of occurrences, and *Australian Capital Territory* and *South Australia* with 2% and 4% are the regions with the lowest percentages.

To further interrogate the observed accident and incident records,

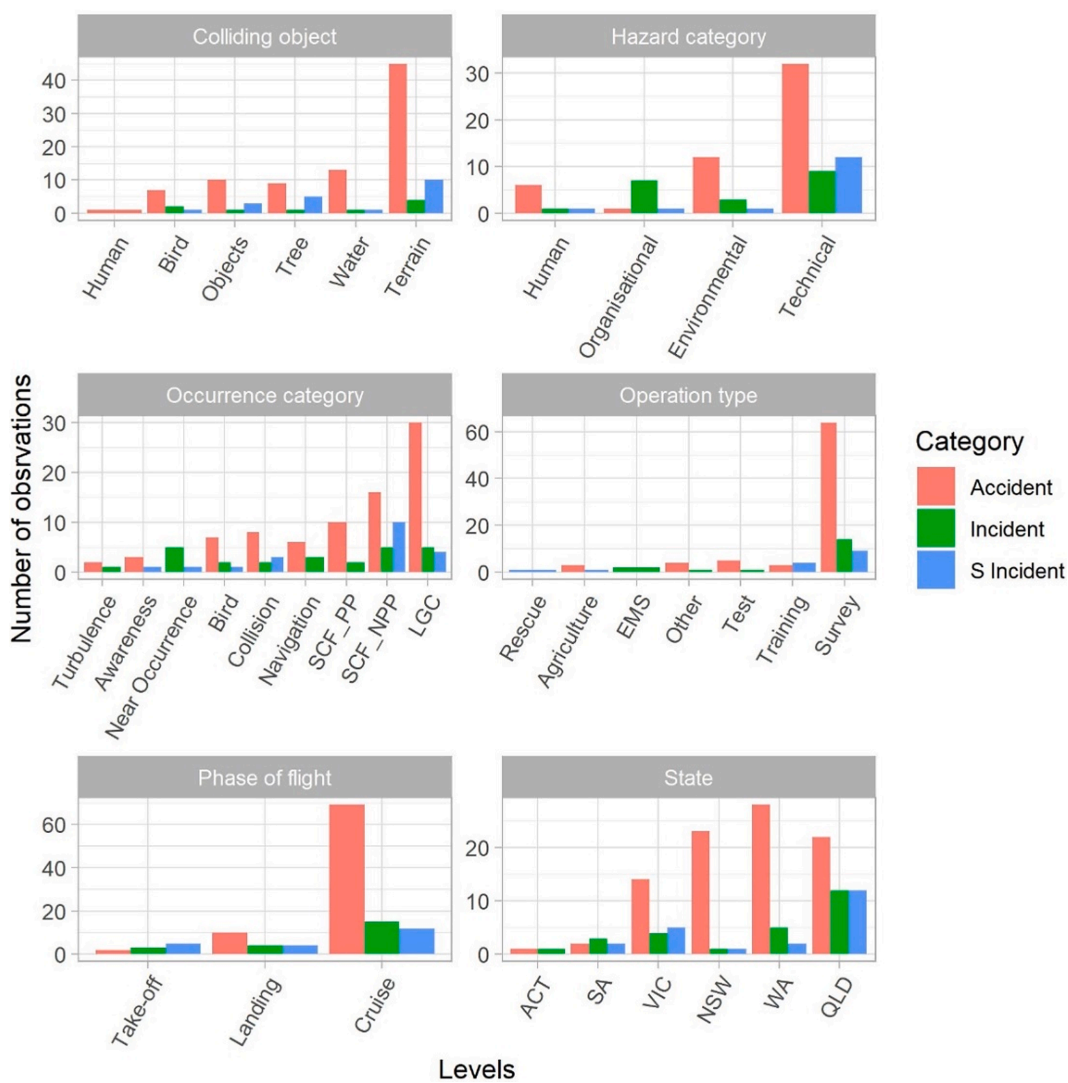

Fig. 1. Distribution of observed variables. The levels for hazard category include: Human factors, Organisational Issues, Environment Issues and Technical issues. For more details refer to section 2.1.2. The levels for the cause of occurrence include: Awareness, Bird, Collision, Loss of Ground Control, Navigation, Near Occurrence, System Component Failure (Non-Power Plant), System Component Failure (Power Plant), and Turbulence. For more details refer to section 2.1.1.

the joint distribution plots for all the variables against "occurrence category" are displayed in Fig. 2. The horizontal axis in all the plots in this figure shows "occurrence category", and the size of the circles represent the number of observations for each combination. It is noteworthy to mention the size of the circles varies on a continuous range. Regarding the join distribution of "colliding object" versus "occurrence category", for most of the occurrence categories, the UAV has collided to terrain or water, except for the categories of *collision*, where *tree* and *static objects* have the highest portion, and *bird*, which obviously indicates the collision was with a bird. The joint distribution of "hazard category" and "occurrence category" shows that *human factor (HF)* was only detected when the occurrence was because of *loss of awareness. Equipment factor* has resulted in *loss of ground control (LGC)*, *navigation* problems, and *system component failure (SCF)*. Also, *near occurrence* is merely observed with *organisational issues (OI)*. The joint distribution of "operation type" and "occurrence category" is not much revealing as the *survey* category is dominant with only some scattered observations in other categories. The joint distribution for "phase of flight" and "occurrence category" suggests that *LGC*, *navigation* and *SCF_NPP* are the main observed occurrence categories for the accidents and incidents during *landing* and *take-off*. The last plot in Fig. 2 is the joint distribution of "states and territories" and "occurrence category". In this plot, except for *ACT* and *SA* for which the number of observations is very low, for other regions almost all the occurrences categories are present.

The manual process of creating joint distribution functions to extract meaningful patterns is tedious, cumbersome and highly subjective. Therefore, we employed exploratory factor analysis method, as a more systematic approach, to analyse the structure of data and obtain clear-cut categories for UAS occurrence data.

5.2. Exploratory factor analysis

The EFA of this study is conducted with the assistance *psych* package in the statistical software package of *R*. As discussed in the methodology section, each categorical variable should be transformed into multiple binary variables to allow for calculating polyserial correlation matrix (Starkweather, 2014). To decide about the suitable number of factors, the value of eigenvalues for various number of factors is plotted in Fig. 3.

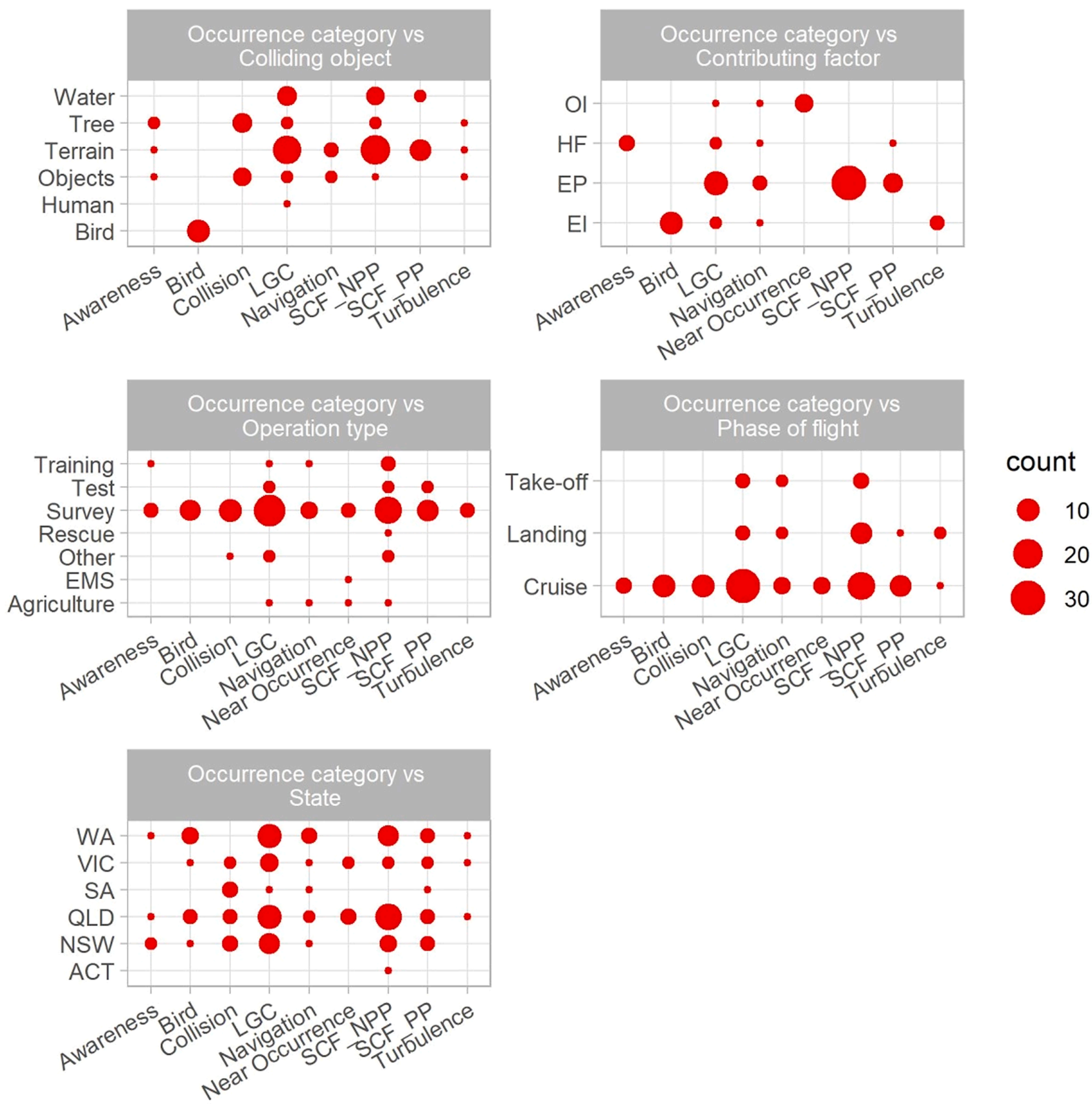

Fig. 2. Joint distribution of observed variables versus occurrence category. The levels for occurrence category include: Awareness, Bird, Collision, Loss of Ground Control, Navigation, Near Occurrence, System Component Failure (Non-Power Plant), System Component Failure (Power Plant), and Turbulence. For more details refer to section 2.1.1 In these plots, the size of the circles depicts number of observations in each category. These values vary on a continuous range, and the legend present three examples as visual references.

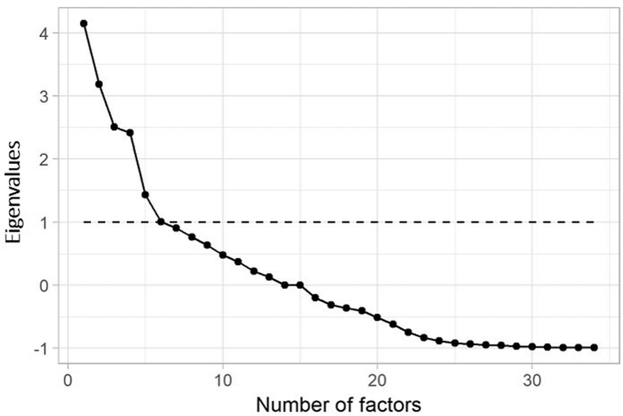

Fig. 3. Eigenvalues versus number of factors.

All the 138 records of accident and incident are utilised to estimate the factor loadings in the models. As a rule of thumb (Revelle and Rocklin, 1979), cases where the eigenvalue of factors is less than 1 are not suitable. This rule leaves us with the maximum number of seven factors. In this study, we develop all the factor models with number of factors from 7 to 1 and select the most suitable model, which is parsimonious in number of factors yet enlightening in terms of summarising observed data into distinct occurrence categories.

The most suitable factor model turned out to include 5 factors. This number of factors is exactly what the rule of thumb (Revelle and Rocklin, 1979) suggested. Table 1 shows the estimated factor loading (Φ). This table only includes the loadings that are either higher than 0.3, or lower than −0.3. This is the threshold we considered for significant impact from factors on variables.

The EFA practice of this study summarises the observed accidents and incidents using five factors. Each factor can be a representative of a common type of collision. In this section, first the prevailing occurrence pattern for each factor is explained, then the improvements in regulations that can prevent each category of accidents and incidents are discussed.

5.2.1. *Human factor in RPAS occurrence*

The first two identified factors cover the occurrences that are related to human factors. Factor 1 represents cases where loss of awareness is the “cause of occurrence”. According to the factor loadings in Table 1, the “hazard category” for this factor is primarily noted as *human factors*, and this type of collision is more frequent during the landing phase. Factor 2 represents colliding to static objects where colliding to trees or other static objects is the primary “cause of occurrence” for the failures represented by this factor. Besides, *Loss of awareness* is also an important “cause of occurrence” for these failures. In both these cases human factor seems to the main reason therefore providing training can help with reducing the risk for these types of occurrences. Current CASA regulations require pilots to have remote pilot licence to fly drones larger than 2 kg, and there are considerably high level of training and education provided by CASA which is an indication of a proactive approach regarding human factors.

5.2.2. *Coordination*

The next two factors pertain to coordination issues. Factor 3

Table 1
Factor loadings.

	Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Category	Accident			−0.484		−0.871
	Incident			0.655		0.342
	Serious Incident					0.727
State	ACT	0.778				
	NSW					−0.402
	QLD					0.307
	SA		0.56			
	VIC					
	WA				0.302	
Operation type	Agriculture	0.587				
	EMS	0.67		0.562		
	Other	0.587				
	Rescue	0.797				
	Survey	−0.35				
	Test	0.491				
	Training	0.422				
Cause of occurrence	Loss of awareness	0.505	0.328			
	Bird				0.994	
	Collision		0.814			
	Loss of ground control					
	Navigation					
	Near miss			0.849		
	Non-power plant system failure				0.327	−0.445
	Power plant system failure					
	Turbulence	0.533				
Hazard category	Environmental Issues				0.809	
	Equipment problem		−0.541	−0.342	−0.399	
	Human factor	0.348				
	Organisation issues			0.984		
Colliding to	Bird				0.994	
	Human	0.821				
	Other objects		0.562			
	Terrain		−0.519	−0.357	−0.353	
	Tree		0.564			
	Water					−0.315
Phase of flight	Cruise				0.374	−0.401
	Landing	0.332	−0.37			
	Take off					0.501

represents the cases where *organisations issues* is the "hazard category". Most of the recorded cases that contribute to this factor are the ones that occurred due to the lack of coordination among multiple aerial operations. Detecting aircrafts, helicopters, parachutes landing, or other drones in the vicinity of the UAV flight path and terminating the operation is the common pattern for these cases. These occurrence cases can be avoided if an integrated coordination system for aerial activities is established.

Factor 4 represents collisions where bird strike has occurred. The "hazard category" for accidents and incidents that contributes to this factor are mainly *environmental issues* (which as mentioned in section 2.1.2 includes bird strike) and the "colliding object" for these cases is *bird*. Also, the dominant "phase of flight" for these accidents and incidents is *cruise*.

5.2.3. Equipment

Finally, the last factor represents the occurrences that are caused by hardware issues, related to the electronical and/or mechanical components of the UAS. In addition to human factor and coordination, this is the third dimension that requires higher attention regarding RPAS safety.

6. Discussion

After identifying the common causes of RPAS accidents and incidents, several recommendations are put forward in this section.

First and foremost, the existing regulations and safety procedures are mainly concerned with human factor, and there is no mechanism to coordinate and organise drone operations and other aerial activities. This is the main shortcoming that led to the accidents and occurrences contributing to factor 3. The recent interruption in helicopters' water bringing operation in the bushfire in Tasmania (Bevin and Dunlevie, 2018), and the disruption caused in the Gatwick Airport which affected 150,000 passengers just before Christmas (Britton and Clarke, 2018), could have been avoided if a proper monitoring and surveillance system for drone operation was in place. Currently, CASA has developed phone apps for drone users to inform them about restricted flying zones and basic safety procedures. This platform can be extended to incorporate aerial activities so drone flyers can be notified about their surrounding aerial activities.

In Australia, before 2019 only a certified pilot can fly a commercial drone heavier than 2 kg, after obtaining flight permission. For commercial drones under 2 kg, licenced pilot is not needed if the fly is within the standard operating conditions. In this case, the operator only needs to notify CASA before the operation. The level of authorities' supervision was even less for non-commercial drone operation. Recently, as this paper was developed, CASA passed a new set of regulations under which operator licence is required for any commercial operation of drones heavier than 250 g.

Second, regular examination of drones' airworthiness can reduce the risk of occurrences due to hardware issues. If drones are to be registered on a yearly basis, in a similar fashion as motor vehicles' registration need to be renewed every year, then low-quality and obsolete drones which have a higher risk of failure can be written-off. The importance of such a procedure is underpinned by the fact that 60% of the observed accidents and incidents are due to equipment failure.

Finally, the compatibility of drone operations with natural environment requires special consideration. The recorded cases related to bird strike is an indication of impact on habitats and wildlife. Investigating the reasons behind bird strike requires further studies in collaboration with zoology.

Before concluding the paper, a technical note about the outcome of EFA is noteworthy. Although the numbers in Table 1 are helpful in identifying common occurrence categorising, some of the numbers in this table can be misleading if not interpreted correctly. On one hand, there is no standard procedure for reporting accidents and incidents so there might be patterns in data that are due to the bias in reporting the occurrence. For example, the estimated factor loadings for the states does not necessarily indicate higher or lower frequency of an occurrence type in a particular state, but it can be due to different attitudes in reporting accidents and incidents in different states. On the other hand, due to the limited dataset of this study, some of the estimated parameters may be inflated. For instance, there is only one case where the "colliding object" is *human*, and depending on other attributes of this occurrence case, the estimated factor loading for colliding to human is artificially high for factor 1. Obviously, this factor loading cannot be indicative of a relation between *loss of awareness* and *colliding to human*.

7. Conclusion

This paper conducted a post-accident analysis on civil unmanned aircraft system accidents and incidents in Australia. First and foremost, this study is advocating for a comprehensive and consistent taxonomy with unique identifiers for each category to permit common coding in UAS accidents/incidents reporting. This is an essential prerequisite to targeted accident prevention, as the first step to rectify risk is recognizing its source.

The analysis of univariate and bivariate distributions of collisions' attributes showed *technical issue* is the "hazard category" for more than 60% of collisions in the dataset of this study (top right plot in Fig. 1). *Equipment factor* has mainly resulted in *loss of ground control (LGC)*, *navigation* problems, and *system component failure (SCF)*. This is while there is no proper mechanism in place to monitor the airworthiness of UAVs. Also, nearly 80% of the collisions occur during the *cruise* phase of flight, which suggests that safety procedures for civil manned aircraft cannot be directly adopted for UAS due to the dissimilarities in their typical operation altitude.

In addition to analysing the attributes' distributions, exploratory factor analysis (EFA) is utilised as a systematic approach to detect potential constructs behind the attributes. Based on the results, accidents and incidents can be divided into five categories of "loss of awareness", "bird strike", "organisation issues", "colliding to static objects" and "equipment failures". Current regulations around UAS is mainly concerned with "loss of awareness" and "colliding to static objects". This paper suggests a comprehensive registration system which imposes regular safety inspections for UAVs can help to reduce the "equipment failures" accident and incident type. Moreover, to avoid the operation of UAVs interfering other aviation sectors, an integrated control system is required to help with coordinating UAVs' operations and other sectors. Lastly, the regulations must consider environmental impacts of UAVs' operations and impose restrictions where UAV can be a threat to the wildlife.

The main direction to continue this study is collecting a more comprehensive dataset. The available dataset in this study is obtained from self-reported accidents and incidents, therefore, cannot provide a holistic view towards drone safety. The limited dataset of this study does not allow for the generalisation of the findings. The proposed registration system with proper legislations, to enforce recording and reporting accidents and incidents can be helpful to collect a more enriched source of data for further investigations.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

Acknowledgment

We are grateful to Mr Noel Arnold for comments that greatly improved the manuscript.

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