Empirical Software Engineering (2023) 28:134
https://doi.org/10.1007/s10664-023-10361-4

Automated detection, categorisation and developers' experience with the violations of honesty in mobile apps

Humphrey O. Obie[1] · Hung Du[2] · Kashumi Madampe[1] · Mojtaba Shahin[3] · Idowu Ilekura[4] · John Grundy[1] · Li Li[5] · Jon Whittle[6] · Burak Turhan[7] · Hourieh Khalajzadeh[2]

Accepted: 12 June 2023 / Published online: 27 September 2023

Abstract
Human values such as honesty, social responsibility, fairness, privacy, and the like are things considered important by individuals and society. Software systems, including mobile software applications (apps), may ignore or violate such values, leading to negative effects in various ways for individuals and society. While some works have investigated different aspects of human values in software engineering, this mixed-methods study focuses on *honesty* as a critical human value. In particular, we studied (i) how to detect honesty violations in mobile apps, (ii) the types of honesty violations in mobile apps, and (iii) the perspectives of app developers on these detected honesty violations. We first develop and evaluate 7 machine learning (ML) models to automatically detect violations of the value of honesty in app reviews from an end-user perspective. The most promising was a Deep Neural Network model with F1 score of 0.921. We then conducted a manual analysis of 401 reviews containing honesty violations and characterised honesty violations in mobile apps into 10 categories: unfair cancellation and refund policies; false advertisements; delusive subscriptions; cheating systems; inaccurate information; unfair fees; no service; deletion of reviews; impersonation; and fraudulent-looking apps. A developer survey and interview study with mobile developers then identified 7 key causes behind honesty violations in mobile apps and 8 strategies to avoid or fix such violations. The findings of our developer study also articulate the negative consequences that honesty violations might bring for businesses, developers, and users. Finally, the app developers' feedback shows that our prototype ML-based models can have promising benefits in practice.

Keywords Human values · Honesty · Mobile apps · Machine Learning · App reviews · Mixed-methods · Developer experience

Communicated by: Nicole Novielli, Shane McIntosh and David Lo

This article belongs to the Topical Collection: *Special Issue on Mining Software Repositories (MSR).*

✉ Kashumi Madampe
kashumi.madampe@monash.edu

Extended author information available on the last page of the article

1 Introduction

Human values, such as *integrity, privacy, curiosity, security,* and *honesty*, are the guiding principles for what people consider important in life (Cheng and Fleischmann 2010). These values influence the choices, decisions, relationships, and the concept of ethics for people and society at large whether or not they are formally articulated in this terminology (Schwartz 1992). The relationship between human values and technologies is important, especially for ubiquitous technologies like mobile software applications (apps) (Obie et al. 2021). Mobile apps are a convenience to modern society and have seen usage in carrying out both simple and complex tasks, from entertainment (e.g., video sharing apps) and health (e.g., fitness trackers) to finance (e.g., banking apps). End-users of these apps hold certain expectations influenced by their human values considerations, e.g., the privacy of data, transparency of processes in apps, and ethical behaviour of platforms and software companies (Obie et al. 2021). The violation of these value considerations is detrimental to the end-user, software platforms, companies, and society in general (Whittle et al. 2011).

Recent work on human values in software engineering (SE), based on the Schwartz theory of basic human values (Schwartz 1992, 2012), has mapped human values to specific ethical principles. For example, Perera et al. mapped values to the GDPR principles (Perera et al. 2019) and Winter et al. mapped values to the ACM Code of Ethics (Winter et al. 2018). Other studies such as Obie et al. (2021) have explored the violation of human values in mobile apps using app reviews as a proxy. The recent study by Obie et al. showed that the value of *honesty* (a sub-item of *benevolence* based on Schwartz theory (Schwartz 1992)) is violated by mobile apps (Obie et al. 2021).

Honesty, often perceived to be a very important human value (Miller 2021), describes a character quality of being sincere, truthful, fair, and straightforward, and refraining from lying, cheating, deceit, and fraud (Dictionary 2012). The importance of the value of honesty is clearly articulated in the ACM Code of Ethics: *"Honesty is an essential component of trust. A computing professional should be transparent and provide full disclosure of all pertinent system limitations and potential problems. Making deliberately false or misleading claims, fabricating or falsifying data, and other dishonest conduct are a violation of the Code."* (Gotterbarn et al. 2017). Nonetheless, there have been many flagrant violations of the value of honesty by mobile app platforms and software companies in ways that are collectively called *dark patterns* (Dong et al. 2018; van Haasteren et al. 2019; Hu et al. 2019; Samhi et al. 2022; Gao et al. 2022). These dark patterns, a violation of the value of honesty, entail sophisticated design practices that can trick or manipulate consumers into buying products or services or giving up their privacy (Barr 2022). Furthermore, some of these dark patterns and honesty violations have been flagged in a recent report by the Federal Trade Commission (FTC) (Henderson 2022). Other examples include companies deliberately hiding data breaches from the authorities and customers (Bowman 2021; Shaffery 2021). These violations of the value of honesty result in decreased trust from users, poor uptake of apps, and reputational and financial damage to the organisations involved. This also emphasises the need to consider human values more proactively in software engineering practice.

This work aims to gain a comprehensive understanding of honesty violations in mobile apps. To this end, we conducted a mixed-method study. Given that user's comments expressed in app reviews have been shown to be a proxy for detecting users' challenges and requirements (AlOmar et al. 2021; Obie et al. 2021; Shams et al. 2020; Di Sorbo et al. 2016; Guzman and Maalej 2014), we first developed and evaluated seven machine learning models to learn the features that are representative of the violation of honesty in app reviews. The best-performing model (a Deep Neural Network) has an F1 score of 0.921, a precision of 0.911, and a recall of 0.932. Beyond the automatic detection of honesty violations, we then manually analysed 401 reviews containing honesty violations. Our resulting taxonomy shows that honesty violations can be characterised into ten categories: **unfair cancellation and refund policies, false advertisements, delusive subscriptions, cheating systems, inaccurate information, unfair fees, no service, deletion of reviews, impersonation,** and **fraudulent-looking apps**. Finally, we conducted a developer study[1] with mobile app developers to explore their experiences with honesty violations. The analysis of qualitative data from the developer study resulted in identifying a set of causes (business, developer, app platform, user and competitor drivers), parties responsible for the honesty violations (product owners, managers, business analysts, user support roles – in addition to developers, and business), consequences of honesty violations on businesses, app developers, and end users (e.g., bad reputation for the company, developers experiencing negative emotions, and identity theft of users), and strategies the app developers use to avoid (e.g., strengthening designing practices) and fix (e.g., thoroughly investigating the violation and fixing it) honesty violations in the apps they develop. The developer study also shows that the automatic detection of honesty violations in app reviews bring several benefits to businesses, developers, app platforms, and users. From this point onwards, the terms "mobile app developer" and "developer" are used interchangeably.

We published preliminary results of our machine learning-based classification work at the Mining Software Repositories (MSR) conference in 2022 (Obie et al. 2022). We substantially extend this previously published work here by (i) the inclusion of two new machine learning models, deep neural network (DNN) and generative adversarial network (GAN), with the new DNN replacing the prior support vector machine (SVM) as the best model; (ii) evaluation of these new models; and (iii) adding a new research question (**RQ3**). **RQ3** includes four subquestions to seek mobile developers' views on the causes behind honesty violations in mobile apps (**RQ 3.1**), the potential consequences of honesty violations (**RQ3.2**), possible solutions to avoid or fix such violations (**RQ3.3**), and potential benefits of automated identification of honesty violations in mobile apps (**RQ3.4**).

This work makes the following key contributions:

– We present several machine learning models and datasets to aid the automatic detection of the violation of the human value of honesty in app reviews. Our publicly available replication package supports researchers and practitioners to adapt, replicate, and validate our study (Obie et al. 2022).
– We provide insights into the different categories of honesty violations prevalent in app reviews by creating a taxonomy based on a manual analysis of the honesty violations dataset.
– We survey 70 app developer practitioners and interview 3 practitioners to get their feedback on the prevalence of honesty violations in their mobile apps, the causes of these issues, and feedback on our proposed machine learning-based classifier to help identify such violations from user app reviews.
– We present an actionable framework for developers which gives a better understanding of the causes and consequences of honesty violations and strategies that can be used to avoid and fix honesty violations.
– We present a set of practical implications and future research directions to deal with the challenges of the violations of the human value of honesty in apps that would benefit end-users and society.

[1] Approved by Monash Human Research Ethics Committee. Approval Number: 35070.

The rest of the paper is organised as follows: Section 2 highlights motivating examples of honesty violations. Section 3 summarises the related studies. In Section 4, we elaborate on the research design. The findings of this study are reported in Sections 5, 6, and 7 for different research questions. Section 8 reflects on the findings and provides implications, followed by reporting on possible threats in Section 9. We conclude the paper in Section 10.

2 Motivating Examples

Consider an example review of dubious charges to a user account for a calendar reminder app: *"I've been charged $45+ on 2 separate occasions in the month I've had the 'premium' version. It advertises $3.50 for a premium subscription but saw nowhere where it said they would make additional charges.*

Such reviews are common for many subscription-based apps. They are also very common for apps with optional premium versions where users find themselves unwittingly signed up to the premium charges. Many end users perceive these as deliberate attempts by app providers to dishonestly make money. Some companies have been convicted of such dishonest practices. For example, Shaw Academy offered users a free trial to its online education platform and charged them a subscription fee even if they had cancelled before the end of the trial period and refused to refund the users (Yiacoumi 2021). The outcome of an investigation by the Australian Competition & Consumer Commission (ACCC) ordered the company to refund approximately $50, 000 to the affected users and pledge to improve their system (Yiacoumi 2021).

Consider another example of dishonesty from a dating app. The dating platform (http://www.Match.com) has been accused of faking love interests using bots and fake profiles to fool consumers into buying subscriptions and exposing them to the risk of fraud and other deceptive practices (Perez 2019). During a period of over three years, the company allegedly delivered marketing emails (i.e., the *"You have caught his eye"* notification) to potential consumers after the company's internal system had already flagged the message sender as a suspected bot or scammer. The company also violated the "Restore Online Shopper's Confidence Act" (ROSCA) by making the unsubscription process tedious. Internal company documents showed that users need to make more than six clicks to cancel their subscription. This resulted in the U.S. Federal Trade Commission (FTC) suing http://www.Match.com for "deceptive advertising, billing, and cancellation practices" (Perez 2019).

3 Related Work

Mining App Reviews: Many works have provided insights into app user reviews and how these reviews can aid software professionals in app requirements, design, maintenance (Pelloni et al. 2018; Carreño and Winbladh 2013; Seyff et al. 2010) and evolution (Ciurumelea et al. 2017; Li et al. 2018, 2010; Palomba et al. 2015). Guzman and Maalej adopted Natural Language Processing (NLP) techniques to locate fine-grained app features in reviews with the aim of supporting software requirements tasks (Guzman and Maalej 2014). A related work utilised Latent Dirichlet Allocation (LDA) technique and linguistic rules to group feature requests from users as expressed in their reviews, and the results from this study showed that users care about frequent updates, improved support, more customisation options, and new levels (for game apps) (Iacob and Harrison 2013).

Some studies have focused on the automatic classification of app reviews into useful categories. To aid software professionals in prioritising accessibility issues, AlOmar et al. developed a machine learning model for identifying accessibility-related complaints in app reviews (AlOmar et al. 2021). Panichella et al. introduced a taxonomy for classifying app reviews and, using a combination of NLP and sentiment analysis, classified app reviews into their proposed taxonomy (Panichella et al. 2015).

Other works have introduced tools to support the extraction of insights from app reviews. For example, Vu et al. proposed MARK, a keyword-based tool for detecting trends and changes that relate to occurrences of serious issues in reviews (Phong et al. 2015). Similarly, Di Sorbo et al. introduced SURF, a tool that condenses thousands of reviews into coherent summaries to support change requests and planning of software releases (Di Sorbo et al. 2016). Our own work has classified various app reviews into different human value violations (Obie et al. 2021, ?), human-centric issues discussed in app reviews (Mathews et al. 2021; Khalajzadeh et al. 2022), and a myriad of problems users have with eHealth apps (Haggag et al. 2022).

The above studies show that app reviews are a useful resource for gathering requirements, detecting issues, and more generally supporting software professionals in evolving their apps. This work also aims to support app maintenance and evolution by effectively detecting potential violations of the value of honesty from the user's perspective in app reviews. In addition, it would aid software professionals in delivering software products that build trust in users, as the honesty (real or perceived) of companies can affect how users engage with their products (Zhu et al. 2021).

Human Values in Software Engineering (SE): Human values are enduring beliefs that a specific mode of conduct or end state of existence is personally or socially preferable to an opposite or converse mode of conduct or end state of existence (Rokeach 1973). Human values have been well-studied in the social sciences and have begun to see adoption in other fields, including design (Aldewereld et al. 2015) and software engineering (SE) (Mougouei 2020; Li et al. 2021).

The study of human values in SE is a relatively nascent line of research (Perera et al. 2020; Mougouei et al. 2018) and is mostly based on the widely accepted and adopted Schwartz theory of basic human values (Schwartz 1992, 2012). The Schwartz theory is built on a survey conducted in over 80 countries covering different demographics. This theory categorises values into 10 broad categories, namely: *self-direction, stimulation, hedonism, achievement, power, security, conformity, tradition, benevolence,* and *universalism*. These 10 categories, in turn, are made up of 58 value items, e.g., the value category of ***benevolence*** covers the value items of ***honesty***, responsible, helpful, forgiving, loyal, mature love, a spiritual life, meaning in life, and *true friendship* (c.f (Schwartz 1992)). However, our focus in this work is on the value item of *honesty*, based upon the prevalence of the value category of *benevolence* in prior research (Obie et al. 2021), the recent cases of the violations of *honesty* by companies in the media, e.g., Perez (2019); Yiacoumi (2021), and the need to understand this phenomenon more closely in SE.

Studies in the social sciences have investigated the value of (dis)honesty at the individual and organisational levels (Fochmann et al. 2021), and the policy implication of dishonesty in everyday life (Mazar and Ariely 2006); while others have explored the motivation for dishonest behaviours (Cheating 2016) including students in classroom settings (Lang 2013) and workers in crowd-working environments (Jacquemet et al. 2021). Keyes argues that euphemising the violation of the value of honesty desensitises people to its implications and consequences in society (Keyes 2004).

However, within the context of SE, Whittle et al. argued that software companies need to consider human values in the development of software systems and make them “first-class” entities throughout the software development life cycle (Whittle et al. 2011). Another study made a case for the evolution of current software practices and frameworks to embed human values in technology, instead of a revolution of the SE field (Hussain et al. 2020).

Another line of research considered methods for measuring human values in SE. For example, Winter et al. introduced the Values Q-sort instrument for measuring human values in SE (Winter et al. 2018). Applying the Values Q-sort instrument to 12 software engineers resulted in 3 software engineer values “prototype”. Similarly, Shams et al. utilised the portrait values questionnaire (PVQ) to elicit the values of 193 Bangladeshi female farmers in a mobile app development project (Shams et al. 2021). The result of the study showed that conformity and security were the most important values, while power, hedonism, and stimulation were the least important. More recently, Obie et al. argued that the instruments for eliciting and measuring values should be contextualised to specific domains (Obie et al. 2021).

App Reviews and Human Values: Recent studies have adopted the use of app reviews as an auxiliary data source for eliciting values requirements. Shams et al. analysed 1,522 reviews from 29 agricultural mobile apps to understand the values that are both represented and missing from these apps (Shams et al. 2020). Obie et al. proposed a keyword dictionary-based NLP classifier to detect the value categories violated in app reviews (Obie et al. 2021). The results of the application of the classifier to 22,119 reviews showed that benevolence and self-direction were the most violated categories, while conformity and tradition were the least violated.

Related works such as Shams et al. (2020); Obie et al. (2021) have provided insights to violations of value categories. Our work complements these by zooming in on a specific value item; ***honesty*** (within the most violated category of ***benevolence*** (Obie et al. 2021)), to provide a more nuanced understanding of its violations. In addition, we provide a taxonomy of the different categories of honesty violations in reviews to better understand how the violation of the value of honesty is reported. Our practitioner survey and interviews suggest that the automated identification of honesty violations from app reviews would be practically useful. We hope that other researchers would be encouraged to investigate other specific value categories, their discussion of violations by users in app reviews, and more generally to explore the field of human values in SE.

4 Research Design

Our goal in this study is to develop a deep understanding of honesty violations in mobile apps by automatically identifying reviews discussing honesty violations, categorising the types of honesty violations, and exploring the perspectives of app developers about their perspectives on such honesty violations. To do this, we have formulated the following research questions that we need to answer (RQs):

- **RQ1.** *Can we effectively identify reviews documenting honesty violations automatically?* We formed a large labelled dataset of app reviews and then trained a variety of machine learning classifiers to answer this RQ. Our best-performing classifier has an F1 score of 0.921.
- **RQ2.** *What types of honesty violations are reported in these app reviews?* We manually inspected a sample of 401 honesty violation reviews and classified the honesty violations represented by each into ten distinct categories.

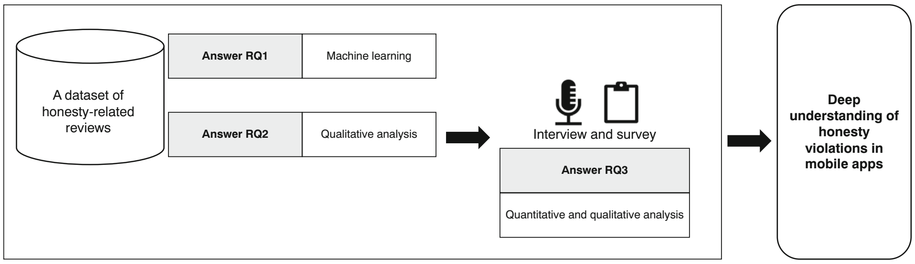

A dataset of honesty-related reviews
Answer RQ1
Machine learning
Answer RQ2
Qualitative analysis
Interview and survey
Answer RQ3
Quantitative and qualitative analysis
Deep understanding of honesty violations in mobile apps

Fig. 1 High-Level Overview of Mixed-methods Approach

– **RQ3.** *What is app developers' experience with honesty violations in the mobile apps they develop and their perspective on automatic detection of honesty violations?* We developed three subquestions to answer this RQ. We use in-depth interviews and a broad survey with the participation of 73 mobile app practitioners.

  RQ3.1.*What are the causes of honesty violations in mobile apps, and who is responsible for them?* We want to know, according to developers' experience with honesty violations in mobile apps they develop, what causes these honesty violations in mobile apps and who is responsible for them.

  RQ3.2.*What are the consequences of honesty violations in mobile apps on the end users and app developers/owners according to developers' experience?* The goal of this RQ is to understand the impacts of honesty violations on end users, and the developers themselves/owners of the mobile apps, as experienced by the mobile app developers.

  RQ3.3. *What strategies do developers use to handle honesty violations in mobile apps?* This RQ aims to identify what strategies the mobile app developers use to avoid and/or fix reported honesty violations in mobile apps (or if they indeed do so).

  RQ3.4. *What are the benefits of automatically detecting honesty violations in mobile apps?* Through this research question, we target exploring the potential benefits of automatic detection of honesty violations.

Approach for answering the above research questions. A high-level overview of our mixed-methods approach is given in Fig. 1 and elaborated in figures and text in the respective sections answering the research questions.

5 Automatic Classification of Honesty Violations (RQ1)

5.1 A Dataset of Honesty-Related Reviews

Our first step for answering RQ1 and RQ2 is creating a dataset of user reviews documenting perceived honesty violations by apps.

5.1.1 Data Collection

To build this dataset, we collected a total of 236,660 reviews - 214,053 reviews from the public dataset of Eler et al. (2019), and an additional 22,607 reviews from the public dataset of Obie et al. (2021). These reviews were collected from a total of 713 apps in 25 categories. The apps and reviews were intended to cover a diverse range of categories and audiences.

Table 1 Statistics of the dataset

Number of Apps	713
App Categories	25
All Reviews	236,660
Honesty-related Reviews (after keywords filter)	4,885
Honesty Violation Reviews (after manual validation)	401

Table 1 summarises the statistics of our combined app review dataset. Our dataset can be found here Obie et al. (2022).

5.1.2 Data Labeling

Given the sheer size of the dataset and the manual labour required to label the dataset, we used two approaches to label the 236,660 reviews: a keyword-based approach and manual labelling. We first adopt a set of keywords to filter the 236,660 reviews to include those related only to the value of honesty. These keywords are based on the dictionary of human values created by Obie et al. (2021). The set of keywords comprises a total of 48 words semantically related to honesty. The keywords are available here Obie et al. (2022).

After applying this keyword filter, the number of reviews was reduced from 236,660 reviews to 4,885 potential candidate honesty-related reviews (we call these 4,885 reviews ***honesty_potential*** reviews).

However, adopting a keyword-based approach is error-prone and may result in a lot of false positives. Hence, we manually analysed the ***honesty_potential (4,885)*** reviews to exclude the false positives. The application of keywords filter and subsequent manual analysis check have been applied in recent studies (Eler et al. 2019; AlOmar et al. 2021).

The ***honesty_potential (4,885)*** reviews were labelled and validated in 25% increments in the following manner. The first analyst labelled the first 25% percent of the ***honesty_potential*** reviews to determine which of the reviews contain the violation of the value of honesty as perceived by the user in the review. The second analyst validated the outcome. The disagreements were resolved in a meeting using the negotiated agreement approach to address issues of reliability (Campbell et al. 2013; Morrissey 1974). Then the next 25% were labelled by the first analyst, validated by the second analyst, and disagreements resolved in a meeting as in the first round. The same procedure was repeated for the third and fourth rounds of the labelling process. Also, the labelling and validation were done over eight weeks to avoid fatigue. Based on our manual labelling, we found that out of the 4, 885 filtered reviews (the ***honesty_potential*** reviews), only 401 were honesty violations reviews, i.e., true positives. We refer to these 401 honesty violations reviews as ***honesty_violations*** reviews. During the labelling process, we had a total of 105 reviews among the 4,885 *honesty_potential* reviews that we discussed further and resolved. Due to the fact that we adopted the negotiated agreement technique, measures like inter-rater agreement are not applicable. The negotiated agreement technique was employed because it is beneficial in research like ours where the main objective is to generate novel insights (Campbell et al. 2013; Morrissey 1974).

Next, we randomly selected 401 reviews from the remaining 4,484 ***honesty_potential*** reviews (4,885 ***honesty_potential*** reviews - 401 ***honesty_violations*** reviews). We refer to these 401 reviews, which contain honesty-related keywords (but not violations), as ***honesty_non_violations*** reviews. We used a total of 802 reviews: 401 ***honesty_violations*** and 401 ***honesty_non_violations*** reviews to build a **balanced dataset** called **honesty_discussion** dataset for training and evaluating machine learning models in Section 5. We note here that using the manually validated false-positive *honesty_non_violations* reviews is important for machine learning models. It is because these reviews include certain keywords syntactically related to honesty but semantically irrelevant to honesty violations - an important difference we want our models to learn. In summary, the **honesty_discussion** dataset consists of 802 reviews: 401 ***honesty_violations*** reviews and 401 ***honesty_non_violations*** reviews. These 802 reviews were the accurate results of manually labelling 4,885 reviews - a verified, accurate and balanced dataset for a more effective classifier. Other studies have used similar numbers of text documents in classification tasks (Levin and Yehudai 2017, 2019).

5.2 Classification Approach

Manually classifying honesty violations in app reviews is challenging for practitioners because it is error-prone, labour-intensive, and demands substantial domain expertise. Hence, an automated approach is required to recognise honesty violations in app reviews. This research question aims to develop machine learning models to differentiate between honesty and non-honesty reviews automatically. As shown in Fig. 2, the machine learning models are applied on the 802 **honesty_discussion** dataset which consists of 401 ***honesty_violations*** reviews and 401 ***honesty_non_violations*** reviews.

5.2.1 Data Preparation

We applied some common techniques to remove possible noise from the **honesty_discussion** dataset. This step was needed so a learning model can classify reviews correctly. To achieve this, we applied natural language processing techniques such as removing capitalisation, removing emojis, tokenising, removing stop words, and removing punctuation.

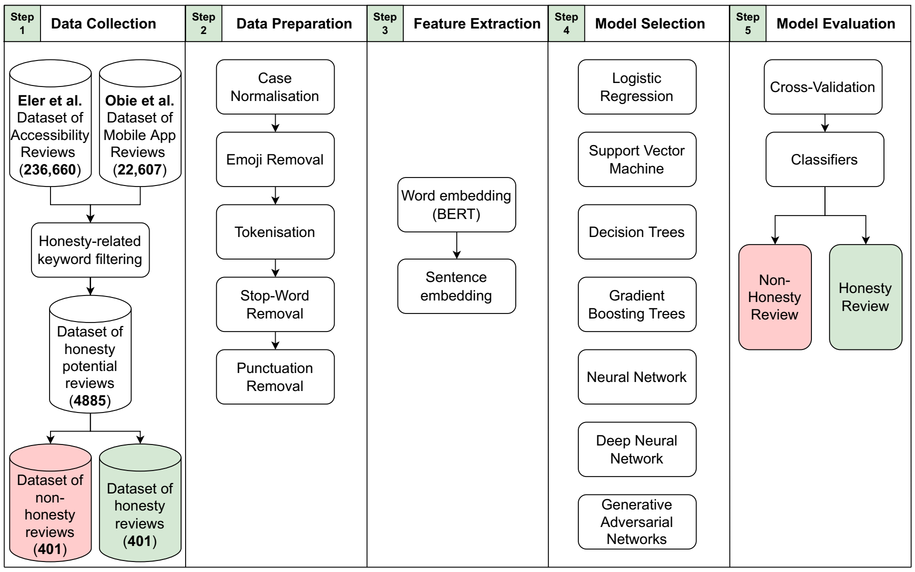


Fig. 2 Honesty app review classification process

Case Normalisation: is the process of transforming original review texts into lowercase. This type of text cleaning helps us avoid repeated features of the same words with different font cases (e.g., “Honesty" and “honesty"). Furthermore, converting the text into lowercase does not affect its context as well as the users’ expressions in our scenario.

Emoji Removal: Emojis are icons or a few Unicode characters that allow users to convey ideas, concepts, and emotions. If emojis are not carefully preprocessed, they can potentially affect the performance of a model in terms of accuracy. Hence, we removed emojis from the review texts.

Tokenisation: is the process of splitting each original text into a set of words that do not contain white space. We divided apps reviews into their constituent set of words.

Stop-Word Removal: Stop words such as *is*, *am*, *are*, *for*, *the*, and others do not contain the conceptual meaning of a review and create noise for a classification model. Removing stop words from the review texts helps us avoid repeated features of the same phases (e.g., “the bank account" and “bank account"). In our experiment, we used a comprehensive set of stop words that are well-known to the natural language processing community.[2] While the removal of negative contractions such as “doesn’t", “couldn’t", “won’t", and others can affect the decision of machine learning models in classifying text in some cases, our empirical analysis shows that in this instance, this approach does not have a large influence on the overall performance of our model.

Punctuation Removal: We observed many reviews in the data collection containing punctuation such as *“..., ??,:(,"* and others that do not significantly contribute to a classification model. Hence, we removed punctuation from the app reviews.

5.2.2 Feature Extraction

After cleansing and preprocessing the dataset, we converted the app reviews in the dataset into their vector representation by using the pre-trained Bidirectional Encoder Representations from Transformers model (Devlin et al. 2019), so-called BERT[3]. This is a language representation model trained on the BooksCorpus with 800 million words (Zhu et al. 2015) and English Wikipedia with 2.5 billion words. The model receives a sequence of words as input and outputs a sequence of vectors. The model converted the review texts with different words into 768-dimensional vectors used as input into a machine learning model. Each of these vectors is estimated by the average of embedded vectors of its constituent words. For instance, given a review text s that consists of n-words, $s = (w_1, \ldots, w_n)$, then, $\mathbf{s} \approx \frac{1}{n}(\mathbf{w_1} + \ldots + \mathbf{w_n})$, where $(\mathbf{w_1} + \ldots + \mathbf{w_n})$ are the embedded vectors of $(w_1, \ldots, w_n)$. Furthermore, these vectors capture both a semantic meaning and a contextualised meaning of their corresponding app reviews.

5.2.3 Model Selection and Tuning

Selecting a classification model that yields the optimal result is challenging. We selected seven models, such as Support Vector Machine (SVM), Decision Trees (DT), Neural Network (NN), Logistic Regression (LR), Gradient Boosting Tress (GBT), Deep Neural Network (DNN), and Generative Adversarial Networks (GANs) that are commonly used for text classification in the natural language processing community (Aggarwal and Zhai 2012). Below is a brief description of each classification model used in our work.

[2] The stop words can be accessed at https://gist.github.com/sebleier/554280#gistcomment-3126707

[3] The pre-trained BERT uncased model can be downloaded at https://huggingface.co/bert-base-uncased.

Logistic Regression (LR) is a linear classifier. The data is fitted into a logistic function that generates the binary output such as 0 (i.e., an honesty_non_violation app review) or 1 (i.e., an honesty violation app review) based on probability.

Support Vector Machine (SVM) (Noble 2006) is a classifier that finds hyperplane(s) in N-dimensional space (i.e., the number of features), which can further distinguish the data into multiple categories.

Decision Trees (DT) are a non-parametric supervised learning method used for classification and regression. DT predict the value of a target variable by learning simple decision rules inferred from the data features. Given a 768-dimensional vector representation of a particular review text, DT classifies the review text into the category selected by most trees.

Gradient Boosting Trees (GBT) is one of the ensemble learners that builds trees and boosts them for classification. When a new tree is created, it corrects errors of previous trees fitted on the same provided data. This repeatedly correcting errors process is known as the boosting process. In addition, the gradient descent algorithm is used for optimisation during the boosting process. Thus, the method is called gradient boosting trees. The model classifies app reviews into a category based on the entire ensemble of trees.

Neural Network (NN) is a multilayer perceptron model which contains a set of interconnected layers where each layer contains a finite number of nodes. Each neural network architecture has one input layer, at least one hidden layer, and one output layer. The input data is transformed layer by layer via the activation function(s). During the training process, optimisation techniques such as stochastic gradient descent are used to optimise the performance of the model. The classified category of a particular app review is the collected result from the output layer.

Deep Neural Network (DNN) is the extension of NN with a larger number of hidden layers that support the model to deeply learn the features in the vector representation of an app review (i.e., the embedding vector). Layers in the DNN are placed in consecutive order where the number of nodes subsequently decreases layer by layer. The first layer of the DNN is an input layer which contains N number of nodes corresponding to N-dimensions of the embedding vector. Nodes in one layer are, then, fully connected to nodes in the next layer. The Sigmoid function is applied to transform the last hidden layer of the DNN to the output layer, which contains the classified category of an app review.

Generative Adversarial Networks (GANs) (Goodfellow et al. 2014) is a generative neural network model that is widely used to generate high-quality data for evaluating machine learning tasks such as classification and prediction. The model consists of two networks; the generator network and the discriminator network. The generator network learns to curate the embedding vector of an app review with an incorrect category. Both embedding vectors with the correct category and generated embedding vectors are, then, used to train the discriminator network to classify the category of app review. This aims to increase the robustness of the discriminator in classifying the category of app reviews with less amount of labelled data.

Finding the hyperparameters for models to generate optimal results is known as the fine-tuning process. We use grid search cross-validation to perform an exhaustive search to find the best set of hyperparameters for each classifier. To reproduce our results, we provide the selected hyperparameters for each selected model and the open-source GitHub repository in Obie et al. (2022).

5.2.4 Cross Validation

To estimate the variance of the performance for each classification model, we used a K-fold cross-validation technique (Kohavi et al. 1995). The technique splits the data into K equal-

Table 2 Comparison of the confusion matrix and Matthews correlation coefficient (MCC) of classification models

	SVM	LR	NN	RF	GBT	DNN	GAN
True negative	0.432	0.407	0.358	0.371	0.358	0.407	0.383
True positive	0.457	0.469	0.482	0.420	0.420	0.506	0.482
False positive	0.025	0.049	0.099	0.085	0.099	0.049	0.074
False negative	0.086	0.074	0.062	0.124	0.124	0.037	0.062
MCC	0.785	0.753	0.676	0.581	0.555	0.826	0.726

sized subsets where one of the subsets is used for validation, and the remaining subsets are used for training. This process is repeated K times, the average of the validation scores is used to measure the performance for each classification model. In this study, we used a 10-fold cross-validation technique. Here, we split the dataset in Sect. 5.1 into 10 chunks of data that contains an equal number of app reviews. Then, we perform the evaluation process where the training dataset contains 9 chunks of data, and another chunk of data is used as the testing dataset. Note that this is repeated until each chunk of data has been used as the testing dataset once. This approach helps us understand how well our selected models perform on unseen data.

5.3 Results

In this section, we report the results of our experiment evaluating the performance of the different machine learning models. We adopted the generally accepted metrics of ***accuracy, precision, recall***, and ***F1 score*** for this purpose. Other metrics such as the Matthews Correlation Coefficient (MCC) and confusion table are shown in Table 2. We note here that all of the models performed well (with F1 scores of 0.79 and above).

Table 3 shows the results of our 7 different machine learning classification algorithms. **The DNN algorithm came out to be the best performing model with an accuracy of 0.914, precision of 0.911, recall of 0.932, and an F1 score of 0.921**. The second-best performing algorithm is the SVM model, with an accuracy of 0.889, precision of 0.949, recall of 0.841, and an F1 score of 0.892. The high performance of our DNN model makes it useful in practical applications for detecting the violation of the value of honesty in reviews.

One of the aims of our work is to introduce an automatic method for detecting honesty violation reviews that performs better than current approaches. Similar studies on text classification have compared their approaches to either the current state-of-the-art or a baseline classifier (AlOmar et al. 2021; Maldonado et al. 2017). Hence we compare our

Table 3 Comparison of classification models

	SVM	LR	NN	RF	GBT	DNN	GAN
Accuracy	0.889	0.877	0.840	0.790	0.778	0.914	0.864
Precision	0.949	0.905	0.830	0.829	0.810	0.911	0.867
Recall	0.841	0.864	0.886	0.773	0.773	0.932	0.886
F1 score	0.892	0.884	0.857	0.800	0.791	0.921	0.876

best-performing machine learning model (DNN) with a baseline classifier only since there is no current state-of-the-art in detecting the violation of honesty in app reviews, similar to what recent works have done (AlOmar et al. 2021; Maldonado et al. 2017).

We used the statistics of our dataset to compute the metrics of the baseline classifier. The precision of the baseline classifier can be computed by dividing the number of honesty violation reviews by the total number of ***honesty_potential*** reviews:

$$precision = \frac{401}{4,885} = 0.0821$$

The recall is 0.5, as there are only two outcomes for a review classification: honesty violations reviews or honesty_non_violations reviews, with a 0.5 probability of a review containing the violation of the value of honesty. Based on the precision and recall values, we compute the F1 score of the baseline classifier as:

$$F1\ score = 2 * \frac{0.0821 * 0.5}{0.0821 + 0.5} = 0.1412$$

Table 4 summarises the comparison of our best-performing machine learning model (DNN) with the baseline. As can be seen, the DNN model has a better performance than the baseline classifier. Our DNN model has an F1 score of 0.921, while the baseline classifier has an F1 score of 0.1412, respectively. Table 4 also shows that our DNN model surpasses the baseline classifier by 6.523 times in detecting honesty violation reviews.

The robustness of the DNN model on the unseen samples was evaluated by using 401 data samples which were randomly selected from the remaining 4, 083 (4, 885 − 802) ***honesty_non_violations*** reviews. Based on the data in Table 2, we can show that the accuracy of the DNN model on classifying ***honesty_non_violations*** reviews is 0.814 which is calculated as:

$$Accuracy(\boldsymbol{honesty\_non\_violations}) = \frac{TN}{0.5} = \frac{0.407}{0.5} = 0.814$$

where TN indicates true negatives. The accuracy of the model on the unseen samples (verified honesty_non_violations reviews only), however, reduces to 0.768. To further understand the limitations of the DNN model, the false positive reviews (incorrectly predicting true negatives) were selected and analysed. Examples of these reviews include:

> 👎 *"It was great! I loved it! But then there was a little problem. At day 5 of me using it, there was a bit of lag on the app. I checked my connection and my phone but everything was fine, then the next morning when I opened the app, it was pure black. I waited for 4-7 minutes but nothing happened. I restarted the app then open it again then everything was fine. Please fix this problem I just don't want this to happen. I really love this app so please fix it. Thank you."*

Table 4 Comparison of our model to a baseline classifier

	Our (DNN) approach			Baseline classifier		
	Precision	Recall	F1	Precision	Recall	F1
Classification	0.911	0.932	0.921	0.0821	0.5	0.1412
Improvement	-	-	-	11.096x	1.864x	6.523x

👎 *"It was nice to see the changes you made. It is easier to delete and move things but, you then overdo it. You overcompensated. More ads. Now, it keeps telling me I'm offline when I'm not. I get to the page, touch visit, nothings happening except it telling me I'm offline, check my network connection. It was fine the other day. All my other apps are working, not sure what is going on. Help."*

👎 *"Pinterest used to be a great app for recipes with the occasional ad. Now it's the single worst app to have because of the overabundance of ads. My screen jumps up and down and will not hold the recipe in place and when I finally do get to the recipe, my screen goes black and the app closes. With all my prep work on the counter ready to go I have to go back and endure the same pain of finding the recipe, scrolling past the ads, and hoping it doesn't do the same again."*

In these cases, the reviews focus on describing technical issues while using app rather than the fact that the app provides inaccurate information. Furthermore, the reviews mentioned "ads" but not mentioning whether the ads were relevant to the user's preferences. Given the sentiment of such reviews, the content of the populated ads in app may be neutral or relevant to the user's preferences. These examples demonstrates that there are two potential limitations of the DNN model such as (1) the confusion between technical issues and inaccurate information; and (2) the confusion between ads and false ads.

RQ1 Answer: The DNN model surpasses the baseline classifier in identifying the violation of the value of honesty in reviews. Our model achieves an F1 score of 0.921 with an improvement of 6.523 times the baseline classifier in classifying honesty violation reviews from honesty_non_violation reviews.

6 Categories of Honesty Violations (RQ2)

6.1 Categorisation Approach

While the machine learning models in Section 5 could effectively distinguish between honesty violations reviews and honesty non-violations reviews, we are also interested in understanding the types of honesty violations reported in reviews. To this end, we applied the open coding procedure (Glaser et al. 1968) on the 401 ***honesty_violations*** reviews. As discussed in Sect. 5.1, these reviews include honesty violations. First, an analyst followed the open coding technique to label all these 401 reviews and identified 10 types of honesty violations. The 401 ***honesty_violations*** reviews were assigned to these 10 categories. The results of the open coding were stored in an Excel spreadsheet file and shared with the second and third analysts. Then, the second analyst cross-checked the first 100 labelled reviews while the third analyst cross-checked the remaining 301 labelled reviews. Next, the first analyst held Zoom meetings with the second and third analysts to discuss and resolve the conflicts and disagreements. Note that the disagreements were resolved using the negotiated agreement approach (Campbell et al. 2013; Morrissey 1974). During the labelling, we had a total of 21 reviews among the 401 *honesty_violations* reviews that we discussed further and resolved. Sometimes we discussed the reviews not because we had different labels, but because the analyst identified the review and recommended further clarification and discussion. However, we were able to come to an agreement for all of the reviews after discussions. Due to the fact that we adopted the negotiated agreement technique, measures like inter-rater agreement are not applicable. The negotiated agreement technique was employed because it is beneficial in research like ours where the main objective is to generate novel insights (Campbell et al. 2013; Morrissey 1974).

6.2 Results

Our analysis of the 401 ***honesty_violations*** reviews revealed 10 categories of honesty violations reported in app reviews. Below we provide a definition of these categories, sample reviews, and a summary of their prevalence. While we highlight the different categories within the violation of the value of honesty and provide example reviews, we note that the categories are not mutually exclusive. Table 5 shows these categories and the frequency of the corresponding reviews per category.

6.2.1 Unfair Cancellation and Refund Policies

This category covers all reviews where the users perceive the cancellation and refund policy as unfair, nontransparent, or deliberately misleading. It also includes situations where the user feels that the developers deliberately make it difficult for the user to cancel their subscription. For example, in some apps, the user can sign up for a subscription with the click of a button within the app but cannot cancel the subscription from within the app; the user is asked to log in to a website to cancel the subscription. In other cases, the cancellation instruction is not clear and leads to a loop of cancellation steps. Examples of reviews claiming these practices include:

👎 *"The app allows you to accidentally sign up to premium with a push of a button. When you want to cancel, however, you can't do that via the app... You have to go to the webpage, enter details and cancel there."*

👎 *"Deceptive billing practices - information on cancelling is circular; emailed a link that advises to email. [It] doesn't have colour tag functionality across web and app; very poor UX and worse customer service."*

Sometimes, the app also makes it easy for the user to mistakenly activate a premium subscription in the way the interface and flow are designed, e.g.:

Table 5 Frequency (f) of app reviews in the honesty violation categories (out of 401 total ***honesty_violations*** reviews – note that some reviews fall into multiple categories)

Honesty Violation Category	f
Unfair cancellation and refund policies	48 (12%)
False advertisements	55 (14%)
Delusive subscriptions	33 (8%)
Cheating systems	93 (23%)
Inaccurate information	15 (4%)
Unfair fees	106 (26%)
No service	64 (16%)
Deletion of reviews	6 (1.5%)
Impersonation	9 (2%)
Fraudulent-looking apps	29 (7%)

👎 *"Use with caution. It's unscrupulous about signing you up for a subscription when you're skipping past the in-app ads. It's not made clear once you've subscribed, and there's no way of cancelling it through the app."*

Another aspect of this category focuses on situations where the user perceives the refund steps and policies to be dishonest and unfair. This also involves situations where the refund policy does not cater to accidental subscriptions, e.g.:

👎 *"DO NOT SIGN UP FOR FREE TRIAL! IT IS A SCAM. YOU WILL GET CHARGED ANYWAY, AND YOU WILL NEVER GET YOUR MONEY BACK!! Once again, after numerous attempts to blame Google, this developer has still not refunded my $38. Once again, I cancelled 3 full days before the free trial ended but was still charged. Once again, [I] contacted the developer, who told me that I would receive a full refund within 7 to 10 days, and still nothing. I have saved the email, pricing this to be true. DO NOT TRUST THIS DEVELOPER. SCAM!!!!"*

6.2.2 False Advertisements

This category relates to situations where the user perceives that the advertised features and functionalities of the app as described by the developers are not contained in the app. The user downloads the app or pays for a subscription on the basis of accessing certain functionalities or features only to find out the descriptions, including screenshots on the app distribution platform are different from the actual functionalities available in the app. Two examples of these are shown below:

👎 *"Couldn't find Google Assistant integration anywhere. Even though it's been advertised everywhere when searching the web for the app... It's even in the description of the app here. That's false advertising. I will edit my review when it's out of Beta and working in the final version."*

👎 *"The app doesn't listen to the watch at all. I've tried completing and snoozing and it does nothing. The watch app can only add tasks, so the screenshots they're sharing here are DECEPTIVE."*

In some cases, the app lures users into downloading the app on the basis that it is free-for-use only for the user to find out that the free-for-use is a trial version for a specific time period and not perpetually free as implied in the app description:

👎 *"The actual free version doesn't allow you anything, not even to learn how to use the app properly. That role is filled by 7 days of free premium. The free, on the description, is a lie. Is a paid-only app with temporary free access to its full features that gets practically useless after the 7-day trial... I don't like to be lied to."*

In addition, the app developers (through the app description) make promises to users to give them certain benefits like a free premium subscription when a particular action is carried out (e.g., inviting a particular number of friends to sign up). However, they never truly fulfil their promises when the user fulfils their end of the bargain. These unfulfilled obligations are perceived by the end-user as a violation of honesty, e.g.:

👎 *"I love this app however I sent the link to several friends and they got the app and I received no premium time whatsoever. Don't be dishonest with your apps. That's lame."*

Another example relates to scenarios where the user is invited to make certain commitments based on a future reward and the developers bail out on their prior commitment:

> 👎 *"Shame on Them! Liars. I paid for the season pass TWICE (ONCE for my apple device and the other for my Samsung Device). I was falsely promised access to ALL FUTURE CONTENT. Now they are trying to charge me for the Parisian Inspired TOKENS! HOW DARE THEY LIE AND BAIT AND SWITCH."*

6.2.3 Delusive Subscriptions

Any review describing complaints related to unfair or nontransparent automatic subscription processes are classified under this category. There are instances where no notifications are provided to let the user know they are subscribed to the app or premium version of the app, and the user only finds out about the subscription from the deductions in their bank accounts:

> 👎 *"I just realised that I have been charged for some crappy premium service fee which I had no idea about when using the app. Why is this charge by default? Why was I not informed in the first place? Beware of scam for useless monthly premium fees!"*

> 👎 *"I can't believe I was charged 55.99. What are you giving me? Gold? I unsubscribed but saw mysterious charge in my bank account."*

Additionally, there is the issue of lack of user consent in the subscription process where certain apps do not provide a confirmation mechanism that prevents accidental subscriptions by the user, e.g.:

> 👎 *"Made me pay 1 year worth of subscription without my confirmation. Only used its free trial because I had to use it once. What a scam..."*

In some scenarios, the automatic subscription is hidden behind an in-app ad/feature, and an unsuspecting user who clicks on the feature is automatically subscribed to the premium version of the app without a clear warning or confirmation, e.g.:

> 👎 *"Deceptive practices. If you click the in-app "ad" that simply says enable notifications, you'll automatically be signed up and billed for their premium service. This bypasses the Google/Apple stores subscription model and bills your card directly. Not to mention it's impossible to downgrade from this service in the app itself; you have to visit their website, which is a deliberately obstructive hurdle considering you can upgrade in the app just fine."*

6.2.4 Cheating Systems

All reviews concerning the user's perception of fraud by other persons or cheating within the inner workings of the app are classified under this category. Users complain of unfairness in either the process or outcome of the app, especially processes/outcomes that are supposedly statistically random. While accusations of this kind from the users are prevalent and subjective, they may not really be the case. However, we labelled these kinds of reviews based on the *perception* of the users as captured in their comments. Reviews related to this category are mostly found in games or game-like systems. For example:

👎 *"This game cheats. It uses words not found in the dictionary. Also it told me a word was unplayable, but it was the first best word option."*

👎 *"I play it with my sister often. However, there is the problem of the game and AI cheating. I rolled a 2 and a 3 at the start of the game and it moved me FOUR spaces forward not five. Four. That happened several times and I can assure you I was looking everytime it happened. I am very disappointed at the fact this game is cheating..."*

In some of the reviews, users complain that the game works properly when the user loses and parts with money and only freezes when the AI system in the app is about to lose. Based on the reviews, the users seem to be using real money in the games/apps. This complaint is a recurring theme within this category:

👎 *"You have to pay for it, then the game just freezes when you win against the CPU? Reset it over and again, keeps freezing unless it rolls something to not land on my property. Also, is the dice rigged against the CPU? Honesty? With as much as I owned in the beginning, none of the 3 CPUs would land on anything I owned. Anytime the last CPU needs to raise money, game freezes, guess ya just can't win."*

👎 *"there's a glitch in it that freezes the game from continuing when you're winning. The dice just disappears, but the trains and clouds and aircrafts keep moving. It's like It is designed so that one doesn't win them."*

👎 *"When playing against the computers when you're about to win and bankrupt the final computer the game conveniently freezes. It does not allow you to win. Not a very fun game to play, I want my money back."*

We consider this category important as some of these apps require the use of real money to play or for in-app purchases. If apps are dishonest in the underlying process of the systems that are expected to be fair, then that constitutes not only a violation of the value of honesty, it might potentially be a crime. This is worth considering, especially when the exact issue is raised by several users:

👎 *"Although you say that the dice is random, i cannot help but feel that it is rigged. Take a look at your reviews, there are many other players that feel the same. Can't be all of us are wrong. Or maybe we are suffering from mass hysteria?"*

Other non-game examples include cases where the user reports not having the full value of the fee they were charged for the app and feels cheated. For instance:

👎 *"Whenever I pay for parking the app always steals 5 minutes off my parking time. For example, I pay for 60 minutes and the timer starts at 54 minutes and 59 seconds. I am very upset, this has been happening for a while and probably to many more people as well. That is a lot of money!"*

👎 *"This app will not give you re requested amount of parking time. If you park for 15 minutes it will immediately say you have 11 minutes left. I understand that you have to charge but at least give me the requested amount of parking time."*

6.2.5 Inaccurate Information

This category covers where users perceive that the app provides false or inaccurate information as captured in their reviews. This includes situations where inaccurate information can increase the likelihood of the user inadvertently making wrong selections at a cost to them. In the review below, the user complains the design of an app feature tricks them into paying for the wrong parking spot:

> 👎 *"When you need to pay for additional time, and click 'Recent' to pay for the most Recently parked in place - the first item is not the place you just parked in so it tricks you into paying for the wrong place (dark pattern). Please make the Recent accurately reflect the most recently parked in place."*

Another example review in this category is quite severe as it relates to a health emergency app providing potentially inaccurate information that might be detrimental to the user:

> 👎 *"Try to use this in an actual emergency and you'll just end up as a dead idiot holding a cellphone. The information is either useless or completely false in most cases. Don't bother downloading."*

Other less severe but important reviews where the user perceives the app provides inaccurate information or notification are shown below:

> 👎 *"Do not buy unless you are sure you want to. You will NOT be able to get it set up and working within the 15 minute refund window. The instructions online are so cryptic it (and wrong)."*

> 👎 *"Very annoying every time when you open the app it shows you have a notification. Then checking your notifications you don't have any."*

6.2.6 Unfair Fees

This category relates to issues surrounding what the user considers to be unfair fees or charges. This also applies to cases where the user feels that they have not received a fair deal or that the app charges more money than it ought to. Because the definition of honesty also covers fairness, we also consider these kinds of issues a potential violation of the value of honesty. In the example below, the user complains of being charged more than they think is fair; they were charged a car parking rate for parking a bike.

> 👎 *"Went through the sign up process and parked my bike in a bike parking zone. Put in the correct zone details for the bike parking area and got charged a car parking rate. Rang support and they said there is no bike parking at that location. I explained there was and they told me to ring the council."*

Other examples of fees considered by the user to be unfair are:

> 👎 *"The app charges you 0.25 per transaction. So I paid 0.75 to pay for parking it charged me 0.25 service fee then I extended my parking 0.25 and it charged me again 0.25!!! Biggest scam in the world."*

👎 *"The only annoying things are that I have to buy any extra Monopoly Board in the same game when I already paid the main game. Can you not give extra Monopoly Boards in the same game for free. You are not fair!"*

This category is also reflected in the form of hidden charges where the user is not aware of subsequent charges made to their account. These hidden charges can take the form of a vague bill (as shown in the review below) or not notifying the user with respect to extra charges.

👎 *"This is a notorious company with horrible app I've ever used. They hide the history and details very deep for you to check and trace. And the monthly bill is also vague. I experienced they secretly bill me!"*

👎 *"LOOK OUT PEOPLE. THIS IS A SCAM. THEY DID NOT WARN OF A DEPOSIT FEE AND THEY TOOK 33% OF THE DEPOSIT. I RECOMMEND SUING THEM NOW."*

Another related issue within this category is dubious charges where the user account has been charged, and it is not clear why those charges occur. Abnormally high fees (more than the standard subscription fees) and overcharging of the user account are also captured under this category. For example:

👎 *"It charged me £74.50 when I bought a ticket for £1.50 it's a absolute scam I want my money back!"*

6.2.7 No Service

This category mainly covers reviews in which the user complains of not being able to access the app's main functionality after purchase, leading to undesirable consequences for the user. The main difference between the *false advertisement* category and this category is that the former deals with features/functionalities of the app that do not work as advertised. The latter deals with situations where the app does not work at all, i.e., does not even serve its main purpose for the user after the user has made financial commitments in the form of a purchase or subscription. In the example below, the user is fined for illegal parking after paying for parking using the app:

👎 *"Horrible experience with this app. Causing a lot of frustrations with users. when it fails and I get a ticket there is no much help I can get. sometimes I just pay the fines just because the complaint system is awfully inconvenient. I feel cheated and it looks like a money making tool for whoever is collecting the fines."*

Another related example is shown below:

👎 *"I spent 20 euros with all the DLCs included, I feel pretty deceived not being able to play the game."*

6.2.8 Deletion of Reviews

This category highlights reviews where the app developers are suspected of deleting reviews left by the user, especially negative reviews. A review captures user feedback, describing their experience of an app, and intending users of an app typically consult the reviews left by other users on the app distribution platform before downloading the app (Obie et al. 2021). Thus, the act of deleting unfavourable reviews by the app developers is perceived as a dishonest practice by the users because leaving only positive reviews may not paint an accurate picture of the app. Users may also feel like the app developers are trying to hide their complaints or other nefarious practices.

It can be argued that certain comments are deleted by app developers because those comments contain ad hominem attacks from the users instead of complaints relating to the app itself. While it is debatable whether app developers are justified in deleting perhaps vitriolic ad hominem comments, we do not make any judgement as to this but simply categorise users' perceptions and complaints of this practice as captured in their reviews. Examples of reviews depicting this accusation are shown below:

👎 *"I left them a negative review and the developer deleted it. Now I'm going to review them on YouTube and all social media platforms. Basically, they are scammers."*

👎 *"Deleted my honest review. Warning. Steer clear. They keep trying to make you slip up and pay for premium. I signed up for a free trial last year and they make it too difficult for you to find where to cancel. Was charged about $40... shame such a good app is tarnished by such shady practices."*

6.2.9 Impersonation

An impersonation is an act of pretending to be another person or entity (Dictionary 2021). It also involves the act of giving a false account of the nature of something. This category covers all reviews relating to impersonation or misrepresentation by the app or app developers. This includes scenarios where an app pretends to have the authority of (or relationship to) an organisation when in reality, it has no such relationship. An example review is captured below:

👎 *"STAY AWAY... this app is a scam. the stickers make it look like it's Brisbane council approved. it's not and they are no help. I still got a fine for using the app correctly and the Brisbane council parking police have no access to check if you have paid or not and do not accept this as a payment method."*

Another example in this category reflects situations where users feel that they are interacting with bots instead of humans when they have signed up to the platform to interact with humans. This is similar to false advertising-related lawsuits of the Match.com platform described in Section 2. An example of this is:

👎 *"Good game, fake players online. I wanted a challenging Monopoly game. But when I start. I can tell that some are bots not real people online. For example, they quickly trade when it is their turn. A normal human will take some time to choose options."*

6.2.10 Fraudulent-looking Apps

This category includes reviews reporting suspicious-looking apps based on observations of users or apps deemed to be fake by the users. We created a separate category for these kinds of reviews. Although the users flag the apps in these reviews as fraudulent, they do not provide specific reasons for their accusations beyond their perception of the app as fake or fraudulent. Furthermore, these types of reviews do not fit any of the categories described above, and we sought to highlight them based on the user accusations captured in their reviews. Examples of these reviews include:

👎 *"...Be careful with this kind of dishonest apps"*

👎 *"This is a fraud app don't download"*

Furthermore, Table 6 shows the breakdown of honesty violations across different app categories. Out of the 401 ***honesty_violations*** reviews, Games (28.9%), Auto & Vehicles (22.2%), and Finance (12.7%) are the app categories with the most number of honesty violations, while Medical (0.2%) and Music & Audio (0.2%) are the app categories with the least number of honesty violations.

The Games category with the highest number of honesty violations often experiences a high degree of competition, as developers strive to attract users to their apps amidst a crowded marketplace. This fierce competition might lead some developers to misrepresent or exaggerate the features of their games to improve visibility and attract a larger audience.

Apps within the Auto & Vehicles category may experience a similar pressure to compete for users. These apps often target niche markets and specific user demographics, such as those searching for parking services. In an attempt to attract these users, developers might also stretch the utility of their app features to increase exposure, and perhaps hide certain features that the users expect to be standard behind a paywall, e.g., a notification that parking is about to expire. Knowingly or unknowingly, the designs of these apps sometimes mislead users into accidentally signing up for a premium subscription to access these features. The Finance category often includes apps that provide services related to money management, investment, and banking. Due to the lucrative nature of the financial sector, dishonest developers may engage in deceitful practices to target users seeking financial advice or services (e.g., crypto trading), which can lead to increased revenue for the app and the developers.

The Medical category is likely to have a lower number of honesty violations due to the critical nature of the information and services provided by these apps. Users rely on medical apps for accurate information and reliable tools, and any violation of honesty could significantly affect their health and well-being. As a result, there is a higher expectation of

Table 6 Frequency (f) of honesty violations across different app categories

App Category	f
Games	116 (28.9%)
Auto Vehicles	89 (22.2%)
Finance	51 (12.7%)
Productivity	47 (11.7%)
Photography	26 (6.5%)
Tools	19 (4.7%)
Maps Navigation	11 (2.7%)
Travel and Local	10 (2.5%)
Health Fitness	7 (1.7 %)
Video Players Editors	7 (1.7%)
Social	6 (1.5%)
Communication	5 (1.2%)
Entertainment	3 (0.7%)
Education	2 (0.5%)
Music Audio	1 (0.2 %)
Medical	1 (0.2 %)

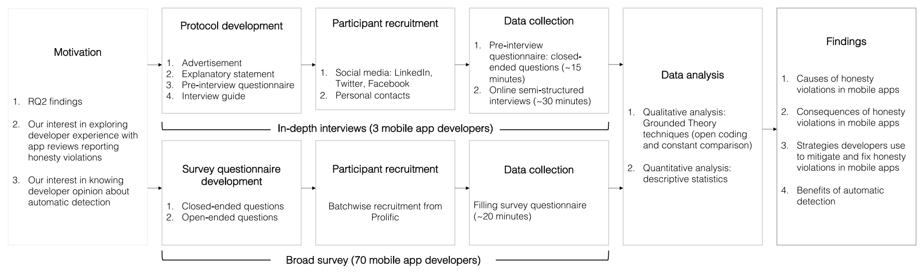

Motivation
1. RQ2 findings
2. Our interest in exploring developer experience with app reviews reporting honesty violations
3. Our interest in knowing developer opinion about automatic detection
Protocol development
1. Advertisement
2. Explanatory statement
3. Pre-interview questionnaire
4. Interview guide
Participant recruitment
1. Social media: LinkedIn, Twitter, Facebook
2. Personal contacts
Data collection
1. Pre-interview questionnaire: closed-ended questions (~15 minutes)
2. Online semi-structured interviews (~30 minutes)
In-depth interviews (3 mobile app developers)
Survey questionnaire development
1. Closed-ended questions
2. Open-ended questions
Participant recruitment
Batchwise recruitment from Prolific
Data collection
Filling survey questionnaire (~20 minutes)
Broad survey (70 mobile app developers)
Data analysis
1. Qualitative analysis: Grounded Theory techniques (open coding and constant comparison)
2. Quantitative analysis: descriptive statistics
Findings
1. Causes of honesty violations in mobile apps
2. Consequences of honesty violations in mobile apps
3. Strategies developers use to mitigate and fix honesty violations in mobile apps
4. Benefits of automatic detection

Fig. 3 Developer Study

integrity from developers and a stronger regulatory environment for such apps, which may contribute to the low number of honesty violations in this category. Apps in the Music & Audio category may experience fewer instances of dishonesty due to the relatively straightforward nature of the services they provide. Users typically expect to access music or audio content, and there may be less room for misrepresentation or exaggeration.

RQ2 Answer: The result of our analysis of the honesty violations dataset shows that honesty violations can be characterised into ten categories: unfair cancellation and refund policies, false advertisements, delusive subscriptions, cheating systems, inaccurate information, unfair fees, no service, deletion of reviews, impersonation, and fraudulent-looking apps.

7 Developers' Experience With Honesty Violations in Mobile Apps (RQ3)

7.1 Practitioner Study Design Approach

Our analysis of app reviews in RQ1 and RQ2 indicates that honesty violations exist in mobile apps from the perspective of end users. But what about app developers' experience with them? This motivated us to explore mobile app developers' experience with honesty violations in mobile apps.

We took an interview and survey-based approach, referred to as the developers' study, (Fig. 3) to understand developers' experience with honesty violations in the mobile apps they develop. In parallel, we conducted a set of in-depth semi-structured interviews, and we conducted a broad survey – both with mobile app developers. Collecting data from both interviews and surveys strengthened our findings well. The replication package, which consists of the artefacts we developed to collect data in both studies, is available online.[4] In this section, first, we explain the interview study and then the survey study.

7.1.1 Step Int: Interview Study

Step Int.1: Protocol Development: For the interview study, to recruit participants, we prepared an advertisement and an explanatory statement; and to collect data, we prepared a pre-interview questionnaire and an interview guide. The details about the artefacts are explained under participant recruitment and data collection below.

[4] https://github.com/kashumi-m/ReplicationPackageMobileAppsHonestyViolations.

Step Int.2: Participant Recruitment: We recruited participants by sharing the explanatory statement and posting an advertisement on social media platforms such as LinkedIn, Twitter, and Facebook with a link to the explanatory statement. The explanatory statement consisted of details of the study, including the procedure, potential benefits, and how we preserve the confidentiality of the participants. Potential participants contacted us, showing their interest in participating in the interview study. We recruited three participants to proceed with the data collection.

Step Int.3: Data Collection: Data collection for the interview study consisted of two parts: a pre-interview questionnaire and an online interview.

The data collection for the interviews was done by the third author, who has a pragmatic view and has 8+ years of experience working with and interviewing developers.

Pre-interview Questionnaire. Each participant was given a pre-interview questionnaire to fill in before the interview. The questionnaire consisted of questions about their demographics (age, gender, country of residence, professional experience, including total experience in the software industry and total mobile app development experience), context (type of apps the participants develop based on the list of app types as in Google Play Store, types and frequency of honesty violations the participant had experienced for their apps), who is responsible for honesty violations in mobile apps, and the participant's opinion about automatic detection of honesty violations in mobile apps (usefulness, beneficiaries, how beneficial). We included the definition of honesty and honesty violations at the beginning of the pre-interview questionnaire so that participants' interpretation of the terms aligns with ours. We also repeated the definition of honesty violations at the beginning of each relevant question section to ensure that participants' interpretation of the term remains the same until the end of the questionnaire. The pre-interview questionnaire was hosted on Qualtrics[5] and took around fifteen minutes to complete. Having a pre-interview questionnaire helped us in collecting data on closed-ended questions early so that we had a high-level understanding of participants' background with honesty violations in mobile apps and also led us to have more time for in-depth discussions during the interviews.

Online Interview. After we confirmed that participants had filled out our pre-interview questionnaire, we conducted online interviews with them at an agreed time using Zoom. Each semi-structured interview lasted approximately thirty minutes and was audio recorded. During the interviews, we focused on asking open-ended questions from the participants so that we could gain much more rich data on their experiences with honesty violations in mobile apps. The interviews started by showing some examples of honesty violations reported in mobile app reviews to the participants. This made it easy for the participants to answer the questions. First, we asked the participants about the reasons for honesty violations happening in mobile apps, then asked about the impact of honesty violations on end users and developers/owners of the mobile apps. After that, we asked participants what possible strategies exist to avoid honesty violations. We also asked them what strategies they adopted to address honesty violations that they had encountered in their mobile apps (if any). The interviews ended with an open question, allowing the participants to share anything else they liked to share about honesty violations in mobile apps. After the interviews ended, the audio recordings were transcribed using Otter.[6]

[5] https://www.qualtrics.com/

[6] https://otter.ai/

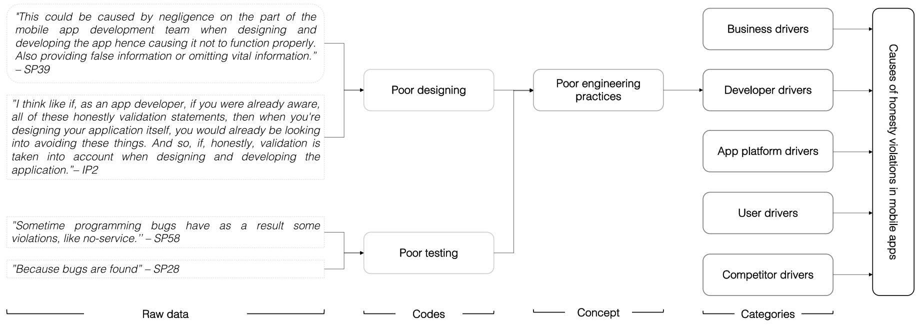

"This could be caused by negligence on the part of the mobile app development team when designing and developing the app hence causing it not to function properly. Also providing false information or omitting vital information." – SP39
"I think like if, as an app developer, if you were already aware, all of these honestly validation statements, then when you're designing your application itself, you would already be looking into avoiding these things. And so, if, honestly, validation is taken into account when designing and developing the application."– IP2
"Sometime programming bugs have as a result some violations, like no-service." – SP58
"Because bugs are found" – SP28
Poor designing
Poor testing
Poor engineering practices
Business drivers
Developer drivers
App platform drivers
User drivers
Competitor drivers
Causes of honesty violations in mobile apps
Raw data
Codes
Concept
Categories

Fig. 4 Example of Qualitative Analysis: Investigating Causes of Honesty Violations in Mobile Apps

Step Int.4: Data Analysis: *Qualitative data analysis.* The qualitative data collected were analysed using open coding and constant comparison techniques as in Glaser and Strauss's Grounded Theory (Glaser et al. 1968). The third author analysed the data and findings were shared with the team in weekly meetings. We used MAXQDA[7] to analyse the data. The responses to the questions (raw data) were interpreted in small chunks of words (codes), and they were constantly compared to group similar codes together to develop the concepts. The concepts were then constantly compared to develop categories. Figure 4 shows an example of qualitative analysis. *Quantitative data analysis.* As some closed-ended questions of the interview study were repeated in the survey study, the quantitative data were analysed together with the quantitative data collected from the survey study. Descriptive statistics were used to analyse the data.

7.1.2 Step Survey: Survey Study

Step Survey.1: Survey Questionnaire Development: We developed a questionnaire with a mix of open-ended and closed-ended questions. The survey contained demographics, contexts, causes, consequences, strategies, and automatic detection of honesty violations in mobile apps. The questions on demographics, context, and automatic detection were the same questions we used in the pre-interview questionnaire of the interview study. We further used open-ended questions to allow participants to freely share their experiences about causes, consequences, and strategies.

Step Survey.2: Participant Recruitment: We used Prolific[8] to recruit participants for the survey study. The participants were recruited batch-wise, i.e., 10 x 7, which altogether resulted in recruiting 70 participants.

Step Survey.3: Data Collection: The data collection of the survey study was straightforward. The link to the survey questionnaire hosted on Qualtrics was shared through a Prolific post. The participants took around twenty minutes on average to complete the survey.

Step Survey.4: Data Analysis: The same procedure as in the interview study was followed to analyse the collected data.

7 https://www.maxqda.com/

8 https://www.prolific.co/

7.2 Interview and Survey Study Results: Participant Information and Their Context

7.2.1 Participant Information.

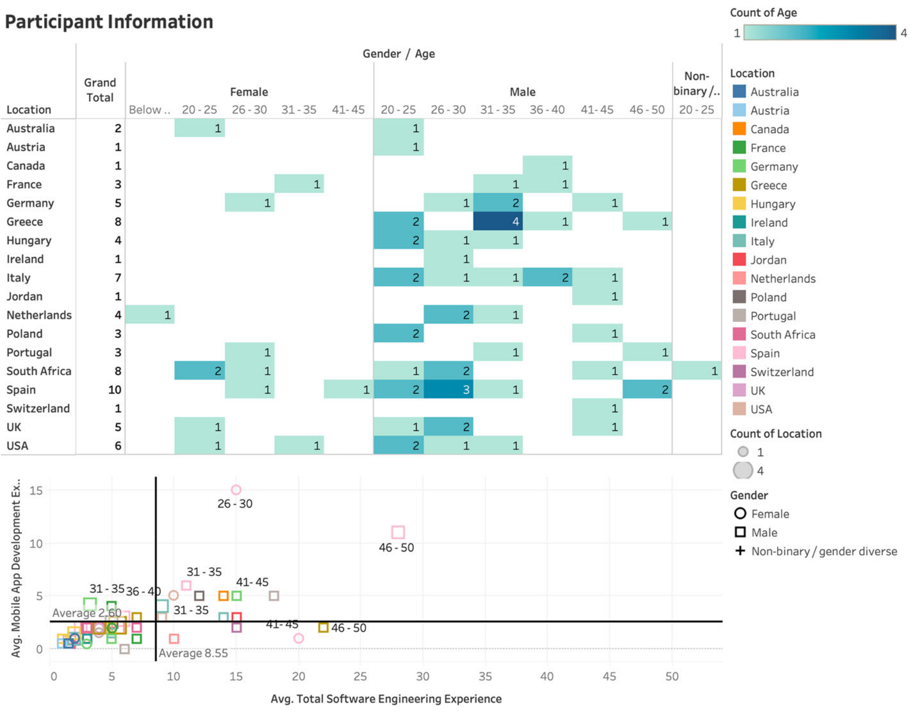
Figure 5 is a summary of the participant information (location, gender, age, total experience, mobile app development experience). The majority of the participants were from Spain (10 participants), followed by South Africa and Greece (8 participants each); were male (59 participants); had an average total software engineering experience of 8.55 years, and an average mobile app development experience of 2.60 years.

7.2.2 Types of Mobile Apps Participants Develop.

A summary of the types of mobile apps our participants develop is shown in Fig. 6. While the developers are not limited to developing one type of app, our participants selected many types, and the key app type they mentioned as they develop is *tools* (13.33%).

7.2.3 Developer Experience: Reported Honesty Violations In App Reviews.

We asked our participants which types of honesty violations they received for their apps they developed for the company that they worked for. The results are shown in Fig. 7. According



		Gender / Age											
	Grand Total	Female					Male						Non-binary /..
Location		Below ..	20 - 25	26 - 30	31 - 35	41 - 45	20 - 25	26 - 30	31 - 35	36 - 40	41 - 45	46 - 50	20 - 25
Australia	2		1				1						
Austria	1						1						
Canada	1									1			
France	3				1				1	1			
Germany	5			1				1	2		1		
Greece	8						2		4	1		1	
Hungary	4						2	1	1				
Ireland	1							1					
Italy	7						2	1	1	2	1		
Jordan	1										1		
Netherlands	4	1						2	1				
Poland	3						2				1		
Portugal	3			1					1			1	
South Africa	8		2	1			1	2			1		1
Spain	10			1		1	2	3	1			2	
Switzerland	1										1		
UK	5		1				1	2			1		
USA	6		1		1		2	1	1				

Fig. 5 Participant Information (Excluded in Figure: One participant had mentioned total work experience as 82 years but within the age range of 31–35; Included in Figure: One participant with less than 1 year of mobile app or without mobile app development experience)

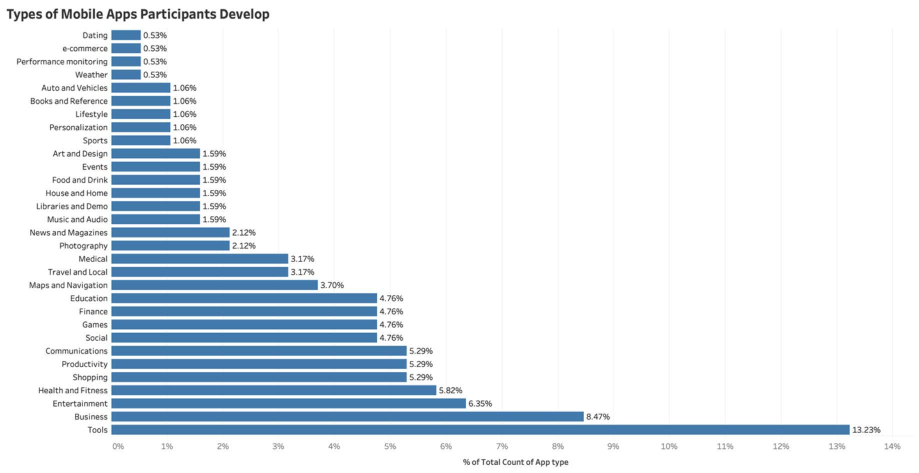


Fig. 6 Types of Mobile Apps Participants Develop

to our participants' experience, the most reported honesty violation by the users is *inaccurate information* (sometimes+about half the time+most of the time=73.97% of participants). This is followed by *no service* (sometimes+about half the time+most of the time=54.79% of participants).

7.3 Interview and Survey Study Results

We found several causes, consequences, and mitigation and fixing strategies for honesty violations in mobile apps. Further, we found how useful automatic detection of honesty violations is, the benefits of automatic detection which mitigates many causes, and consequences of honesty violations, and helps improve strategies in handling honesty violations in mobile apps. These are summarised in Table 7 and explained in the subsections below. We quote interview participants by IP<ID> and survey participants SP<ID>.

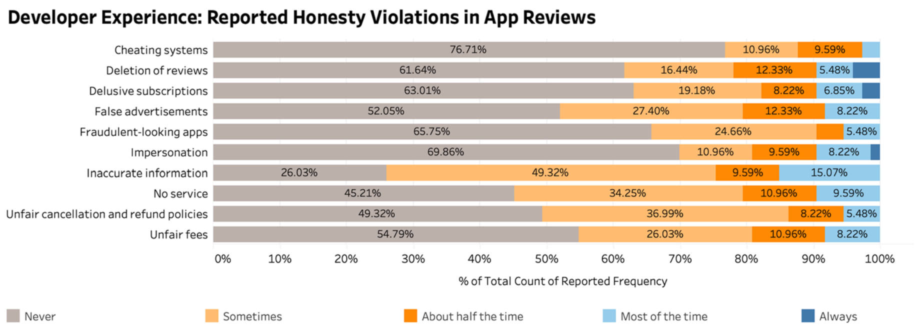


Fig. 7 Developer Experience in Receiving Honesty Violations in Mobile App Reviews

Table 7 Findings (Automatic detection mitigates causes, consequences, and improves the strategies marked in **bold**); (#): participant count)

	Business	Developers	App Platforms	Users
Honesty violations in mobile apps				
Causes	Maximise revenue (31)	Poor designing (12)	**Vague audits (1)**	False claims (competitors in addition to users) (7)
	Market competition (6)	Poor testing (6)		
	Improper definition of target audience			
Consequences	**Bad reputation (22)**	Extra work to fix honesty violations (6)		Identity theft (9)
	Face legal issues (8)	Experience negative emotions (7)		**Experience negative emotions (21)**
	Lose user trust (8)	Harm work performance (3)		Lose trust in apps/ company/ developers (14)
	Lose users (7)	Harm personal reputation (7)		Lose money unknowingly (19)
	Lose revenue/ business (18)			Lose time (4)
				Stop using/ uninstall/ not install apps (13)
Avoiding strategies		**Strengthen designing practices (7)**		
		Strengthen development practices (6)		
		Strengthen testing practices (20)		
		Be transparent with customers/ users (16)		
		Have moral standards (5)		

Table 7 continued

	Business	Developers	App Platforms	Users
Fixing strategies		Thoroughly investigate the violation and fix (30)		
		Hotfix (17)		
		Be transparent about the violation with customers/ users (14)		
		Have tools in place to resolve honesty violations (2)		
Automatic detection of honesty violations				
Benefits	Retain/ improve reputation (11)	Quick detection of honesty violations (20)		Transparency by knowing what to expect from the app (15)
	Reduce/ avoid legal risks (4)	Improve developer satisfaction (5)		Find honest apps in stores (4)
	Gain more revenue (3)	Avoid fixes (2)		Improve user satisfaction (13)
	Retain/ gain users (3)	Reduce effort on fixing (2)		
	Improve user trust (6)			

7.3.1 Causes (RQ3.1)

QUANTITATIVE FINDINGS: The majority of the participants (22.65%) selected the choice *product owners* as responsible for honesty violations in mobile apps, followed by developers (20.54%), managers (19.34%), business analysts (13.81%), and user support roles (7.18%) (Fig. 8). But, as the answers to the open–ended questions, and during the interviews, the experiences they shared were about businesses, developers, app platforms, users and competitors causing honesty violations (explained under qualitative findings below). However, in agile contexts, as a common practice at present, the developers are cross–functional and play multiple roles.
QUALITATIVE FINDINGS: Our participants identified several causes of the existence of honesty violations in mobile apps. We categorised them according to what the driver of the violation seems to be: business drivers, developer drivers, app platform drivers, user drivers, and competitor drivers. Some honesty violations in mobile apps may of course have multiple of these drivers.

Business Drivers. We found intentional and unintentional reasons driven by business needs or perceived needs, for the existence of honesty violations in their mobile apps.

Intentional reasons: Businesses intentionally violate honesty in mobile apps, as identified by our participants. The reasons for ill-intended activities mentioned include due to revenue maximisation and market competition.

Maximise revenue: Our participants mentioned that when the objective of a business is to gain more profit, they may be tempted to scam/fool their app users:
🗨 *"I try to think these 'violations' aren't meant to be there, but I did see 'tricks' to implement them, mostly: unfair fees or hidden fees, and mostly is because corporate greediness" - SP46*

This has become relatively easy as the smartphone user population is high and most users are not knowledgeable enough to understand the violation:
🗨 *It's an easy way to make money since most of the population has a smartphone and many of those users are not knowledgeable. - SP26*

As shared by SP37, tricking users into gaining more money has also led to bad practices such as doing R & D on these tricks:
🗨 *"I think though that most app developers that do that kind of violations are not at all naive and do it for the money. In every app store (Apple or Google) there are tons of apps that aim to make the most money with the cheapest tricks. I feel like that a good chunk of the market is only there to milk naive consumers. I have heard stories of fellow developers/managers that pour more R & D on how to trick people out of their money rather than put time and effort to come up with a good idea for an app and polish it" - SP37*

Market competition: Due to high competition in the mobile app market, businesses may make releases that include honesty violations. These could be innovative features:
🗨 *"It is more and more difficult to publish applications, and the need to stand out from the*

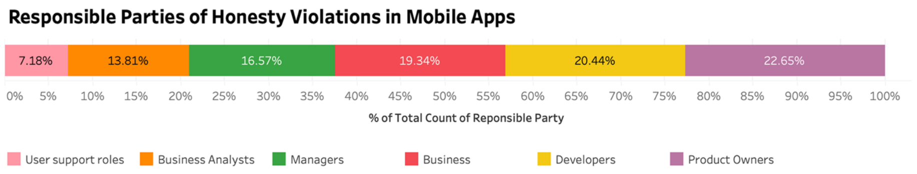


Fig. 8 Responsible Parties of Honesty Violations in Mobile Apps

competition requires to release innovative things requiring more interaction with the user (camera, localization,...) and it is often a hinders adoption" - SP23

And exaggerations and misleading information:

🗨 *"..with all of the competition in the mobile space it is hard to stand out which makes companies feel a need to often exaggerate details to gain an edge"- SP38*

Unintentional reason: The reason shared by one participant is that businesses **improperly define their target audience**, which results in broad markets, and not being able to follow local laws. For instance, if the market is too broad and the app is available for various countries and regions, the laws of particular countries or regions may not be followed specifically:

🗨 *"Also can happen in my opinion unintentionally:... Market too broad, not targeting your users correctly, Not following the local laws" - SP64*

Developer Drivers. We found poor engineering practices were reported to cause honesty violations in mobile apps, including poor design and inadequate testing.

Poor design: As shared by our participants, developers not considering honesty when designing the app functionality can result in many kinds of honesty violations in the apps. This could be because of the developers' unawareness of the user expectations of honesty, neglecting the requirement of honesty when designing the app, and poor product analysis:

🗨 *"This could be caused by negligence on the part of the mobile app development team when designing and developing the app hence causing it not to function properly. Also providing false information or omitting vital information." - SP39*

Poor testing: Our participants mentioned that bugs that were not found before releasing the apps can result in honesty violations:

🗨 *"Probably due to malware or because of a bug during the planning or construction phase. Especially for the no service situation, most of the time it happens due to limited internet connection." - SP56*

App Platform Drivers. One of our participants mentioned that **vague audits** done by app platforms allow honesty violations to exist in mobile apps:

🗨 *"This is because app platforms like PlayStore and others do very vague audits for these types of applications; an ethical developer will never create an app with those purposes, what he will do is provide a real service and then try to gain some benefits if possible. The blame is on these fake 'developers' and digital platforms who make them public without performing a proper audit." - SP69*

User Drivers. Some of our participants mentioned that app reviews with honesty violations do not always indicate that there is an honesty violation in the app i.e., **false claims** exist, which may also be unfair to the app. As shared by our participants, the reasons for users making false claims may include:

(a) end-user ignorance, i.e., they have not paid attention to what they signed up for:

🗨 *"I think usually they happen because people are distracted and don't pay attention to what they sign up for" - SP55*,

(b) faulty understandings because similar apps have honesty violations:

🗨 *"I think people are confused and may think they are getting scammed when they aren't. There are also a lot of apps out there that are scammy so it puts the customer in a state of paranoia or fear" - SP26*,

(c) misusing their right to honesty by lowering the threshold, which seems to be unfair:

🗨 *"The fact that there's a general discrepancy in how much an app is worth to the user compared to a developer who puts effort into making and improving gives the users the idea that they can rightfully lower their honesty threshold" - SP22*,

(d) hate towards the purpose of the app from diverse user groups:

🗨 *"Once, I got a lot of bad reviews (claiming it's a scam, and similar) during a very short* *time period (1 day), all from Russia. It seems my app was a target of some gay hating group, since this app was a gay dating app" - SP19*,

and (e) claims from unintended target market:

"In my opinion, it happens when you don't define the scope of your app well, meaning: Intended target (age, for example)* Market.... So you have many variables, many different laws, moral systems/opinions, cultural differences, so things that are seen as normal here are not in other places." - SP46.*

Our participants did not mention the quantity of such false claims they receive. Therefore, an interesting research question to be explored in the future would be, what percentage of honesty violations reported by mobile apps are false claims.

Competitors. One of our participants mentioned that competitors also report honesty violations through app reviews, which we think assume to be **false claims**:

"People might be from other company that produces similar product" - SP2

7.3.2 Consequences (RQ3.2)

We asked the participants about the impact of honesty violations in apps on owners (businesses), developers, and users. From what the participants shared, we found the consequences of honesty violations in mobile apps.

Business. Bad reputation, facing legal issues, loss of user trust, loss of users, and loss of revenue/business are the consequences of honesty violations in apps on businesses as we found.

Bad reputation: The majority of the participants mentioned that if honesty violations exist in the apps, that will create a bad reputation for the business. For example, the businesses may look like they are frauds, incompetent, and dishonest:

"If the violation is found, it's a huge setback to business reputation" – SP25

One participant mentioned that if the violation is intentional, then the business deserves a bad reputation:

"It could worsen their reputation, but again if they happen to do fraudulent acts they kind of deserve having their reputation down." – SP12

Bad reputation will also lead to the rest of the consequences discussed below.

Face legal issues: As shared by some participants, users may take legal actions in some cases. As mentioned by SP64, businesses may get sued for not following the law of the country. Therefore, businesses need to be mindful and follow the laws according to the country/region before releasing the product:

"Getting removed from the store, having to make urgent changed, getting sued if the laws of the country are not being followed." – SP64

The impact if the found violations are not fixed could be heavy, as shared by SP68:

"They could impact them heavily if they don't act on solving possible problems that caused those violations in the first place especially where there is relative legislations." – SP68

Lose user trust: If honesty violations are found in apps, then the users might not trust the app/business anymore. This could even lead to not trusting the future apps of the company as well:

"It could impact the owners of the mobile app because their customers would end up not trusting other future apps from the owner" – SP40

Even if the violations are fixed, regaining the trust back from the users is difficult:

"no matter how much developers try to fix their issues when users have lost trust it's hard to regain it back they move to other apps which is bad for developers because creating an app takes time and money" – SP3

Lose users As shared by the participants, the businesses may lose users if honesty violations are found in the apps. The users could be existing users or new users. The users may not download or subscribe/re-subscribe to the services in the app or switch to other apps. Sometimes, the users might discuss the violations in public, which will discourage new users from installing the app:

"It could impact downloads and/or subscriptions or re-subscriptions." – SP58

Lose revenue/business All the above-mentioned consequences may lead to revenue loss and in extreme cases where the app gets removed from the store, businesses may lose their businesses too as shared by our participants:

"The developers or owners of the mobile apps can be impacted by negative reviews, which would lead to decreased sales" – SP62

Developers. Extra work to fix honesty violations, experiencing negative emotions, harming work performance and harming personal reputation are the consequences of honesty violations on developers as we found.

Extra work to fix honesty violations Irrespective of the claim being true or false, the developers will have to work extra. Additional tasks may need to be done to look into the reported violations. If the app reviews are false, then as shared by our participants, the developers will lose time unnecessarily by looking for a violation which does not exist in the app:

"The developers will be confronted with additional tasks and will try to search for eventual bugs mentioned by the users. In case of dishonest reviews, the app developers may lose time looking for bugs that don't even exist." – SP66

Experience negative emotions As mentioned by our participants, the developers experience negative emotions such as stress and anger when they receive honesty violation reported reviews. They also feel guilt about having the app developed with honesty violations:

"Developers and owners can experience a lot of stress." – SP1

Harm work performance Three participants mentioned that finding honesty violations damage the work performance of the developers. They could get demotivated to work, which harms their performance:

"maybe they are ashamed and in the long run it kills motivation" – SP38

Harm personal reputation Our participants also stated that finding honesty violations in the apps developers develop impacts their personal reputation negatively, which is problematic for the career of the developers:

"A bad thing that could happen to developers is the result of negative reviews they receive from customers, thus resulting in a declining career." – SP70

Also, SP67 stated that it is common for developers to get the blame as they are at the bottom of the tree of the team structure:

"It could affect the developers because they are usually the ones to get the blame for these violations. The blame just gets pushed down the tree until it hits the developers that just have to take it." – SP67

Users. Identity theft, experiencing negative emotions, loss of trust in apps/company/developers, loss of money unknowingly, loss of time, stop using/uninstalling/not installing apps are the consequences of having honesty violations in apps on users.

Identity theft One of the concerns our participants mentioned (as an impact on end users due to the existence of honesty violations in mobile apps) is identity theft. The apps with honesty violations could compromise personal and sensitive data. For example, their home address and credit card details. These could be used by third parties in various activities. This could even lead to frustration in users, affecting their mental health as well:

"It could make the end users prone to fraudulent activities on their finances by making

use of their personal information to extract money or some resources from them without their consent. It could also make them prone to some physical attacks such as the end users' home address being exposed, thereby making their locations traceable." – SP40

Experience negative emotions If honesty violations are found in mobile apps, users may experience negative emotions as shared by our participants. These include frustration, unhappiness, stress, and anger:

🗪 *"End users become very frustrate due to these honesty violations." – SP41*

Lose trust in apps/company/developers As stated by our participants, when users find honesty violations in the apps they use, no matter how legitimate the brand of the company is, users may end up not trusting and distancing themselves from the app and company:

🗪 *"They create a feeling of lack of trust with the company responsible for the violations" – SP65*

This is more related to cancellations and refund policies:

🗪 *"if we look at cancellations and refund policies, I think everyone as if you're a user of a mobile app, you would want to be able to trust the app that you're using. And especially if you're paying money for it, for example, a subscription service or even just a one-time payment. If it's a subscription model then you would want to be able to save the cancel your subscriptions without having any issues. If the app that you're using doesn't actually provide that sort of honesty, capabilities like then you and I personally wouldn't be comfortable using an app that was an honest to their users" – IP3*

Lose money unknowingly Users losing money without them knowing is one of the key impacts of honesty violations claimed by our participants. This could also lead to a problematic living in physical life as money plays a huge role:

🗪 *"Honesty violations can impact users in various ways. In my opinion, the worst effect it can have is when a person loses money that they weren´t expecting to lose, it can very realistically impact their ability to buy essentials - pay rent - pay bills - etc, if not refunded." – SP38*

Lose time Similar to losing money, losing time due to the existence of honesty violations can cause negative effects on the lives of people by wasting the valuable time they could use to do other important work:

🗪 *"People will be made addicts to apps and forced to spend huge amounts of time, which they could use for more productive work." – SP34*

Stop using/uninstall/not install apps When users find honesty violations in apps, they are likely to either stop using them or uninstall them. If any potential new users get to know the existence of the violations in the apps, they might not even install them:

🗪 *"It could scare them away from using the app or ever downloading it. This would be very negative for everyone involved if the app does do what it is supposed to do." – SP67*

7.3.3 Strategies (RQ3.3)

We explored strategies that developers use to avoid honesty violations, and strategies the developers use to fix honesty violations when they receive feedback containing honesty violations for the app.

Mitigating strategies. The mitigation strategies include having better engineering practices, being transparent with the customers/users, and having moral standards.

Having better engineering practices We found that having better engineering practices in place helps software teams to avoid honesty violations to occur in the apps they develop. This includes strengthening design practices, development practices, and the testing process.

(a) Strengthening design practices: Viewing the app from the user perspective helps in avoiding honesty violation occurrences in the apps being developed, as reported by participants:

🗨 *"Keep clear communication with your manager, Keep on top of the timeline that is given, explain how users will see the app to your manager." – SP67*

Having honesty as a first-class app requirement, and complying with regulations/policies (e.g., GDPR) also helps to mitigate occurrences of honesty violations in apps according to our participants:

🗨 *"...Other than that, we gotta respect the GDPR." – SP29*

(b) Strengthening development practices: Some participants mention that they have codes in place to flag honesty violations:

🗨 *"We also have codes in place which will flag an app in violation" – SP14*

They also believe that having security measures in place avoids honesty violations from happening. For example, as SP18 mentioned, the violations could occur by attacks on the app, so they use security measures accordingly. Measures such as pen tests could avoid risks, and encryption could avoid data leakages and thefts:

🗨 *"Of course as always we use source code encryption. Attackers generally repack renowned apps into rogue apps using reverse-engineering techniques. Then they upload those apps into third-party app stores with the intent to attract unsuspecting users. It has been a consistently good practice to test our application against randomly generated security scenarios before every deployment. Especially, pen testing can avoid security risks and vulnerabilities against our mobile apps. Detecting loopholes in the system is an absolute necessity. Since these loopholes could grow to become potential threats that give access to mobile data and features. The sensitive information that is transmitted from the client to the server needs to be protected against privacy leaks and data theft. When it comes to accessing confidential data, the mobile apps (yes, we have more than one app in our company) are designed in a way that the unstructured data is stored in the local file system and/or database within the device storage. We use encryption methods like AES with 512-bit encryption, 256-bit encryption and SHA-256 for hashing. We have security measures in place to safeguard against malicious attacks at backend servers." – SP18*

(c) Strengthening the testing process: A strong pre-release testing process is necessary. As shared by our participants, getting the QC teams to do stringent reviews, and having multiple testing rounds helps to avoid having honesty violations in apps after release:

🗨 *" The app goes through multiple rounds of testing to make sure such violations do not happen. – SP25*

Through our analysis, we also found that testing for honesty violations during UAT and testing the app with diverse users helps to mitigate honesty violations. Approaches such as sending the beta version of the app to users, and asking a variety of users to test the app help in looking at the app from different angles, which eventually helps in identifying honesty violations early. As shared by one participant, having users involved in testing before releasing could help in identifying 50% of the problems with regard to honesty violations:

🗨 *"Before I release the application, to say general public, you, you might want to test it out on a certain set of users and look into the things that they feedback on and try and figure out where all whether the feedback that they give violates any of these honesty statements, and from there onwards you might be able to improve on specific ones that are being violated. But if, yeah, that would be the initial thing. Then once I think from there, you can sort of read out maybe like 50% of the problems regarding honesty violations. Then maybe once you've actually released your application to the general public, then from there on, you would have a much larger audience size and also a lot more feedback that you can work on." – IP3*

Being transparent with customers/users Being more transparent with customers/users helps identify and address honesty violations "reported" in the apps as reported by our participants. For example, they commented that having additional confirmation steps, and being transparent in the app description helps inform the users about the app:

"Present the end user with correct information and make them do additional confirmation steps." – SP57

Having moral standards Being a person who values things such as honesty, fairness, and credibility helps to avoid honesty violations in mobile apps, as shared by our participants:

"We are simply not designing and developing apps in such a way. Honesty and integrity is key" – SP8

Fixing strategies. The fixing strategies shared by our participants include thoroughly investigating honesty violations flagged by users and fixing, hot-fixing, being transparent about the violation with customers/users, and having tools in place to help resolve honesty violations.

Thoroughly investigate the violation and fix The majority of our participants mentioned that they thoroughly investigate any reported honesty violation by users and then move forward with fixing it. For that, they said that they have team discussions, consult supervisors, and even get more developers involved in fixing:

"I usually consult my supervisors on how to best go about handling such situations if and when they occur." – SP6

One participant mentioned, they talk with the legal department as well before fixing, and then change the code:

"Talk with the legal department and change the code respectively." – SP68

Thorough investigation includes checking the reliability of the claims, checking the alignment of the claim with business policies – which sometimes hinders fixing the violation, internally validating the policy applied, removing the app temporarily from the app store, testing the app thoroughly, and adding to the sprint, prioritise, and then fix:

"I have to consult the architect to discuss the solution. Sometimes it's not possible to fix it due to business policies" – SP25

Hotfixing Some participants mentioned that they do 'hotfixes', i.e., they fix the honesty violation in the app immediately:

"If I had any, I would immediately make the violation in question disappear by fixing the violation." – SP35

Some stated that hotfixes depend on the size of the company. For example, if the app is owned by a solo developer/small company, then they will fix it quickly rather than large established companies which may have long processes:

"If you are the solo developer of your own application, then you can address it pretty quickly. So you got your feedback, then you probably can use that feedback to generate a list of things that you can improve on. Then there will be a pretty quick turnaround based on user feedback, but usually on larger company sizes. There's a lot of feedback and you probably want to address the feedbacks that are more serious. And so that would take some time and then that's usually a really long process before it gets like from gathering the requirements to putting it into user stories and having developers work on it and then push to production might take potentially months. So it's not a quick process. If it's a big company, but obviously it depends on how the company works." – IP3

Be transparent about the violation with customers/users We found that our participants consider being transparent about the issue and changes they make in the app as important. They mentioned that they inform their users through app descriptions about temporal deactivations due to technical issues, and also do the same after fixing by sharing what was fixed.

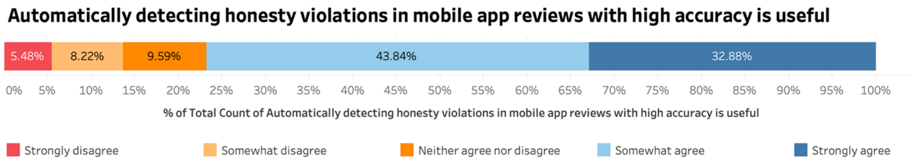


Fig. 9 Participants' Opinion about Automatic Detection of Honesty Violation in Mobile App Reviews

However, we could not find if they mention the type of honesty violation in their temporary app description updates. Some also mentioned that they share a report with full transparency with their users/customers:

🗨 *"Summarily, I put out a notice to users that there'll be a temporal downtime in order to address technical issues that could affect their use of the app after I do this, I temporarily deactivate the app and identify the vulnerability, write a code that can patch it up, then I activate it and announcer to the users that the app is running again." – SP40*

Have tools in place to resolve honesty violations Two of our participants mentioned that they would have measures/tools implemented to resolve the honesty violations:

🗨 *"My team investigates them and implements tools to resolve them." – SP39*

7.3.4 Usefulness And Benefits Of Automatic Detection Of Honesty Violations (RQ 3.4)

Usefulness Our participants shared their opinion about the automatic detection of honesty violations in mobile app reviews (Fig. 9). Note that, participants did not use our tool to answer this question, but shared their general opinion about the automatic detection of honesty violations in mobile app reviews. The majority of the participants somewhat agreed (43.84%) that automatically detecting honesty violations in mobile app reviews with high accuracy is useful, then 32.88% strongly agreed with it, and the rest neither agreed nor disagreed/somewhat disagreed/strongly disagreed.

Benefiting Parties According to our participants, end users (20.80%) will be majorly benefited from automatic detection, followed by businesses (20.07%), developers (19.34%), product owners (14.23%), managers and user support roles (8.76% each), and business analysts (7.66%). 0.36% of the responses were for *no one* too. This is summarised in Fig. 10. However, from the qualitative data, we found businesses, developers, app platforms, and end users have the potential to get the most out of automatic detection.

Benefits We asked our participants how automatic detection of honesty violations could be beneficial. They shared a variety of benefits which we categorised as benefits for businesses,

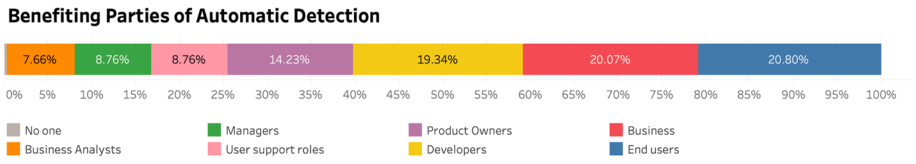


Fig. 10 Benefiting Parties

developers, and users. In this section, we use the term “automatic detection” as a short term for “automatic detection of honesty violations”.

Businesses. Retain/improve reputation, reduce/avoid legal risks, gain more revenue, retain/gain users, and improve user trust are the benefits for businesses from automatic detection.

Retain/improve reputation As automatic violation accelerates the honesty violation fixing process, businesses are able to fix them early before that can negatively impact their reputation, and also users may leave positive user reviews which will improve the businesses’ reputation:

🗨 *“They will be aware of the violations in time and fix them before it can ruin their reputation” – SP9*

Reduce/avoid legal risks Since automatic detection helps improve the fixing process in the software team, the team will be aware of the honesty violations, and they will take action to fix the issues in a timely manner, which will avoid any legal issue occurrences, and if any risks were there, those will get reduced too as shared by our participants:

🗨 *“Just avoiding further issues with the law, and economic backlash.” – SP64*

Retain/gain users Since automatic detection improves the app and how users see it, businesses will not lose users and also will gain new users as shared by our participants. This is interconnected to gaining more revenue – as not losing any users and gaining new users means better revenue, and a good reputation – as users will be retained with the business because of the good reputation of the business:

🗨 *“I think they will benefit in a sense that once the reviews are there it can be fixed with immediate effect, this resulting in good customer care service as well as prompting user to give good/positive reviews which could lead to new clients in the end, which benefits the app/business in the end.” – SP17*

Maintain or increase revenues Happy customers may result in better revenue as noted by some of our participants. While some honesty violations are done to increase revenue, in contrast, ensuring that users enjoy the app with better user experience and less concern about dishonest practices being reported in reviews can lead to an increase in customer attraction, retention and hence revenue. For example, one participant stated:

🗨 *“The consumers will benefit from having a better experience through the app, and the developers and owners of the app will, in turn, benefit from satisfied customers leaving better reviews, resulting in increased sales and a good reputation.” – SP62*

Improve user trust As an app will be improved by having automatic honesty violation detection, users will trust the app as shared by our participants:

🗨 *“The app will improve and other users are going to trust in the app and download it” – SP36*

Developers. Through our analysis, we found the potential benefits the developers may have due to automatic detection. The benefits for developers are quick detection of honesty violations, improve developer satisfaction, avoiding fixes, and reduced effort on fixing.

Quick detection of honesty violations Having the detection of honesty violations automated could benefit the developers by accelerating the detection process. They will spend less time doing investigations, and will focus on fixing more:

🗨 *“For the owners and developers of the app, it will be easier to sort them out and do what they have to do.” – SP12*

Improve developer satisfaction As their work gets easier and less hectic, developers’ satisfaction will be benefited from automatic detection as shared by our participants:

🗨 *“And also having a good state of mind.” – SP46*

Avoid fixes If honesty violations are found early and fixed early, that will avoid future fixes as mentioned by our participants. Because of this, the developers may use their time to improve the app rather than spending time on fixing:

“Developers and product owners can employ their time in improving the app instead of fixing it.” – SP42

Reduce effort on fixing The developers’ time spent on the entire fixing process including reading the app reviews, analysing them, and then moving forward with fixing will be reduced by having automatic detection involved in the process, as stated by our participants:

“Automation will create less work for them. Also, it will take automatic action rather than slow and expensive human interference.” – SP53

App platforms. One of the participants mentioned that app platforms could benefit if they use automatic detection.

Improve audits One of the causes found for the existence of honesty violations in mobile apps is vague audits by app platforms. This could possibly be improved if the app platforms use automatic detection to examine apps with several app reviews reported with honesty violations:

“I think that the one group that would benefit the most is end users. App stores might be finally cleaned up from scummy apps and trashy developers.” – SP37

Users. Not only businesses, developers, and app platforms can benefit from automatic detection, but also users, as mentioned by our participants. The benefits to users are transparency by knowing what to expect from the app, finding honest apps in stores, and improved user satisfaction.

Transparency by knowing what to expect from the app: As stated by our participants, if automatic detection is available for users, they may also use it to better understand the app. A high level of transparency will be available through it and because of that users will know what to expect from the app – whether to expect honesty violations in apps or not. This will help users in deciding whether to download an app or not:

“They will have a framework which guides and informs them regarding the apps they are using/working.” – SP14

Find honest apps in stores If the businesses, developers, and app platforms adopt maximum use of automatic detection, the users will obviously find honest apps in stores as shared by our participants:

“They will limit the ability of some companies to mock customers and try to curry favour with them. In addition, they will guide end users not to use apps that cheat them.” – SP67

Improved user satisfaction The user satisfaction will be improved if the software teams use automatic detection as apps will be improved which will give less frustration to the users and better user experience, which result in better user satisfaction:

“Customers won´t feel as if they are being lied to and so they will have a much happier experience with the product, and therefore customer support will have fewer unhappy customers to deal with.” – SP38

RQ3 Answer: The developer study revealed seven causes, seven responsible parties, sixteen consequences of honesty violations, nine strategies developers use to avoid/fix the honesty violations, and thirteen benefits and nine benefiting parties of automatic detection of honesty violations in mobile apps.

8 Discussion and Recommendations

8.1 Technology (Mobile Apps) as values artefacts

Software artefacts such as mobile apps, like other technological artefacts, express human values (Whittle 2019). Although less formally articulated, human values may be reflected throughout the different phases of the software development life cycle (Nurwidyantoro et al. 2021). Values are represented in the conception and abstraction of ideas, in the way software features are arranged, described and even implemented and these embodied values are typically those of their creators, e.g., software developers and other stakeholders (Lennox 2020).

Some studies have argued that technological artefacts are value-agnostic tools that can be used for good or bad (i.e., theory of the social determination of technology) (Joerges 1999), while others contend that technological artefacts are not value-agnostic, i.e., they hold value qualities and promote certain values over others (Winner 1980), e.g., the bitcoin blockchain technology (Nakamoto 2009) is an embodiment of the value category of self-direction. Irrespective of the sociotechnological stance on values in technological (software) artefacts, there is an agreement on the role of software artefacts in changing habits in people and influencing society in general, despite the intentions of the software companies behind these artefacts (Obie et al. 2021; Agre 1997). Sullins writes, “Since the very design capabilities of information technology influence the lives of their users, the moral commitments of the designers of these technologies may dictate the course society will take and our commitments to certain moral values will then be determined by technologists" (Sullins 2018).

Furthermore, while we do not conflate values with ethics (values are the guiding principles of what people consider important in life (Rokeach 1973), while ethics are the moral expectations that society agrees upon to decide which values are acceptable or not (Whittle 2019)), the value of honesty is an ethically desired value in most societies. Thus we argue for a conscious effort in developing honest software artefacts, including mobile apps, and the promotion of honesty in software development practices. Our intention in this paper is not to serve as moral arbiters of values in mobile apps (or other software artefacts) but rather to promote a healthy discussion of these issues in the software research and development community, and point the field towards a critical technical practice of mobile SE, i.e., the reflective work of sociocultural criticisms, highlighting the hidden assumptions in technical processes, and the interaction between the social, cultural and technical aspects of (mobile) SE.

8.2 The Role Of App Distribution Platforms

App distribution platforms such as the Apple store and the Google Play store have an important role to play in supporting human values and minimising their violations in apps published on their platforms. They can serve as enforcers of ethical systems supporting values such as honesty, akin to the manner in which they protect end-users’ devices from malicious apps (Li et al. 2015, 2017). For instance, they can ensure that app developers are transparent in their billing process and enforce a mandatory multi-step (at least two steps) confirmation not only for subscriptions but also for in-app purchases.

Another issue on the violation of the value of honesty is related to non-transparency in the subscription process in apps. For example, while some apps provide a reminder to the user before the end of a trial period so the user can decide to cancel their subscription or progress to a premium service, some other apps provide no reminder whatsoever. A reminder-to-cancel (or upgrade) feature for apps can be necessitated by the distribution platforms to protect the end-user from unintentional subscriptions.

In addition, for games or game-like apps involving the use of money for play, end-users perceptions of unfairness in these systems can be assuaged by a practice of auditing the systems to ensure statistical outcomes that are not only probable but fair to both the end-user and app developers alike, similar to the way casino systems are routinely audited for fairness and transparency. The results of the audits can then be shown as part of the app information on the app stores.

8.3 Transparent Policies and Agreements

In cases of disputes between end-users and app vendors, where an end-user perceives that they have been unfairly treated, it is typical for the app vendors to refer the end-user to the end-user licence agreement (EULA) signed by the end-user during installation (King 2017). A EULA is a legally binding contract between the end-user and the app vendor (Chee et al. 2012).

Some app vendors place their data handling and billing processes in the fine print of EULAs that are typically difficult to understand by the average user because they are written in legal terms (King 2017). Some studies have also shown that most end-users who clicked “I agree” do not understand the terms to which they agreed and often expressed genuine concern when the terms are clearly expressed to them Chee et al. (2012). Thus it is important to develop transparent legal policies and easy-to-comprehend EULAs to inform and empower the end-user and help them understand the terms and implications of these kinds of legal contracts. Transparency and comprehensibility would alleviate wariness and misgivings in this area. Also, we reiterate the position of O’Neill (2002), that while transparency may undo secrecy, “it may not limit the deception and deliberate misinformation that undermine relations of trust. If we want to restore trust we need to reduce deception and lies, rather than secrecy” (O’Neill 2002). This area is particularly ripe for interdisciplinary research between the computing sciences, humanities, and law.

8.4 An Actionable Framework for Developers

Figure 11 shows an actionable framework we have developed from the findings of our investigation of developers’ perspective of honesty violations in mobile apps and the potential benefits of automatic detection. Almost every stakeholder involved in mobile app development is responsible for honesty violations in mobile apps, and honesty violations affect individual developers, users, and businesses at various levels. Developers use various avoiding strategies to mitigate the occurrence of honesty violations in the apps they develop, and if violations are found after releasing the apps to the public, they use a variety of fixing strategies. Automatic detection has the potential to avoid certain causes, consequences, and support developer strategies (Table 7). While a minority believe no one will get benefits from automatic detection, it will be beneficial to multiple stakeholders involved, including end users, development team members, businesses, and app platforms.

The framework could be used as a guide to get a deeper understanding of honesty violations in mobile apps. We believe that this understanding will help developers immensely to be responsible for developing mobile apps. Developers may also consider using the avoiding and fixing strategies given in this figure, as these were shared by many developers worldwide.

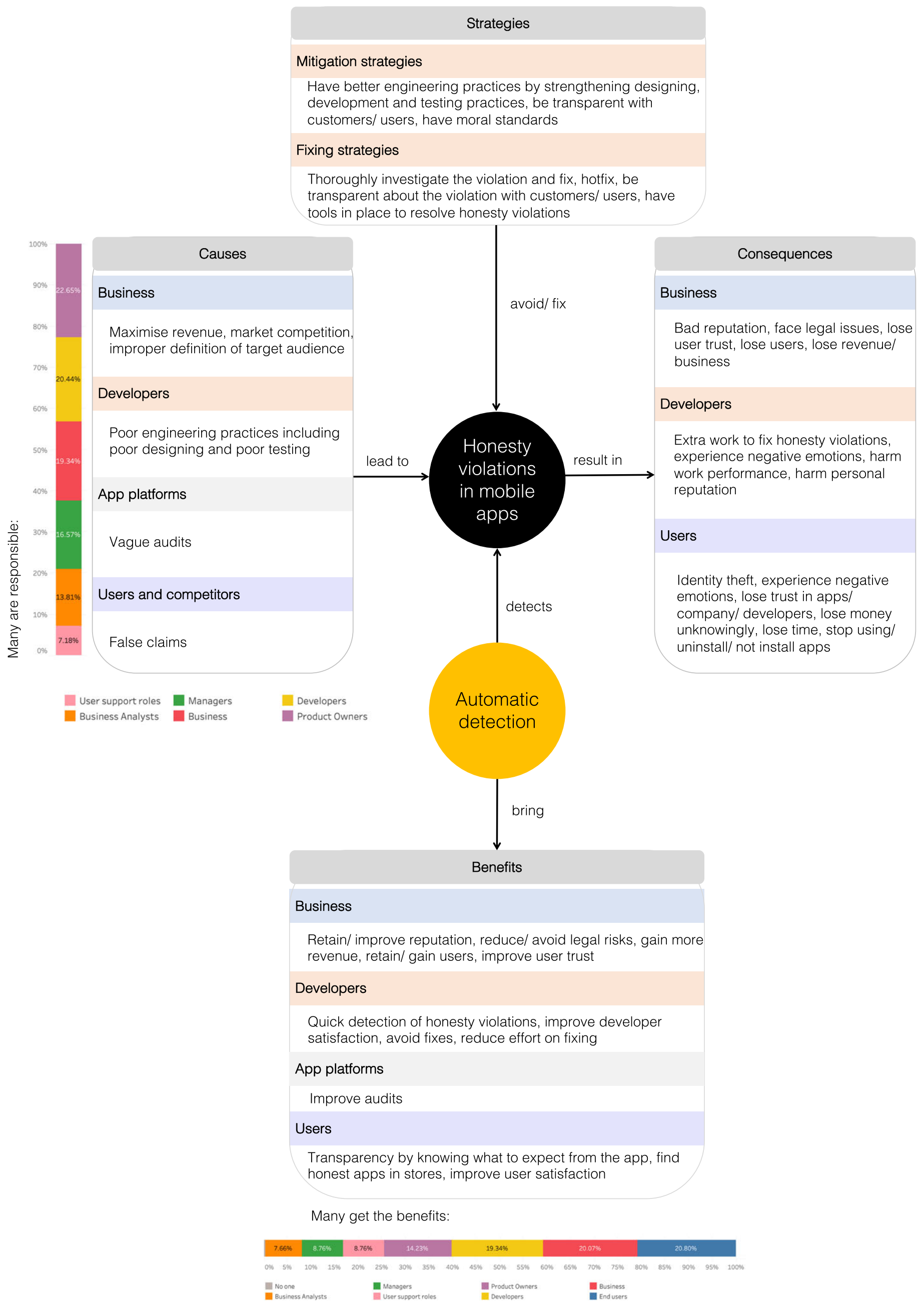

Strategies
Mitigation strategies
Have better engineering practices by strengthening designing, development and testing practices, be transparent with customers/ users, have moral standards
Fixing strategies
Thoroughly investigate the violation and fix, hotfix, be transparent about the violation with customers/ users, have tools in place to resolve honesty violations
avoid/ fix
Causes
Business
Maximise revenue, market competition, improper definition of target audience
Developers
Poor engineering practices including poor designing and poor testing
App platforms
Vague audits
Users and competitors
False claims
lead to
Honesty violations in mobile apps
result in
Consequences
Business
Bad reputation, face legal issues, lose user trust, lose users, lose revenue/ business
Developers
Extra work to fix honesty violations, experience negative emotions, harm work performance, harm personal reputation
Users
Identity theft, experience negative emotions, lose trust in apps/ company/ developers, lose money unknowingly, lose time, stop using/ uninstall/ not install apps
detects
Automatic detection
bring
Benefits
Business
Retain/ improve reputation, reduce/ avoid legal risks, gain more revenue, retain/ gain users, improve user trust
Developers
Quick detection of honesty violations, improve developer satisfaction, avoid fixes, reduce effort on fixing
App platforms
Improve audits
Users
Transparency by knowing what to expect from the app, find honest apps in stores, improve user satisfaction
Many are responsible:
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
22.65%
20.44%
19.34%
16.57%
13.81%
7.18%
User support roles
Managers
Developers
Business Analysts
Business
Product Owners
Many get the benefits:
7.66%
8.76%
8.76%
14.23%
19.34%
20.07%
20.80%
0% 5% 10% 15% 20% 25% 30% 35% 40% 45% 50% 55% 60% 65% 70% 75% 80% 85% 90% 95% 100%
No one
Business Analysts
Managers
User support roles
Product Owners
Developers
Business
End users

Fig. 11 Causes and Consequences of Honesty Violations in Mobile Apps, Common Strategies Developers Use to Avoid/ Fix Them, and The Automatic Detection Benefits

Furthermore, mobile app developers could consider using automatic detection to improve their internal processes, the app, and the end-user experience, which eventually helps in improving the business.

Researchers may consider evaluating the framework proposed in Fig. 11. Additionally, researchers may also consider exploring how various roles in teams (as in Fig. 11) are responsible for honesty violations in mobile apps. They may also consider investigating the impact on those roles as we only focused on businesses, developers, and users. Similarly, as team roles have the potential to get many benefits from automatic detection, a fruitful area to investigate will be the benefits of automatic detection. Ultimately, all of these findings could improve Fig. 11 to give the public and development teams a broad, yet in-depth knowledge of honesty violations in mobile apps, how important it is to address them in mobile apps, and how technology can aid this.

8.5 Human Values in SE Research

Research in the broader area of human values in SE is still in its early stages (Perera et al. 2020). While the investigation of well-known values such as privacy and security has been considerably developed, other values such as honesty, curiosity, and independence have received little attention, possibly due to the subjective and abstract nature of these concepts. This and other recent related works are based on an adaptation of the Schwartz theory of basic human values (Schwartz 1992). However, the nascent field of human values in SE may benefit from new conceptual theories of human values that are more situated closely within SE.

Furthermore, there is a need for the development of tools and techniques, not only in detecting the violation of human values in software artefacts but also providing automatic recommendations for possible fixes. Directions for future work may include the following: the development of approaches for generating end-user comprehensible EULA templates supporting values, approaches for evaluating and auditing fairness in games and game-like systems to support statistically probable results, and modules for static and dynamic analysis tools to detect specific values defects. Another area worth investigating is the development of tools for supporting the inclusion of values throughout the software development lifecycle and the resulting software artefacts, including mobile apps.

9 Threats to Validity

Internal Validity The qualitative process of building the **honesty_discussion** dataset in Section 5.1, categorising the different types of honesty violations in Section 6.1, categorising causes, consequences, strategies of honesty violations and benefits of automatic detection in Section 7 might have errors or omissions. This is due to the qualitative coding approach used, a single author performing the majority of the coding, potential misinterpretation of data, and choice of codes and concepts during analysis. Hence, it might have introduced some threats to the internal validity of the study. We used three techniques to mitigate such threats. First, the qualitative analysis was conducted iteratively over an ample timeframe to avoid fatigue. Second, each review was analysed by one analyst and then was validated by at least one other analyst, followed by several meetings between the analysts to resolve any disagreements and conflicts; and interview and survey findings were analysed by one analyst but were then and shared among other analysts during weekly meetings, including review of raw data, codes and emergent concepts. Third, the analysts have extensive research experience in the area of human values in SE.

Construct Validity The analysts might have had different interpretations of the definition of the value of honesty. Our strategy to minimise this threat was making sure the analysts carefully examined seminal papers (Schwartz 1992, 2012) on the Schwartz theory, formal definition of honesty from dictionaries, and existing software engineering research on human values, including honesty (Obie et al. 2021; Shams et al. 2020). In this study, among many options, we used seven machine learning algorithms to detect honesty violation reviews and four metrics to evaluate the algorithms. Peters et al. (2017) claim that it is impracticable to use all algorithms in one study. Hence, we accept that applying other machine learning algorithms to our dataset may lead to different performances. The metrics precision, recall, accuracy, and F1-score used in this study are widely applied and suggested to evaluate machine learning models in software engineering.

External Validity Our initial sample of app reviews was 236,660 reviews collected from Eler et al. (2019) and Obie et al. (2021), which was further reduced to 4,885 honesty-related reviews after applying the keywords filter. Our keyword filter may have introduced false negatives and potentially excluded honesty violations in the larger dataset. Hence, we cannot claim that our results are generalisable to all app reviews in the Apple App Store and Google Play Store and other platforms (e.g., online marketplaces). Similarly, the sample size of the developer study does not guarantee generalisability as the number of participants is limited (especially interview participants), and the majority represented Europe.

10 Conclusion

Mobile software applications (apps) are very widely used and applied and hence need to reflect critical human value considerations such as curiosity, freedom, tradition, and honesty. The support for – or violation of – these critical human values in mobile apps has been shown to be captured in app reviews. In this work, we focused on the value of honesty. We presented an approach for automatically finding app reviews that reveal the violation of the human value of honesty from an end-user perspective. In developing our automated approach, we evaluated seven different algorithms using a manually annotated and validated dataset of app reviews. Our evaluation showed that the Deep Neural Network (DNN) algorithm provided higher accuracy than the other algorithms in detecting the violation of the value of honesty in app reviews, and also surpasses a baseline classifier with an F1 score of 0.921. We also characterised the different kinds of honesty violations reflected in app reviews. Our manual qualitative analysis of the reviews containing honesty violations resulted in ten categories: unfair cancellation and refund policies, false advertisements, delusive subscriptions, cheating systems, inaccurate information, unfair fees, no service, deletion of reviews, impersonation, and fraudulent-looking apps. We used surveys and interviews to investigate developers' perspectives of honesty violations in mobile apps and how automatic detection might be beneficial. This resulted in the identification of a wide range of causes, consequences, strategies for avoiding and fixing honesty violations, and potential benefits of automatic detection. The results of our study highlight the importance of considering software artefacts, such as mobile apps, as embodiments of human values with consequences on end-users and society as a whole. We emphasise the role of app distribution platforms in supporting human values, such as honesty, on their platforms, recommendations for developers, and discuss the need for the software engineering research community to investigate methods and tools to better minimise the violation of human values in software artefacts.

Acknowledgements This work is supported by ARC Discovery Grant DP200100020. Madampe and Grundy are supported by ARC Laureate Fellowship FL190100035.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

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Humphrey O. Obie received his PhD degree from Swinburne University of Technology, Australia. He is an Adjunct Research Fellow with the HumaniSE Lab, Faculty of Information Technology, Monash University. He has tackled problems in several domains as a data scientist, software developer, product manager, and researcher. His key interests include human-centric software engineering, human-centric IoT and smart cities, value-based software engineering, information visualisation, and visual data storytelling.

Hung Du is a research engineer at Applied Artificial Intelligence Institute (A2I2) in Australia. With a great expertise in both fundamental research and translational research, he has made significant contributions across a wide range of domains of application, including recommendation systems, finance, education, business compliance, automation, and software engineering. He received the ACM SIGSOFT Distinguished Paper Awards at IEEE/ACM 19th International Conference on Mining Software Repositories. His research interests encompass Natural Language Processing, Deep Reinforcement Learning, Machine Learning Operations, Applied AI, and Translational Research, driving his mission to advance knowledge and bridge the gap between theory and real-world applications in the realm of artificial intelligence and machine learning.

Kashumi Madampe received the PhD degree from Monash University. She is a research fellow with Monash University, Melbourne, Australia. Her research interests include developer productivity and experience, software analytics and tools, user experience, and privacy engineering. She worked in the software industry as a project manager and a business analyst prior to her PhD. More details about her can be found at https://kashumim.com.

Mojtaba Shahin is a Lecturer in Software Engineering at RMIT University, Australia. Previously, he was a Research Fellow at Monash University. His research interests include Empirical Software Engineering, Human and Social Aspects of Software Engineering, Software Architecture, and Secure Software Engineering. He has published over 45 papers in premier software engineering journals and conferences, including TSE, EMSE, JSS, ICSE, and MSR. He received an ACM SIGSOFT Distinguished Paper Award (MSR 2022). He completed his PhD study at the University of Adelaide, Australia.

Idowu Ilekura is currently pursuing a Master's degree in Coastal Engineering at the esteemed IHE Delft Institute for Water Education in the Netherlands. He has been awarded the highly regarded Erasmus Mundus Joint Master's Degree Scholarship, which is fully funded by the European Union. Idowu's research interests encompass Data Engineering, Climate Change, Coastal Science, and Cloud Computing. With a solid background in Data Analysis and Science, he has amassed more than three years of valuable experience in the field.

John Grundy is Australian Laureate Fellow and Professor of Software Engineering at Monash University, Australia. His interests include automated software engineering, human-centric software engineering, requirements engineering and software security engineering. He is Fellow of Automated Software Engineering and Fellow of Engineers Australia.

Li Li is a Professor of Software Engineering at Beihang University. Before that, he was an ARC DECRA Fellow and Senior Lecturer at Monash University, Australia. He got his PhD in 2016 from the University of Luxembourg. He has published over 100 research papers at prestigious conferences such as ICSE, ESEC/FSE, ASE, ISSTA, POPL, PLDI, WWW, and prestigious journals such as ACM TOSEM and IEEE TSE, TIFS, and TDSC. Li was named one of the Top-3 most impactful earlier career software engineering researchers. He received the MSR 2023 Ric Holt Early Career Achievement Award. He also received 9 Best/Distinguished Paper Awards, including 4 ACM SIGSOFT/SIGPLAN and IEEE TCSE Distinguished Paper Awards and a FOSS Impact Paper Award. Li is an active member of the software engineering and security community, serving as a reviewer for many top-tier conferences and journals.

Jon Whittle is Director of CSIRO's Data61, the digital and data sciences arm of Australia's national science agency. With over 800 staff and affiliates, Data61 is one of the largest collections of R&D expertise in Artificial Intelligence and Data Science in the world. Data61 partners with over 200 industry and government organisations, over 30 Universities, and works across vertical sectors in manufacturing, agriculture, and the environment. Prior to joining Data61, Jon was Dean of the Faculty of Information Technology at Monash University, the largest university in Australia. He was named CEO Magazine's 2019 Education Executive of the Year. Jon is also a former Technical Area Lead at NASA, where he worked on AI software for NASA space missions. Jon has a PhD in Artificial Intelligence from the University of Edinburgh, UK.

Burak Turhan is a Professor of Software Engineering at the University of Oulu and an Adjunct Professor (Research) in the Faculty of IT at Monash University. His research focuses on empirical software engineering, the interplay between AI and SE, quality assurance and testing, human factors, and (agile) development processes. He is a Senior Associate Editor of the Journal of Systems and Software, an Associate Editor of ACM Transactions on Software Engineering and Methodology and Automated Software Engineering, an Editorial Board Member of Empirical Software Engineering, Information and Software Technology, and Software Quality Journal, and a Senior Member of ACM and IEEE. Please visit: <https://turhanb.net/> for more information.

Hourieh Khalajzadeh is a Senior Lecturer in the School of Information Technology at Deakin University. Previously, she was a Research Fellow in the HumaniSE Lab at Monash University. Hourieh's research is situated at the intersection of software engineering and data science. She is currently looking at the human-centric issues in Software Engineering and is experienced in designing domain specific visual languages for different applications, including big data analytics development.

Authors and Affiliations

Humphrey O. Obie[1] · Hung Du[2] · Kashumi Madampe[1] · Mojtaba Shahin[3] · Idowu Ilekura[4] · John Grundy[1] · Li Li[5] · Jon Whittle[6] · Burak Turhan[7] · Hourieh Khalajzadeh[2]

Humphrey O. Obie
humphrey.obie@monash.edu

Hung Du
hung.du@deakin.edu.au

Mojtaba Shahin
mojtaba.shahin@rmit.edu.au

Idowu Ilekura
ilekuraidowu@gmail.com

John Grundy
john.grundy@monash.edu

Li Li
lilicoding@ieee.org

Jon Whittle
jon.whittle@data61.csiro.au

Burak Turhan
burak.turhan@oulu.fi

Hourieh Khalajzadeh
hkhalajzadeh@deakin.edu.au

1 Monash University, Melbourne, Australia

2 Deakin University, Melbourne, Australia

3 RMIT University, Melbourne, Australia

4 Data Science Nigeria, Lagos, Nigeria

5 School of Software, Beihang University, Beijing, China

6 CSIRO's Data61, Melbourne, Australia

7 University of Oulu, Oulu, Finland