Privacy Intelligence: A Survey on Image Privacy in Online Social Networks

CHI LIU, University of Technology Sydney, Australia
TIANQING ZHU*, University of Technology Sydney, Australia
JUN ZHANG, Swinburne University of Technology, Australia
WANLEI ZHOU, City University of Macau, China

Image sharing on online social networks (OSNs) has become an indispensable part of daily social activities, but it has also increased the risk of privacy invasion. An online image can reveal various types of sensitive information, prompting the public to rethink individual privacy needs in OSN image sharing critically. However, the interaction of images and OSN makes the privacy issues significantly complicated. The current real-world solutions for privacy management fail to provide adequate personalized, accurate and flexible privacy protection. Constructing a more intelligent environment for privacy-friendly OSN image sharing is urgent in the near future. Meanwhile, given the dynamics in both users’ privacy needs and OSN context, a comprehensive understanding of OSN image privacy throughout the entire sharing process is preferable to any views from a single side, dimension or level. To fill this gap, we contribute a survey of “privacy intelligence” that targets modern privacy issues in dynamic OSN image sharing from a user-centric perspective. Specifically, we present the important properties and a taxonomy of OSN image privacy, along with a high-level privacy analysis framework based on the lifecycle of OSN image sharing. The framework consists of three stages with different principles of privacy by design. At each stage, we identify typical user behaviors in OSN image sharing and their associated privacy issues. Then a systematic review of representative intelligent solutions to those privacy issues is conducted, also in a stage-based manner. The analysis results in an intelligent “privacy firewall” for closed-loop privacy management. Challenges and future directions in this area are also discussed.

CCS Concepts: • Security and privacy → Privacy protections; • Computing methodologies → Artificial intelligence.

Additional Key Words and Phrases: online social network, image sharing, privacy protection, privacy intelligence.

ACM Reference Format:
Chi Liu, Tianqing Zhu, Jun Zhang, and Wanlei Zhou. 2022. Privacy Intelligence: A Survey on Image Privacy in Online Social Networks. ACM Comput. Surv. 0, 0 (2022), 33 pages. https://doi.org/10.1145/3547299

1 INTRODUCTION

1.1 Background

As an indispensable component of modern society, online social networks (OSNs) have significantly changed social communication and information exchange in the daily life of humans. Currently, sharing images on OSNs is extremely fashionable with its popularity is only growing. Photo capturing and posting can be completed with a few simple clicks anywhere and anytime, allowing users to instantly express themselves and interact with others. However, the convenience of sharing photos also raises considerable threats to users’ privacy. Even a seemingly non-private OSN image can reveal significantly sensitive personal information. For instance, an online information forensics challenge launched in 2019 [1] showed that, by integrating multi-domain knowledge, a

*Tianqing Zhu is the corresponding author of this research.

---

Authors’ addresses: Chi Liu, Chi.Liu@student.uts.edu.au, University of Technology Sydney, 81 Broadway Ultimo, Sydney, NSW, 2007, Australia; Tianqing Zhu, Tianqing.zhu@uts.edu.au, University of Technology Sydney, 81 Broadway Ultimo, Sydney, NSW, 2007, Australia; Jun Zhang, junzhang@swin.edu.au, Swinburne University of Technology, John St Hawthorn, Sydney, VIC, 3122, Australia; Wanlei Zhou, wzhou@cityu.edu.mo, City University of Macau, 81 Av. Xian Xing Hai, Macao, China.
stranger could work out the photographer’s sensitive information, such as when and where the picture was
taken, from only one “ordinary” OSN photo of the user.

In contrast to the simplicity of sharing images online, the preservation and management of OSN image privacy
is remarkably challenging. There are three root causes, and the interplay of them makes the problem even harder.

**The intrinsic intractability of OSN image privacy.** The interaction of images with OSN introduces
numerous new influence factors into the decision-making process of individual privacy. The privacy sensitivity
of an online-shared image depends not only on the static image content but also on contextual dynamics from
multiple dimensions, such as individuals’ subjective decisions, the strength of social relationships, the nature of
multi-party interactions in OSNs, and the spatial and temporal variations of an image [2, 3]. These variables are
intricately intertwined, making it impractical to address the problem merely from a single dimension, level, or
side [3]. This intrinsic intractability of OSN image privacy significantly increases the difficulties with and cost of
privacy management.

**The natural limitations of human privacy consciousness.** OSN image privacy is subjective, closely
associated with an individual’s cognition and knowledge of privacy. Studies have shown that OSN users are
ubiquitously unaware of how images can compromise privacy [4, 5]. Their common and seemingly innocuous
behaviors in daily OSN image sharing can lead to unwitting violations of individual privacy for themselves
and others, both directly and indirectly. And these infractions are beyond what the user could have imagined.
Moreover, an individual’s privacy preferences can be biased by, say, their education backgrounds, demographic
characteristics, and social role [3, 6, 7], resulting in extraordinarily personalized privacy needs regarding OSN
image sharing, especially when considering multiparty interactions [8].

**Machine learning exacerbates the tension between privacy and OSN image use.** Recent develop-
ments in machine learning have definitely made image sharing online more entertaining and enjoyable. But
these techniques also pose great threats and intensify the difficulty of privacy preservation. The sensitive
visual content of an image can be easily recognized or edited by a machine learning model [9]. Moreover,
machine learning models can help reveal some implicit sensitive information such as occupation [10],
health conditions [11] and even sexual orientation [12] from personal photos. Such machine learning-
powered attacks are often cheap but hard to prevent in practice.

**Case study: Does Alice really protect privacy as she had expected?**

A common OSN image sharing scenario (Figure 1): The image owner Alice shares some photos about her
and her partner Bob’s holiday trip to her own social circle. Supposing she already has certain privacy awareness and
configures the privacy setting as “only visible to people who know me” (which is also very popular in practice).

Despite Alice’s privacy setting, we can easily see some privacy risks from different sides:

**Sender’s side:** Alice may not know which information is truly sensitive and to what extent it can be revealed
by today’s novel attack methods.

**Co-owner’s side:** Bob’s privacy may be violated if he does not want to disclose his relationship with Alice to
people outside his own social circle, e.g., David.
Server’s side: No other fine-grained options are available by the current privacy setting system, albeit the social distances between Alice and each permitted visitor (e.g., Carol or David) may differ significantly.

Recipient’s side: The recipient (e.g., David) may be honest-but-curious and resend the photos to unknown people outside Alice’s social circle, going against Alice’s original privacy preference.

This is a simplified case, whereas, in reality, the situations are much more complicated, and the privacy risks are far greater than those listed above. In Sections 3 through 5, we specify all privacy issues in OSN image sharing.

1.2 Motivation of privacy intelligence

The above analysis and case study indicate considerable difficulties in dealing with the modern privacy issues associated with OSN image sharing. The current real-world managements, such as privacy laws and regulations [13, 14], user agreements, or oversimplified privacy settings provided by OSN photo service providers (PSPs), are insufficient to eliminate the dilemma of OSN image privacy. Across the globe, this privacy crisis has spurred the research community to explore more effective solutions to satisfy modern privacy needs. The promising way requires further exploration and wider adoption of automated, semi-automated and human-computer-interactive techniques. We refer to this cluster of computer-aided privacy-enhancing technologies as privacy intelligence.

To date, various privacy intelligence solutions for OSN image sharing have been proposed. However, one concern remains that existing works mainly consider the problem from isolated views, solving each privacy issue individually. A survey to concatenate these fragments is critically needed to provide fundamental insights into this field and help build a privacy-friendly OSN image sharing environment. To this end, we review the literature published over the last decade surrounding this topic. Considering the user-centric aspiration of modern privacy management, we focus on the privacy needs associated with users’ online image sharing operations. We begin with establishing a high-level privacy analysis framework based on the complete lifecycle of OSN image sharing. Typical user behaviors and their induced privacy issues are identified within the framework. Intelligent solutions targeting each issue are then discovered from the literature and analyzed comparatively.

1.3 Comparison of existing surveys

There are several surveys partially related to this topic, including:

- **Surveys on OSN privacy.** Fire et al. [15] provided a thorough review of different security and privacy risks that threaten OSN users’ well-being, along with an overview of existing countermeasures. Abawajy et al. [16] presented a survey of privacy risks, attacks and privacy-preserving techniques in general for social network data publishing based on graph modelling methods. Alemany et al. [17] provided an in-depth analysis on privacy decision-making mechanisms in OSN.

- **Surveys on multimedia privacy.** Padilla-López et al. [18] reviewed the protection techniques for visual data privacy, outlining useful design principles for privacy-aware intelligent monitoring systems. Ribaric et al. [19] reviewed the de-identification mechanisms for non-biometric, physiological, behavioral, and soft-biometric identifiers in multimedia documents. Patsakis et al. [20] outlined the significant security and privacy risks in exposing multimedia contents in OSN and discussed possible countermeasures. Zhang et al. [21] surveyed typical attack and defense methods for visual privacy in deep learning systems.

Three key points differentiate our survey from these pioneering works. First, previous surveys mainly focus on static OSN privacy or local multimedia privacy independently, while we pay attention to the interplay of the two, considering privacy issues in the dynamic OSN image sharing context. Second, previous surveys were performed from a problem-driven perspective, i.e., identifying different threats and looking for specific countermeasures. In contrast, we try to establish a more global overview of this field from a user-centric perspective with a lifecycle-based privacy analysis framework. Last, previous surveys included many manpower-reliant solutions,
while we purely focus on intelligent solutions, with an eye on interdisciplinary influences stemming from the recent progress of artificial intelligence.

In brief, this article provides a comprehensive understanding of privacy in OSN image sharing with the following contributions: 1) the properties and taxonomy of OSN image privacy; 2) a novel privacy analysis framework based on the OSN image sharing lifecycle; 3) a representation of the potential privacy issues arising from typical sharing-associated user behaviors; 4) an in-depth review of the current advances in privacy intelligence solutions for OSN image privacy; 5) the identification of a set of essential design principles for privacy intelligence; 6) a discussion of the open challenges in OSN image privacy and future directions for addressing them.

The remainder of this paper is organized as follows. Section 2 presents an overview of OSN image privacy, discussing the properties and taxonomy of OSN image privacy and the structure of the privacy analysis framework. In Sections 3 through 5, we identify modern privacy issues, summarize the corresponding intelligent solutions and discuss the common principles of privacy by design for each stage of the framework. Section 6 discusses the future lines for dealing with the open challenges detected. Section 7 offers a brief conclusion.

2 OSN IMAGE PRIVACY: AN OVERVIEW

2.1 Properties and taxonomy

There is no an exact definition of OSN image privacy in the current literature. As a starting point, we consider OSN image privacy with reference to the previous definitions on OSN privacy [22, 23] and visual privacy [18]: OSN image privacy is the sensitivity, visibility and contextual integrity of information exposed explicitly or implicitly from an image throughout the OSN propagation lifecycle. With this definition, we highlight three key privacy properties:

- **Sensitivity** defines what type of information associated with the image is sensitive in the sharing process.
- **Visibility** measures to what degree the sensitive information can be accessed by a specific recipient.
- **Contextual integrity** indicates the completeness of the information in the dynamic OSN image sharing context, which is governed by particular social norms.

OSN image privacy can be categorized into three types shown in Figure 2.

**Observable privacy** refers to sensitive content that can be viewed directly in the image, such as faces, car licenses and location signs. This is the most common type of OSN image privacy, given the main purpose of online image sharing is to convey visual content to others for enjoyment. Observable privacy can be interpreted at different semantic levels, from lower ones such as pixel- and object-level, to higher ones like scene-level. It is the most vulnerable since the sensitive visual content is immediately exposed once images are accessed maliciously.

**Inferential privacy** refers to the sensitive information implied in the image content that can be inferred through reasoning or association. As an example, one might be able to extrapolate a specific event by analyzing the location cues in an image and/or what people are wearing. Soft biometric attributes, such as facial age and sexual orientation, are another typical type of inferential privacy. These underlying attributes are often hard for human viewers to perceive but can be deduced accurately by machines in the latent feature space [10–12].
Contextual privacy refers to the sensitive external information associated with an image in the dynamic OSN context. This type of information might be found in descriptive texts added by external actions during sharing, such as the metadata recorded by cameras or the auxiliary tags or captions provided by OSN users. It can also be found in the properties characterized by social interactions. For example, co-ownership of an image can be regarded as sensitive information since it can be exploited by attackers to reveal private social connections and possible image provenance and propagation paths.

2.2 Privacy analysis framework

We devised a privacy analysis framework to help identify diverse OSN image privacy issues and investigate privacy intelligence countermeasures. Considering the user-centric aspiration for modern privacy management, our focus is on the privacy issues induced by typical user behaviors in OSN image sharing. Hence, the framework covers all typical user behaviors in the entire lifecycle of OSN image sharing to form a closed loop for privacy analysis, as shown in Figure 3. There are three stages in this loop based on the progressive change in image controllability, including local management, online management and social experience. In each stage, the privacy solutions share common design principles of privacy intelligence, which will be discussed in the later sections.

Fig. 3. The lifecycle-based privacy analysis framework, including three main stages: local management, online management and social experience. Each stage involves multiple sharing-specific user behaviors.

2.2.1 User behaviors in local management.

Image creation. The image is captured via a camera.

Image selection. The sender selects the image from a gallery for OSN sharing purposes.

Image description. Before publishing, the sender may attach particular information, such as descriptive tags, to the image to express a sentiment, foster social interaction or to help with image indexing.

2.2.2 User behaviors in online management.

Image configuration. Most current PSPs provide a configuration system for senders to manually set their privacy preferences regarding photo visibility.

Image publishing. The sender publishes the image to make it accessible to the permitted recipients.

2.2.3 User behaviors in social experience.

Image viewing. The shared image is received and enjoyed by the authorized human recipients.

Social application. The shared images are applied to specific online photo-based services. For example, OSN users might upload personal photos to a facial age evaluation application for fun.

Image deletion. Users may choose to delete the image from OSNs after their sharing purposes have been met. Alternatively, some users may periodically or non-periodically check their image sharing records and delete some past photos to avoid long-term exposure online.
2.3 Technical goals of privacy intelligence

A user-friendly privacy intelligence solution in the context of OSN image sharing should never narrowly meet one single goal of privacy protection. Instead, we distil the following crucial technical goals of designing privacy intelligence through the literature review:

Privacy-utility trade-off ($G_1$-PU). OSN users generally share an image with specific purposes, such as social interaction or moment recording. For whatever purposes, the shared image should maintain an essential level of utility after enhancing its privacy.

Personalization ($G_2$-PE). The solution is desired to be as personalized as possible to satisfy different OSN users’ privacy needs.

Independence ($G_3$-IN). A privacy intelligence solution is preferable not to rely on user data or third parties. Accessing user data such as historical records or user profiles is a privacy violation; the involvement of third parties leads to potential risks of information leakage.

Automation ($G_4$-AU). Automation means how “intelligent” the solution is. A more automated solution requires less human participation.

Flexibility ($G_5$-FL). Flexibility has two means; one is whether the solution can adaptively adjust to users’ dynamics of users’ privacy needs; the other one is whether the solution is compatible with present-day commercial OSN services or mobile devices.

Communication-effectiveness ($G_6$-CE). OSN image sharing is expected to be instant and low-latency. Thus, for those solutions involving multi-party communication, the time-effectiveness of communication is always a primary concern.

We provide a qualitative comparison in terms of the above technical goals for each reviewed paper in Table 1, 2 and 3, with the following ranking system: ●: The goal is a major concern with quantitative evaluations or has been fully satisfied in the paper. ○: The goal has been partially or weakly considered without quantitative evaluations in the paper. □: The goal is not considered but worthy of careful concern in the problem formulated in the paper. N/A: The goal is not applicable to the problem formulated in the paper.

3 PRIVACY ANALYSIS IN LOCAL MANAGEMENT

This section provides a thorough privacy analysis in the local management stage, including privacy issues, intelligent solutions and the common design principles of privacy intelligence. Figure 4 offers an overview of the analysis in this stage.

![Fig. 4. Overview of the privacy analysis in the local management stage. Each privacy issue is linked to its user behavior cause and the corresponding intelligent solutions.](image-url)
3.1 Privacy issues in local management

3.1.1 Issues associated with image capture.

**Unintended photographing.** When taking photos, it is sometimes inevitable that sensitive information of non-interested parties, such as bystanders’ faces or military signs, are inadvertently captured. In most cases, users are unaware that the photographing behavior violates the privacy of non-interested parties, and even if they are, they can only delete or edit the photos manually according to their own understanding of privacy.

3.1.2 Issues associated with image selection.

**Cognitive bias of privacy.** Previous studies have shown that users commonly lack a clear awareness of what images should be privacy-sensitive to themselves or related stakeholders. As a result, the selection of personal photos for online distribution often violates users’ real privacy needs. This is also known as the “privacy paradox” [24], which means users’ actions have deviated from their true attitudes in pursuit of personal privacy.

3.1.3 Issues associated with image description.

**Unsafe tagging.** Image tagging has become a prevalent social functionality supported by many PSPs. However, indiscreet tagging behaviors might directly expose certain kinds of individual information, such as facial identity or location [25]. Automatic image tagging functions based on machine recognition algorithms may further exacerbate this risk [26]. In addition, some PSPs adopt linkable tags as access control, which could lead to malicious access if the victim’s face is deliberately tagged as another person [27].

3.2 Privacy intelligence in local management

3.2.1 Solutions for unintended photographing.

**Real-time imaging filtering.** Real-time imaging filtering is a solution that automatically identifies and removes sensitive content during the imaging process inside the camera. The implementations for real-time imaging filtering can be divided into hardware-based methods and software-based methods.

**Hardware-based filtering.** Chattopadhyay et al. [28] designed a digital signal processor for camera devices, which embeds an invertible cryptographic obscuration module to enhance privacy during photographing. The region of privacy interest of the captured image (defined as the person entering a static scene by the authors) was identified and encrypted using the block cipher algorithm Advanced Encryption Standard (AES) during image compression. Pittaluga et al. [29] proposed to filter the sensitive content in the pre-capture process via specific optical element design. A complementary optic layer in the camera sensor anonymizes the facial identity from the incident light field before sensor imaging.

**Software-based filtering.** Aditya et al. [30] developed I-Pic, a platform for individual policy-compliant content filtering in real-time photography. I-Pic maintains a secured signature based on facial features for each user to match his/her pre-defined privacy policies and photo presence. Then, once the user’s presence in a non-related photo is detected, I-Pic will edit the photo according to his/her privacy policies. Another similar platform named Cardea is proposed by Shu et al. [31]. The difference between Cardea and I-Pic is that Cardea supports more fine-grained and context-aware privacy policies decided by four contextual elements: location, scene, others’ presence, and hand gestures.

Although both hardware and software-based methods can ensure privacy protection in real-time photography, they have some limitations. The hardware-based methods often lack flexibility, i.e., their designs always depend on pre-defined private content, such as human faces. In comparison, the software-based methods depend on individual privacy policies and are more personalized. However, the current systems such as I-Pic or Cardea require a third-party cloud for image management, which may be privacy-risky if the cloud provider is dishonest.
**Visual privacy marker.** Visual privacy marker is another solution to prevent unintended photographing, where users use visual signs from the physical environment to express individual privacy needs when being captured.

**Natural visual marker.** Schiff et al. [32] proposed assigning privacy-related meanings to physical objects (such as hats or vests). For example, people could wear specifically colored items to express their unwillingness to appear in a stranger’s photos. The authors also developed a camera with an embedded visual tracker to automatically recognize these privacy hints when capturing an image.

**Artificial visual marker.** Pallas et al. [33] proposed using artificial visual markers instead of natural ones. They designed a set of four visual symbols representing four elementary privacy preferences. The idea is that photo subjects can wear these stickers in the form of stickers or badges that are easily recognizable. Bo et al. [34] designed a customized yet compatible QR code as a privacy marker. Compared with Pallas et al.’s design, the QR codes can be recognized more quickly and accurately by machines, and are more informative, allowing users to convey more personalized privacy needs.

Visual privacy markers allow users to express individual privacy needs directly and actively. This human-computer interactive design ensures great extendibility and applicability in real-world implementations. However, the current methods commonly require a build-in parsing module to translate the marker into structured policies, yet unified parsing rules are unavailable in the current industry. In addition, wearing a conspicuous artificial mark is not always practical for users.

3.2.2 Solutions for cognitive bias of privacy.

**Privacy prediction.** Human’s cognitive bias regarding OSN image privacy often means manual privacy decisions are error-prone and time-consuming. A more efficient way is to automatically learn and predict the privacy pattern of an image with machine learning classifiers in a data-driven manner. The privacy pattern is normally formulated as a binary classification problem with a decision on "is privacy" or "is not privacy". An essential workflow can be determined: privacy-associated features are first determined and extracted, followed by a classifier trained to discover privacy patterns from the features.

**Content-based prediction.** Considering that image privacy is likely tied to visual content, Tran et al. [35] proposed extracting hierarchical features from visual content for privacy prediction. The object-level features and the general privacy features are extracted by two convolutional neural network (CNN)-based extractors respectively, and then concatenated for the final privacy decision. Han et al. [36] proposed using multi-level and multi-scale features for privacy prediction. The multi-level features are extracted by different layers of a CNN and the multi-scale features by a stack of max-pooling layers. An self-attention-based [37] aggregation model was used for feature fusion and prediction.

Some studies suggested learning the relatedness between semantic objects and privacy for privacy prediction. For example, Yu et al. [38] proposed an object-privacy alignment algorithm based on co-occurrence frequencies. The algorithm mines the object-privacy relatedness in a tree-based manner from massive social images. Then the tree-based features are combined with CNN features for detecting privacy-sensitive objects for privacy prediction. Yang et al. [39] built a knowledge graph from a large-scale image privacy dataset to represent the relevance between semantic objects and image privacy. A graph neural network is trained with the object-privacy graph for privacy prediction and explanation. Another graph-based prediction model developed by Yang et al. [40] employs a region-aware graph convolutional network to discover privacy-sensitive regions and model their correlation adaptively. A graph convolutional network combining the self-attention mechanism is adopted to model the dynamic interaction among the crucial regions identified from the spatially-correlated CNN feature maps. The local graph features are then concatenated with a global representation of the image to identify private images.

**Context-based prediction.** OSN image privacy not only depends on the content but also on the associated OSN context (such as tags). In this vein, some researchers have explored the feasibility of using multi-modality
contextual features for privacy prediction. Zerr et al. [41] proposed fusing several hand-crafted visual features and textual features to train a privacy classifier. A similar feature fusion method was provided by Squicciarini et al. [42]. The difference is that the authors additionally investigated the effectiveness of different feature combinations in privacy prediction. Their results revealed that the combination of scale-invariant features and tag features was the smallest best-performing set. Zhong et al. [43] provides another insight using social group tendentiousness as a contextual feature with an assumption that the privacy decisions on the same image might vary in social groups with different privacy preferences. The expectation-maximization algorithm is used to estimate the likelihood for a user to be associated with each group according to users’ historical privacy decisions and demographic information. Then the probability that any given image is private is a user-specific average of the privacy posteriors under each of the groups.

More recently, researchers have attempted to use multi-modality deep representative features instead of hand-crafted features for context-based prediction. Tonge et al. [44] studied the usefulness of deep visual features and deep tag features for classifying image privacy. Deep visual features are represented as the multi-level CNN feature maps learned in an image classification task, while deep tag features are the CNN features associated with the top-\(k\) objects in an object detection task. In a follow-up study [45], the authors proposed a dynamic ensemble learning algorithm which can rank the modality competence of different feature modalities including image objects, scenes and tags in privacy prediction.

Learning-based privacy prediction can improve privacy decisions with data-informed intelligence that reduces human bias. There are two limitations in the current workflow. First, existing methods predicting image privacy from visual contents tend to link privacy with static semantic information, regardless of the dynamics of OSN image privacy. For example, most studies regard the human face as private, but one may feel that faces presented in a party photo are more sensitive than those taken in a public area. Thus, inter-object correlations and object-scene relationships should be carefully considered in feature selection. Second, most existing models formulate image privacy prediction as a “private v.s. public” classification problem. However, since users’ privacy needs are subjective, it is impractical to define a distinct cut-off for privacy sensitivity. By contrast, adopting ranking scores or uncertainty probability [46] are worthy of further investigation.

3.2.3 Solutions for unsafe tagging.

Privacy-aware tag recommendation. Privacy-aware tag recommendation is a set of machine-aided tag recommendation mechanisms aiming at automatically recommending high-quality privacy-aware tags for social images. Tonge et al. [47] proposed a tag recommendation approach based on the correlations between tags and privacy patterns. The approach first identifies the top-\(k\) neighboring images for the target image by both visual content similarity and tag similarity. Then, for each machine-detected tag of the target image, a ranking algorithm calculates the sum of similarities and the probability that the tag is private or not over the neighboring images, such that privacy-aware tags can be recommended empirically for the targeted image. Tang et al. [27] proposed a cooperative photo tagging system, with the aim of preventing malicious access through linkable tags. The system consists of two cascading stages: The first one is an initialization stage where new users’ portrait samples are collected from their OSN profiles for identity matching and tagging; The second one is a cooperative tagging stage where the remaining unidentified participants are tagged cooperatively by the users identified in the first stage. This cooperative mode prevents malicious tagging behaviors from any single user side.

3.3 Design principles in local management

Table 1 provides a breakdown of the reviewed solutions in this stage. By examining the methods applied in these solutions, we can identify several common design principles regarding OSN image privacy in this stage.
Table 1. A summary of the solutions of privacy intelligence in the local management stage. OP: observable privacy; IP: infer-
tential privacy; PU: privacy-utility trade-off; PE: personalization; IN: independence; AU: automation; FL: flexibility; CE: communication-effectiveness. The ranking system is explained in Section 2.3.

| Privacy intelligence | Paper; Year | Sub-class | Target privacy | Key technique | G1-PU | G2-PE | G3-IN | G4-AU | G5-FL | G6-CE |
|----------------------|-------------|-----------|----------------|---------------|-------|-------|-------|-------|-------|-------|
| Real-time imaging    | [28]; 2007  | Hardware-based filtering | OP | Digital signal processor | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
|                      | [29]; 2015  | Hardware-based filtering | OP | Optical imaging | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
|                      | [30]; 2016  | Software-based filtering | OP | Wireless communication | ⬤ | ⬤ | ⬤ | ⬤ | ⬤ |
|                      | [31]; 2018  | Software-based filtering | OP | Wireless communication | ⬤ | ⬤ | ⬤ | ⬤ | ⬤ |
| Visual privacy       | [32]; 2009  | Natural visual marker | OP | Human-computer interaction | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
| marker               | [33]; 2014  | Artificial visual marker | OP | Human-computer interaction | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
|                      | [34]; 2014  | Artificial visual marker | OP | Human-computer interaction | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
| Privacy prediction   | [35]; 2016  | Content-based prediction | OP; IP | Deep neural network | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [36]; 2022  | Content-based prediction | OP; IP | Deep neural network | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [37]; 2017  | Content-based prediction | OP; IP | Deep multi-task learning | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [38]; 2017  | Content-based prediction | OP; IP | Deep multi-task learning | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [39]; 2020  | Content-based prediction | OP; IP | Graph neural network | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [40]; 2022  | Content-based prediction | OP; IP | Graph neural network | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [41]; 2012  | Context-based prediction | OP; IP | Feature engineering | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [42]; 2014  | Context-based prediction | OP; IP | Feature engineering | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [43]; 2017  | Context-based prediction | OP; IP | Machine learning | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [44]; 2018  | Context-based prediction | OP; IP; CP | Deep neural network | N/A | ⬤ | ⬤ | ⬤ | N/A |
|                      | [45]; 2019  | Context-based prediction | OP; IP; CP | Ensemble learning | N/A | ⬤ | ⬤ | ⬤ | N/A |
| Privacy-aware tag    | [46]; 2018  | CP | Deep neural network | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
| recommendation       | [27]; 2019  | OP | Rule design | ⬤ | ⬤ | ⬤ | ⬤ | N/A |
• **Offline mode.** In the local management stage, the image is prepared by the sender in an offline mode. In most cases, the image owner is the original sender with full control right of the image, and the image is only accessible by the sender. Therefore, all the reviewed solutions in this stage can be implemented in an offline mode. It offers the chance to integrate these solutions within a local modular that can be embedded into end camera applications or the initial user interfaces of OSN services. In this way, some privacy issues can be resolved immediately before getting further complicated in the subsequent OSN interactions.

• **Sensitivity.** Recall the sensitivity property of OSN image privacy in Section 2.1. This should be a primary design consideration in this stage. Since images are held and controlled by the owners with few online interactions with others, most privacy issues in this stage are derived from the owners’ unawareness or knowledge limitations about OSN image privacy. Hence, one crucial goal is to assist users in identifying which kind of information in the image should be privacy-sensitive facing the OSN sharing process and help filter the sensitive information automatically in the presence of users’ lack of privacy consciousness.

• **Preventive intelligence.** As discussed above, the principal target of privacy intelligence in this stage is to automatically detect privacy-sensitive information to assist user decisions on OSN image sharing. Meanwhile, since the image owner has complete control of the image, it is preferable for most solutions to be performed in a human-computer-interactive fashion instead of automatically processing images directly. The computer alerts users of the privacy risks and offers appropriate recommendations before photo sharing online, forestalling photos from undesirable information leaks. In this way, privacy intelligence in this stage can be referred to as *preventive intelligence*.

4 PRIVACY ANALYSIS IN ONLINE MANAGEMENT

This section focuses on privacy analysis in the online management stage. Figure 5 offers an overview of the analysis in this stage.

| User behaviors | Privacy issues | Privacy intelligence solutions | Common design principles |
|----------------|----------------|-------------------------------|--------------------------|
| Image configuration | Coarse-grained privacy setting | Intelligent policy generation | Online mode |
| | Multi-party privacy conflict | Smart access control | Visibility |
| | Visual content exposure | Visual obfuscation | Protective intelligence |
| | Malicious machine recognition | Encryption | |
| | | Adversarial perturbation | |

Fig. 5. Overview of the privacy analysis in the online management stage. Each privacy issue is linked to its user behavior cause and the corresponding intelligent solutions.

4.1 Privacy issues in online management

4.1.1 *Issues associated with image configuration.*

**Coarse-grained privacy setting.** The current privacy preference systems provided by most PSPs only support simple options, e.g., setting an image as publicly visible or private. Such coarse-grained settings cannot satisfy...
modern personalized individual privacy needs. Moreover, the configurations are heavily manpower-dependent, which is error-prone and tedious.

**Multi-party privacy conflicts.** Normally, the shared images are closely related to multiple stakeholders. As users behave differently regarding how they disclose information [48], they may have different opinions on what content is sensitive. Conflicts occur when the privacy settings of the sender override the privacy preferences of other stakeholders. The current OSNs cannot handle this issue effectively: the sender fully controls the configuration, whereas others are not granted any say in the matter.

### 4.1.2 Issues associated with image publishing.

**Visual content exposure.** A common risk of online image publishing is the undesirable exposure of visual content. Users may get in trouble by disclosing sensitive visual content to unwanted viewers since it may cause a social impression suppression or economic loss. The unpredictability of the viewers’ actions and morality further exacerbates this risk.

**Malicious machine recognition.** Nowadays, the pervasive machine learning-based recognition systems bring considerable risks to individual privacy. Users’ face photos can be easily collected online and applied to unknown face recognition systems. Meanwhile, the implicit information in images, such as health condition [11] and sex orientation [12], can be accurately captured by machine learning models. These types of implicit information are associated with high-level image features, which is difficult to address with naive visual content processing.

### 4.2 Privacy intelligence in online management

#### 4.2.1 Solutions for coarse-grained privacy setting.

**Intelligent policy generation.** Intelligent policy generation is a cluster of computer-aided policy generation methods for mining fine-grained and personalized privacy policies according to environmental variations and user profiles.

**Rule-based policy.** The descriptive information of OSN images such as tags and captions can be leveraged to design rules for privacy policy generation. Yeung et al. [49] developed a policy recommendation mechanism using both tags and linked data provided by Semantic Web. The core idea is matching different groups in users’ social circles to specific tags. For example, a photo tagged as "birthday” can only be accessed by a friend group. Klemperer et al. [50] investigated the usability of privacy rules based on tags created for organization, search, description, and communication. The rules are in the form "If tagged / not tagged with tag, then allow / deny", combined with and or as appropriate. The authors also found that when participants tagged photos with access control in mind, they were able to develop more coherent and accurate rules.

**Learning-based policy.** Squicciarini et al. [51] proposed a two-level learnable adaptive policy inference framework. The first-level component focuses on inferring individual privacy policies. It first learns to cluster a user’s images using image content and metadata, then assigns initial rules to the images along with predicting the user’s privacy tendencies. The second-level component adaptively adjusts the privacy policies over time by learning a multi-criteria inference network according to the user’s historical social data and privacy attitudes. Yu et al. [52] suggested that content sensitivity and user trustworthiness are inseparable for determining privacy policy, and proposed a tree classifier-like policy generator exploiting the integration of the two types of information accordingly. The image content sensitivity is learned from both the deep representative features and the privacy-sensitive object features. User trustworthiness is represented by social group clustering based on the users’ social behaviors.
There are two challenges in the current policy generation models. First, since human relationships develop and the personal information exchange occurs in OSNs, mutual trustworthiness becomes more critical for the sharing activity. However, it is difficult to directly model real-world experience as numerical values in a virtual environment. One promising way is to employ automated tools to measure different metrics of trust in OSNs [53, 54]. Second, the strength of the social connection between two OSN users may vary over time even when their friendship persists. Also, a user’s understanding of privacy may change as their environment changes [6]. A personalized policy generation method is therefore preferable to adapt to these changes immediately. However, many existing approaches ignore this dynamism because they are actualized by pre-defining a limited number of factors for policy learning.

4.2.2 Solutions for multi-party privacy conflicts.

**Smart access control.** Intelligent policy generation can be considered as a single-side access control mechanism that recommends policies to the image sender only. This solution is insufficient to address the problem of multi-party privacy conflicts since the sender-side policies are isolated from other stakeholders. A promising solution is smart access control, a set of mechanisms centralized on the PSP server to manage image accessibility considering all involved OSN users’ interests.

**Identity-based control.** Some smart access control mechanisms leverage the personal identifiable information extracted from the shared image to decide accessibility. For example, Ilia et al. [55] designed a facial identity-based access control model. The model exploits a three-dimensional relationship matrix involving users, photos, and faces in photos to manage multi-owner control policies. Each co-owner, i.e., the person depicted in the photo, sets a specific permissible viewer list as an entry of the relationship matrix. When an access request arrives, the model first identifies the co-owner’s facial identity, then decides which face should be hidden according to the matrix. Similarly, Li et al. [56] developed a framework that grants control rights to every co-owner. The difference is that Li et al.’s method provides an automated access control mechanism instead of setting policies photo-by-photo by users themselves. For a given photo, the mechanism identifies each co-owner and associates the photo with temporal, spatial, interpersonal, and attribute factors corresponding to the co-owner, to establish a scenario-level access control. Morris et al. [57] proposed location-aware multi-party image access control mechanism allowing individual user to specify sensitive locations and timestamps for any photo in which their faces are identifiable. Each user pre-defined a privacy policy describing location range, location type, time and date interval and sensitiveness. Once a user is identified and the location of the photo is deemed sensitive, the user’s face will be replaced with a virtually generated human face according to the user’s privacy policy.

**Social norm-based control.** Another way for smart access control is employing social norms to regularize image propagation. Methods in this line usually formulates access control with the entire social graph $G = (V, E)$, where $V$ is the set of users in this social network and $E$ is the set of edges connecting pairs of users with a specific relationship. Xu et al. [58] designed a trust-based access control model involving a collective incentive mechanism. This model relies on the maintainability of the mutual trust between OSN users. In each propagation round, the PSP selectively anonymizes the stakeholders according to their privacy loss and updates the trust value according to all stakeholders’ feedback on whether their own faces have been anonymized correctly. Consequently, users taking others’ privacy into account when sharing photos will gain more trust. Lin et al. [59] proposed an access control mechanism by estimating the risk of image disclosure over unanticipated social graphs. Based on the image sharing historical data recorded by PSPs, the authors built a probability model that estimates the disclosure probabilities of different propagation channels, then aggregates the probability that other users will see the image shared by one user over various channels. The privacy policy of a given image is adjusted accordingly if the disclosure probability of this image is high.
Agent-based control. To respect co-owners’ privacy, some works explored the multi-agent mechanism to collect agreements on sharing an image from the co-owners of the image. Kurtan et al. [60] proposed an multi-agent approach where each user agent automatically predicts a policy for a new image according to the historical privacy policies of previous images. When in doubt, an agent analyzes the sharing behavior of other users in the same social network to recommend to its target user about what content should be private. Since each agent only accesses the privacy policies shared by users, this model is compatible with image-distributed environments. Motlagh et al. [61] proposed an agent-based negotiation model available for both online and offline co-owners. The model consists of a coordination agent, a predictor agent, and a filtering algorithm. When an image is ready to be published, the coordinating agent associated with the sender collects opinions from online users and user agents operating on behalf of offline users. The predictor agent supports the user agents in opinion mining from previous opinions provided by affected users in similar contexts. Finally, the coordination agent uses the filtering algorithm to obscure all privacy-invasive information from the image based on the collected opinions.

A persistent challenge with smart access control solutions is how to handle the privacy of all stakeholders to ensure everyone’s privacy is respected as desired. Since a stakeholder’s social relationship can be multiform (e.g., either interdependent or independent of the sender and the recipients), the complexity of the social graph rises significantly, making the multi-party access control more intractable. Meanwhile, the current access control mechanisms commonly underestimate the influence of social relationship [62]. Most methods simplify social relationships into various groups, such as family, friends and colleagues, allocating a unified and static privacy policy to each group. However, it is more rational in practice that the relationship strength varies for each user pair and may change over time.

4.2.3 Solutions for visual content exposure.

Visual obfuscation. Visual obfuscation is widely used to prevent online images from undesirable exposure by hiding or removing sensitive regions with direct image modification. Figure 6 shows examples of different visual obfuscation methods. The intuitive methods such as blurring, pixelation, cartooning and abstracting have been well summarized in previous surveys [18, 20]. Hence, our focus is on some of the emerging methods, including obfuscation with natural inpainting and obfuscation with measurable privacy.

![Fig. 6. Different visual obfuscation methods described in [63].](image)

Natural obfuscation. One major concern of visual obfuscation is how to patching the modified region naturally to make the image realistic. Otherwise, the images’ social utility will be compromised, and an adversary could easily perceive that the image has been edited. The images processed by intuitive methods such as blurring and pixelation cannot meet this need. Recently, some natural inpainting methods based on generative adversarial nets (GANs), a generative machine learning model that adversarially learns to map a target data distribution by contesting with a discriminative model [64], have emerged. These methods can seamlessly blend the scene surrounding the patched region to created authentic-looking images.

For example, Uittenbogaard et al. [65] proposed an inpainting framework to remove privacy-sensitive pedestrians and vehicles in street-view imagery. The framework leverages the depth consistencies for detecting and
removing objects. Next, a GAN employs multi-view information to inpaint the object-removed region. Sun et al. [66] proposed a head inpainting approach for preserving facial identities. The challenge of head inpainting is that heads in photos usually appear with diverse motions and orientations. The authors address this problem by a GAN to generates sensible head and facial characteristics (e.g., facial landmarks) according to the image content (e.g., a body pose). Then another GAN synthesizes the non-existing heads aligned with the generated facial characteristics. In a subsequent study [67] of the same team, the authors improved the head generator to support controllably different identities. The identity-related component of an original face is abstracted as a semantic parameter vector. Then the semantic parameters are modified and clustered into different identity groups, providing an explicit manipulation of identity. Kuang et al. [68] proposed a seamless face replacement model based on the pix2pix model [69] and U-Net [70]. By integrating the constraints over foreground (face) regions, background regions, and identity-related features, the model can synthesize faces that are naturally fused with the image background and significantly different from the original appearance.

Privacy-measurable obfuscation. Another concern of conventional intuitive visual obfuscation methods is that they mostly manipulate the privacy-sensitive regions in a qualitative manner and fail to provide rigorous, quantitative and provable privacy guarantees. Recently, differential privacy (DP) [71], a mathematical mechanism for measuring the privacy loss led by data publishing, has been studied for visual obfuscation. Fan et al. [72] proposed an obfuscation approach based on metric privacy, a privacy measurement generalized from DP. The core idea is applying a sampling mechanism which satisfies metric privacy to the low-dimensional feature vectors transformed from the sensitive image region for privacy filtering. Li et al. [63] proposed a privacy-preserving attribute selection algorithm with privacy guarantees for facial image obfuscation. A set of facial attributes are identified by machine classifiers and then modified subject to $\varepsilon$-DP constraint. A new face is reconstructed based on the anonymized attribute set with a GAN. Yu et al. [73] proposed to encode the privacy-sensitive objects into latent feature space using a GAN, and then introduce the Laplace noise into the latent features to ensure the DP-guaranteed de-identification.

Natural filling and rendering the obfuscated regions is crucial for retaining the images’ social usability. However, high-quality filling and rendering may lead to another challenge of computational complexity, which is usually underestimated in the reviewed papers. Computational complexity is a particular concern for OSN services, given the necessity of time efficiency in real-time OSN image sharing. Most PSPs prefer traditional intuitive methods, such as blurring and pixilation, as these methods are easy to implement and have low latency. In comparison, sophisticated image reconstruction methods often require more computation in the feature space, which need to be further improved to adapt the OSN environment.

Encryption. Encryption is another automated solution widely adopted to avoid exposing undesirable visual content. The current methods can be divided into two bunches according to different technical goals. One is to maintain the recoverability of encryption in the presence of lossy image transformations. The other is to perform personalized and fine-grained encryption, which allows partial or hierarchical encryption according to recipients’ access authority, rather than encrypting the entire image.

Recoverable encryption. OSNs normally apply various transformations to uploaded images for efficient storage and communication. However, these lossy operations can significantly affect the encryption/decryption performance. More resilient encryption/decryption methods are needed against these lossy transformations to ensure the lossless recovery. Tierney et al. [74] proposed a photo encryption system tolerant to JPEG transformations. The authors defined $q,p$-Recoverability to guarantee the authorized recipient can decrypt the original image with a high probability $p$ under a minimum quality loss $q$. The system encrypts an image under a specific class of JPEG embedding protocols satisfying the $q,p$-Recoverability operated in the encrypted bit space. Sun et al. [75] considered the black-box problem where the lossy operations applied by OSNs are usually unknown to users and out of their control. Taking Facebook as a case, they estimated the parameters of four types of operations.
Facebook applies to the uploaded images through an offline training procedure, providing prior knowledge of developing a specific robust DCT-domain image encryption/decryption scheme.

Image steganography [76], a technology that hides cryptographic data in an image, offers another promising avenue for recoverable encryption. For example, Fu et al. [77] proposed a reversible data hiding scheme in encrypted images based on an adaptive encoding strategy. The original image content is encoded by block permutation and stream cipher. Then the most significant bits are identified for embedding additional data with reversed Huffman codes. With the encryption key and data hiding key, the recipient can extract hidden data, decrypt and recover the image separately and efficiently.

**Personalized encryption.** Another set of encryption methods focus on personalized content encryption, where the encryption strategies differ for different recipients according to the sender’s privacy policy. For example, Ra et al. [78] proposed a secure image sharing system which separates an image into private and public parts by a signal component-based threshold. The system encrypted private component, leaving the remainder in a public and standards-compatible plaintext form. Different secure protocols were designed for the two parts: the authorized recipient can access both to recover the image, while others, such as the OSN provider, can only access the public part to perform server-side transformations to conserve bandwidth usage. A more fine-grained way is to hide the visual objects privacy-sensitive specific to recipients while keeping the remaining parts accessible. For instance, He et al. [79] proposed a partial encryption system for OSN images. The system leverages an automated detection and recommendation mechanism to determine the private part. It also allows users to customize the sensitive regions of their photos. The encryption is performed on DCT spectral coefficients, which is transparent to image transformations and can freely support most image processing libraries.

Encryption can completely keep sensitive visual content from being disclosed to unauthenticated recipients. Most encryption methods assume an honest third party, commonly the OSN service provider, to maintain the encryption information such as cryptographic keys or communication protocols. However, this assumption is not always solid. Some OSN services may be interested in user photos for commercial purposes and therefore they may behave dishonestly. Further, these OSN services might be hacked. Hence, ways to perform encryption in extremely untrusted OSN environments is an open challenge.

### 4.2.4 Solutions for malicious machine recognition.

**Adversarial perturbation.** Since machine recognition for images is often performed at the global-view level rather than at the object or region level, visual obfuscation of a region is impractical to defeat malicious machine recognition. Studies have shown that deep learning models can still make correct inferences on a partially obfuscated image [81, 82]. Therefore, solutions specific to machine adversaries are needed to prevent implicit attributes from disclosure. Recently, adversarial perturbation has shown efficacy in dealing with this problem. Adversarial perturbation is a technology that introduces imperceptible perturbations to an image, typically in the form of noise, in order to mislead deep learning recognition models [83], as shown in Figure 7.

**Facial-level perturbation.** Today’s powerful machine learning-based facial recognition systems poses a real threat to OSN image privacy. To prevent user photos from unauthorized collections for training facial recognition models, Shan et al. [84] proposed an adversarial perturbation to add imperceptible pixel-level perturbation to user photos before sharing. The perturbations are computed via an image-specific optimization that maximizes the deviation of facial features for the target face recognition model. Then once these perturbed images are used as the training dataset for a facial recognition model, they can lead to a model consistently misidentifying the user’s normal images.

More scholars focus on the inference phase of pre-trained unauthorized facial recognition models. A typical method is designing a perturbation objective function and optimizing it with the gradient sign method [85] to search for image-specific perturbations [86, 87]. The optimization objective normally comprises two components: one is to make the target face recognition system predict the perturbed face as a different identity, which can
be done by maximizing the identity feature distance between the target image and the candidate images of the same identity; the other one is minimizing the visual similarity between the perturbed face and the original face. Given that the real-world facial recognition models are often in black-box, an effective strategy is to perform the perturbation searching on an ensemble of surrogate white-box models [86]. Another work from Shen et al. [88] further investigated how to make adversarial perturbation imperceptible. First, the authors conducted user studies to explore human sensitivity to feature-level visual changes on images, resulting in a sensitivity map that indicates the distribution of human visual sensitivity levels for a given image. With the guidance from the sensitivity map, the authors designed a sensitivity-aware adversarial perturbation model, which can precisely adjust the adversarial noise distribution to minimize visual distortion without compromising perturbation efficacy.

Attribute-level perturbation. Images also contain sensitive auxiliary information related to implicit soft biometric attributes, such as age and gender, that machine learning models can recognize. Some works focused on perturbing biometric attributes in personal photos to resist unauthorized recognition while, optionally, preserving facial identity to maintain social usability. Mirjalili et al. [80] proposed an adversarial perturbation algorithm to make an image evade gender recognition while retaining biometric identity. The algorithm iteratively perturbs face images using the gradient sign method [85]. In their follow-up study [89], the authors investigate how to conceal multiple biometric attributes simultaneously. A GAN-based perturbation model is designed to reconstruct images with selective attributes concealed automatically. The key idea is to embed the perturbation objectives and a visual consistency constraint in the GAN’s training objective. Another GAN-based gender perturbation model is proposed by Tang et al. [90]. The aim is to obfuscate gender information while preserving the utility of other facial attributes. To this end, a selective transmission unit [91] is employed in the latent feature space for disentangling gender attribute and other attributes, and a face matching loss is imposed to ensure the face recognition ability is well retained. Chhabra et al. [92] proposed a universal adversarial perturbation framework that can guarantee \( k \)-anonymity [93] for selective facial attributes. The perturbation is learned with an objective function, ensuring that the \( k \) facial attributes are anonymized as per the user’s preferences. The framework also allows for a user control mechanism where users can select single or multiple attributes to be passed over.

Applying adversarial perturbation to OSN images can effectively confuse deep learning models, and protect sensitive faces and facial attributes from unauthorized machine recognition. There are two challenges in this field. The first is transferability, which means the ability of an adversarial perturbation to remain effective even against a threat model other than the one originally targeted. The second challenge is universality, which indicates that a perturbation can fool a given model on any random images with high probability, also known as image-agnostic perturbation. Compared with the image-specific perturbation applied in most current methods, image-agnostic perturbation may be more feasible when confronting a large volume of images.

Fig. 7. An example of adversarial perturbation workflow described in [80]. After adding perturbation noise to the original image, the gender recognition model is misled to make a wrong decision on the modified image. Both face images are synthesized by GAN.
4.3 Design principles in online management

Table 2 provides a breakdown of the reviewed solutions in the online management stage. Similar to the first stage, several shared design principles regarding OSN image privacy can be identified in this stage.

- **Online mode.** In the online management stage, the image is uploaded to the OSN server. In most cases, the image owner needs to allocate certain control rights to the server to configure and process the image. In this way, the OSN server is assumed to be willing to not only comply with the user’s requirements but also to help actively manage image privacy. Ideally, all the reviewed solutions in this stage can be implemented and integrated into a PSP server as a cloud-based control engine. This centralized mechanism in the server can activate multiple protective solutions in an orderly and efficient manner, free from the user’s perceptions or intervention. Meanwhile, an additional audit mechanism should be critically considered for OSN services whose honesty is in question.

- **Visibility.** The visibility property of OSN image privacy in Section 2.1 should be a primary design consideration in this stage. This property defines to what extent a specific recipient can access the sensitive information (identified in the local management stage). Hence, one fundamental goal of the solutions in this stage is to actualize feasible, efficient, and user-friendly access control in complex OSN contexts that can adjust the visibility of visual content or implicit attributes accordingly.

- **Protective intelligence.** In contrast to the preventive intelligence of the local management stage, the principal target of privacy intelligence in this stage is to put in place tangible protections over the images to be released as per the user’s need. The OSN server, which operates on the premise of having been empowered by the image owner, may conduct several privacy-enhancing operations directly on the image itself or in the image allocation and communication process. In this way, privacy intelligence in this stage can be referred to as protective intelligence.

5 PRIVACY ANALYSIS IN SOCIAL EXPERIENCE

This section focuses on privacy analysis in the social experience stage. Figure 8 offers an overview of the analysis in this stage.

![Fig. 8. Overview of the privacy analysis in the social experience stage. Each privacy issue is linked to its user behavior cause and the corresponding intelligent solutions.](image-url)
Table 2. A summary of the solutions of privacy intelligence in the online management stage. OP: observable privacy; IP: inferential privacy; CP: contextual privacy. PU: privacy-utility trade-off; PE: personalization; IN: independence; AU: automation; FL: flexibility; CE: communication-effectiveness. The ranking system is explained in Section 2.3.

| Privacy intelligence | Paper; Year | Sub-class | Target privacy | Key technique | G1-PU | G2-PE | G3-IN | G4-AU | G5-FL | G6-CE |
|----------------------|-------------|-----------|----------------|---------------|-------|-------|-------|-------|-------|-------|
| Intelligent policy generation | [49]; 2009 | Rule-based policy | OP; CP | Rule design | N/A | | | | | |
| | [50]; 2012 | Rule-based policy | OP; CP | Rule design | N/A | | | | | |
| | [51]; 2014 | Learning-based policy | OP; CP | Machine learning | N/A | | | | | |
| | [52]; 2017 | Learning-based policy | OP; CP | Deep learning | | | | | | |
| Smart access control | [53]; 2015 | Identity-based control | OP; CP | Rule mining | | | | | | |
| | [54]; 2019 | Identity-based control | OP; IP; CP | Rule mining | | | | | | |
| | [57]; 2021 | Identity-based control | OP; CP | Rule mining | | | | | | |
| | [58]; 2019 | Social norm-based control | OP; CP | Graph model | | | | | | |
| | [59]; 2020 | Social norm-based control | OP | Graph model | N/A | | | | | |
| | [60]; 2021 | Agent-based control | OP | Multi-agent model | N/A | | | | | |
| | [61]; 2021 | Agent-based control | OP; CP | Multi-agent model | N/A | | | | | |
| Visual obfuscation | [65]; 2019 | Natural obfuscation | OP | GAN | | | | | | |
| | [66]; 2018 | Natural obfuscation | OP | GAN | | | | | | |
| | [67]; 2018 | Natural obfuscation | OP | GAN | | | | | | |
| | [68]; 2021 | Natural obfuscation | OP | GAN | | | | | | |
| | [72]; 2019 | Privacy-measurable obfuscation | OP | Metric privacy | | | | | | |
| | [63]; 2019 | Privacy-measurable obfuscation | OP | Differential privacy | | | | | | |
| | [73]; 2021 | Privacy-measurable obfuscation | OP | Differential privacy | | | | | | |
| Encryption | [74]; 2013 | Recoverable encryption | OP | AES bit encryption | | | | | | |
| | [75]; 2018 | Recoverable encryption | OP | DCT encryption | | | | | | |
| | [77]; 2019 | Recoverable encryption | OP | Image steganography | | | | | | |
| | [78]; 2013 | Personalized encryption | OP | DCT encryption | | | | | | |
| | [79]; 2016 | Personalized encryption | OP | DCT encryption | | | | | | |
| Adversarial perturbation | [84]; 2020 | Facial-level perturbation | OP | Adversarial attack | | | | | | |
| | [86]; 2021 | Facial-level perturbation | OP | Adversarial attack | | | | | | |
| | [87]; 2021 | Facial-level perturbation | OP | Adversarial attack | | | | | | |
| | [88]; 2019 | Facial-level perturbation | OP | Adversarial attack | | | | | | |
| | [80]; 2017 | Attribute-level perturbation | IP | Adversarial attack | | | | | | |
| | [89]; 2020 | Attribute-level perturbation | IP | GAN | | | | | | |
| | [90]; 2022 | Attribute-level perturbation | IP | GAN | | | | | | |
| | [92]; 2018 | Attribute-level perturbation | IP | Adversarial attack | | | | | | |
5.1 Privacy issues in social experience

5.1.1 Issues associated with image viewing.

**Shoulder surfer.** Shoulder surfer refers to the unauthorized viewers who visit private images by peeping at the victim’s device screen over the victim’s shoulder. This is a type of privacy intrusion from the physical world. Peoples’ enthusiasm for viewing images on mobile devices further exacerbates this risk.

5.1.2 Issues associated with social application.

**Third-party applications.** One crucial purpose for modern OSN image sharing is to enjoy online third-party photo-based applications or services, such as facial emotion recognition or ancillary life loggers. These services usually employ automated recognition systems deployed in the cloud [94, 95], where the image owner exercises little if any, control. An untrusted application may overstep its original access authority, performing excessive recognition beyond the user’s request to steal personal information for commercial benefit [96].

5.1.3 Issues associated with image deletion.

**Deletion delay.** The right to be forgotten is a critical modern privacy property required by the European General Data Protection Regulation (GDPR) [14]. Once the original sharing purposes are satisfied, the image should be removed from the Internet by specific strategies to avoid unknown distribution. However, the present OSN services easily suffer from deletion delay [97], which means an image exists much longer online than the user expects, even when the user’s delete request has been executed [98].

5.2 Intelligent solutions in social experience

5.2.1 Solutions for shoulder surfing.

**Privacy-respecting browsing.** Humans are able to recognize images (especially face images) when they have seen the images before or know the face identity, even when the images are highly distorted [99]. Some studies exploit this human capability to develop privacy-respectful photo browsing approaches to prevent unknown shoulder surfers. Zezschwitz et al. [100] designed a new privacy-respectful digital reading pattern on smartphones to defend against unwanted observations. The proposed method distorts images in specific ways, rendering the visual content hard to recognize by an onlooker who does not know the photograph. By contrast, because the device owner knows the original photo and the details of how it was distorted, they have no problem recognizing them. Tajik et al. [101] proposed an image transformation mechanism with a thumbnail-preserving encryption scheme. In this scheme, a ciphertext is defined as an image sharing the same thumbnail as the plaintext image but leaks nothing about the plaintext image beyond the thumbnail. With the proposed mechanism, users who know the original image can identify its encrypted version at the thumbnail level, while other people and even machine recognition systems cannot. By controlling the resolution of the thumbnail, users can obtain a good balance between online photo browsing and privacy.

The current privacy-respecting browsing methods assume that the viewer already knows the images they receive or the subjects depicted in the images. This assumption cannot apply to viewers seeing an image for the first time. In addition, the images are transformed into a low-quality format in the current methods. Although the viewers may recognize the transformed version, their viewing experience may be damaged by the low quality. Hence these methods have limited applicability: more suitable for online photo managing than viewing.

**Gaze-based monitoring.** Gaze-based monitoring is an effective technique for privacy protection for public digital devices by tracking eye or motion movements, which has been exploited to protect people from shoulder surfing [102]. Gaze-based monitoring can be applied at either the shoulder surfer or the device owner side. At the shoulder surfer side, the system can decide whether an onlooker is deliberately looking at the screen by
monitoring the onlooker’s eye movements. For instance, Zhou et al. [103] proposed a shoulder surfing detector using motion tracking sensors to locate and orient the onlookers close to the device. When the system detects that a bystander is gazing at the screen, it pops up multiple visual and auditory notifications to raise attention to the device owner. Regarding the device owners, gaze-based monitoring can be leveraged to track their eye movements to decide what content they are focusing on in real-time. For instance, Ragozin et al. [104] proposed a private digital reading approach employing an eye-tracker to decide the content being watched by the device owner. Only this portion of the content is visible, while others are obfuscated automatically and instantly.

Gaze-based monitoring is a promising direction for privacy-preserving image viewing at the end devices. However, there exist several challenges at present. The device owner-side solutions make only the contents the device owner staring at visible, which is less feasible for image data since users tend to enjoy an image in its entirety. The other set of solutions trying to track shoulder surfers’ behaviors may bring its own privacy concerns, given that the monitoring is performed without the bystanders’ permission.

5.2.2 Solutions for third-party applications. The third-party applications can be divided into two groups: the honest applications and the dishonest ones, upon which the privacy intelligence solutions differ. The honest applications are assumed to be willing to respect individual privacy by actively improving their backend model to be privacy-preserving. This improvement can be made by adversarial learning the backend model. Regarding the dishonest applications coveting the valuable private information of user photos, secure multi-party communication can be leveraged to block their malicious actions while maintaining legitimate social functionality.

Adversarial learning. Adversarial learning is a type of machine learning framework designed with adversarial goals: ensuring the availability of the desired recognition task for social functionality while incapacitating the models used for malicious recognition by attackers. For example, Ren et al. [105] proposed an adversarial learning algorithm for privacy-preserving life event monitoring. The algorithm involves two competing components: an anonymizer that modifies the original image to remove privacy-sensitive information while maintaining high-performance spatial action detection; and a discriminator that tries to extract privacy-sensitive information from the anonymized images. The competition between the two components results in a photo anonymizer that can anonymize human faces with barely affecting the accuracy of action detection. Wu et al. [106] provided a universal adversarial learning framework without the need to specify the recognition task of the third-party application. The motivation was that strong privacy protection should be sustainable against arbitrary attack models. The authors developed a learnable degradation transformation for the original image and proposed several training strategies. The resulting degradation makes the image resistant to unseen attack models while usable for legitimate social functionalities.

Secure multi-party computation. Secure multi-party computation aims to prevent client-side images from being directly exposed to the server in an untrusted environment. The client images are normally projected into a minimal feature set before being shared with the server to ensure legitimate social functionality while reducing unnecessary disclosure.

Secure image recognition. Rahulamathavan et al. [107] proposed a privacy-preserving algorithm for facial expression classification in a mutually-untrusted client-server scenario where neither the client nor the server wants to reveal the inputs and outputs to each other. The authors proposed a lightweight algorithm that projects the image onto a low-dimensional feature space in private with a randomization mechanism. Then, the expression is classified by feature distance matching on the anonymized features. In this way, the client-side images and the server-side classification results can be mutually anonymized. Nakamura et al. [108] developed a general privacy-preserving client-server image recognition framework to avoid the server to know the recognition result. First, client users extract a visual feature from their taken photo and transform it so that the server cannot uniquely determine the recognition result. Then, the users send the transformed feature to the server that returns
a set of candidates of the recognition result to the users. Finally, the users compare the candidates to the original visual feature for obtaining the final result.

**Secure image retrieval.** Some studies focus on privacy-preserving cloud image retrieval using secure multiparty computation. For example, Xia et al. [109] proposed a privacy-preserving image retrieval scheme, in which the images are encrypted but similar images to a query can be retrieved from the encrypted images. Secure Local Binary Pattern (LBP) features can be directly extracted as the local features from the encrypted images without server-client communication for similarity matching. Zhang et al. [110] proposed a privacy-preserving scheme for content-based image retrieval and sharing in cloud-based social multimedia applications. The users extract visual features from the images, and perform locality-sensitive hashing functions on visual features to generate image profile vectors. A secure index structure based on cuckoo hashing is then designed for profile vector matching.

### 5.2.3 Solutions for image deletion.

**Digital oblivion.** Given the free dissemination of personal information and the availability of cheap and massive online digital storage means, OSN may "remember" the shared images even if the user has proactively deleted the images from the original social circle. Digital oblivion stands for a set of automated online image deletion techniques.

**Self-destruction-based oblivion.** Some digital oblivion solutions employ a data self-destruction mechanism by injecting an invisible deletion trigger into the image. For example, Backes et al. [111] developed an algorithm allowing users to embed an adjustable expiration date into OSN images. The modified images become inaccessible automatically once the expiration date has been reached, without users performing additional interaction with any PSP. Yang et al. [112] proposed selectively removing photos from a photo gallery to reduce inter-photo relevance on geolocation information. The goal was to decide the minimal set of images for removal from the collection to ensure that the true location was unpredictable in the remaining images. The authors formulated this collection censoring task as a combinatorial optimization problem and resolved it using the mixed-integer linear programming algorithm.

**Collaboration-based oblivion.** Some studies have leveraged collaborative mechanisms for digital oblivion. Domingo-Ferrer et al. [113] designed a set of protocols based on game theory to encourage users who receive information from an individual to rationally help the individual enforce his/her oblivion policy. Different fingerprints for different receivers are added to the content so that the owner can trace any unlawful use or spread of the image after the expiration date has passed. Stokes et al. [114] designed a system enabling the peer-to-peer (P2P) agent community to assist in digital oblivion within OSNs. This is a P2P community made up of individuals who agree to protect the privacy of individuals who request that certain images be forgotten. The system involves a family of protocols to maintain up-to-date information on oblivion requests, and implements filtering functionality based on the authentication of user-to-content relations that are particularly relevant to digital oblivion.

Currently, digital oblivion solutions for deletion delay typically require users to specify an expiration date as a deletion trigger and embed such information within the image file as implicit watermarks or fingerprints. The challenge is in managing the increasing volume of personal information shared and stored online. Users would benefit from more intelligent support for digital oblivion other than pre-defined rules, which would assure the long-term tracking of disclosed information and automatically safeguard users from information relating to a past episode surfacing unexpectedly [115]. Future intelligent digital oblivion designs may be inspired by consensus-based mechanisms, e.g., a blockchain-based deletion scheme [116], which leverages the blockchain technique to build a trusted P2P chain for data deletion.
Table 3 provides a breakdown of the reviewed solutions in the social experience stage. Common design principles regarding OSN image privacy in this stage are as follows:

- **In-the-wild mode.** In the social experience stage, images have been already accessed and are controlled by the recipients. In a sense, images are in the wild from now on, out of the original owner’s control. Given the uncertainty of the recipients’ behaviors, more open privacy issues are raised that is difficult for users to figure out one by one. OSN servers should play a more important role in protecting images from leakage. In this way, the reviewed solutions in this stage can be implemented as add-in plugs in the OSN services, allowing OSN servers to provide persistent preservation.

- **Contextual integrity.** The contextual integrity property of OSN image privacy should be a primary design goal in this stage, which confirms whether the information contained in the shared image is intact during social usage. The design goal can be interpreted from two angles according to whether the recipients are
trusted or not. For a trusted recipient, the goal is to preserve privacy while ensuring the complete images’ social usability for human viewers or functional availability for social applications. For untrusted recipients, the goal is to detect potential image manipulation and infringement to thwart information leaks.

- **Persistent intelligence.** As strong measures regarding privacy have been taken at the previous stage, the main target of privacy intelligence in this stage is to intensify image privacy further in the context of social experience to maintain a privacy-friendly environment in the long run. For this reason, we name privacy intelligence in this stage as *persistent intelligence*.

6 CHALLENGES AND FUTURE DIRECTION

6.1 Modelling OSN image privacy

Many intelligent solutions in this realm provide automated privacy prediction, management or recommendation mechanisms to assist users’ decision-making process. These mechanisms mainly involve a privacy knowledge model, which is able to identify the statistical correlation between individual privacy and image data and OSN contextual factors. Currently, two significant factors are often underestimated in OSN image privacy modelling. One is the spatio-temporal factor which reflects the dynamic of privacy needs changing with time and location in different environments or situations [117]. Another factor is the incident factor, which indicates what is going on in the image, as different content has different degrees of sensitivity (even for the same participants). Incorporating the two factors in privacy pattern modelling requires a higher level of image understanding. The recent advance in deep learning-based social image understanding [118, 119] may be promising direction for this challenge.

Although various privacy knowledge models have been proposed to satisfy different specific scenarios, we believe a universal modelling method will be more attractive in the future. To identify the prior knowledge required for a universal privacy model, we discover three boundaries of OSN image privacy inspired by the theory of privacy boundaries [120], including:

- **The disclosure boundary**, which manages the tension between private and public, i.e., the degree of individual information disclosure from OSN image sharing in subjective self-cognition.
- **The identity boundary**, which manages the tension between self and other in the context of multi-party interactions. Individual privacy needs for OSN image sharing may vary depending on different representations of identity in different social groups.
- **The spatio-temporal boundary**, which manages the tension of privacy decisions changing over time and location.

6.2 Privacy-utility trade-off

The privacy-utility trade-off is always an open challenge in designing privacy-enhancing techniques, especially in the OSN image sharing context where there is a specific purpose regarding the shared images. According to the literature, privacy and utility can be relatively well balanced in solutions relying on access control or encryption techniques since they make little modification directly to the image. However, this problem is still challenging in solutions requiring image processing, such as visual obfuscation or adversarial perturbation, since processing an image will damage its natural information integrity to some extent.

Ensuring the privacy-utility trade-off requires an appropriate formulation of the utility loss. Figure 9 shows the difference in treating image utility with various privacy-enhancing techniques. Image utility is normally defined as accessibility in access control techniques, and the trade-off is satisfied by designing specific access rules [121]. In encryption techniques, utility is often guaranteed by recoverability, where the authenticated users can recover the original image by lawful keys. Regarding image processing techniques, some studies defined the utility as visual quality and evaluated it via subjective human ranking scores [122–125]. In contrast, more studies
prefer to formulate utility as an optimization objective with specific quantifying metrics. For example, photo response non-uniformity (PRNU), structural similarity (SSIM), and perceptual loss [126] are common metrics for visual quality, and recognition accuracy is widely used for assessing functional integrity. In this sense, a promising direction for balancing the privacy-utility trade-off is to optimize the two objectives simultaneously via an adversarial game [127]. Moreover, existing measurements of utility loss are mostly evaluated on static images. The measurements in a dynamic OSN context requires more specific considerations on users’ interests and behaviors, which remains further investigation.

Fig. 9. The difference in treating image utility by different privacy-enhancing techniques.

6.3 DeepFake: challenging the real world
DeepFake is an emerging face forgery technique powered by deep learning, by which an attacker with little image processing knowledge can produce a realistic fake media record based on the victim’s face photos. DeepFake can effectively generate natural and realistic fake faces from a real face photo and seamlessly blend them into other media records. It is a image security issue rather than a privacy issue, but can be more severe along with private image leakage.

Nowadays, there is widespread concern about the malicious application of DeepFake, due to its potentially disruptive consequences to visual security, laws, politics, and society in general [128]. The research community has become an influential force in motivating studies on DeepFake detection and anti-detection [129–131]. Multiple large-scale DeepFake detection datasets have been released, such as FaceForensics++ [132] and Celeb-DF [133]. However, pursuing detection as the only solution may be insufficient, as this is a retroactive countermeasure implemented after the attacks have already had their effect. Moreover, it is extremely hard to defend against DeepFake attacks once malicious viewers have thoroughly accessed face photos because, by then, they are capable of fully controlling the data. Therefore, we believe more effort is needed in forestalling and preventing malicious users from getting the data. More investigations are needed on how to identify malicious users according to the historical internet trails before sharing images [134, 135].

6.4 The right to be forgotten
Unlimited retention of personal images on the web may harm individual privacy. For example, teenagers may suffer long-term disadvantages to their future life and career due to indiscreet photos shared on social media. In the long run, many users desire to dissociate themselves from obsolete information that represents their past identity and behaviors. Therefore, the right to be forgotten, as a critical clause in the GDPR [14], should be guaranteed in a privacy-friendly environment for OSN image sharing.

One considerable challenge to ensure the right to be forgotten is that the shared images are normally associated with multiple information sources. On the one hand, one photo of a user may be correlated with a collection...
of photos owned by other users, such that a simple deletion on the single user side cannot thoroughly erase the sensitive information. On the other hand, user data related to image content is easily exchanged across multiple ad hoc social networks. For example, one’s private presence can be recorded and shared simultaneously by personal photography (shared in the OSN domain) and location information (shared in the vehicular social network domain [136, 137]). Such cross-domain relations pose intractable challenges to achieving the right to be forgotten by only deleting image data from the OSN domain.

6.5 Paradox of privacy dataset publishing

Most ML-based intelligent solutions, such as learning-based privacy prediction and personalized policy generation, are essentially data-driven, heavily relying on datasets with image privacy knowledge. According to our literature review, only five image privacy datasets are publicly available, as shown in Table 4. One cause leading to the scarcity of image privacy datasets is the paradox of privacy dataset publishing, which means that a privacy-relevant dataset naturally contains certain sensitive information and thus should not be fully released to the public. Although some image privacy datasets only release abstract features or masked images as a countermeasure, models will suffer from a certain performance compromise if trained with the incomplete datasets.

| Dataset & Year | Image source | Annotation level | Available annotations | Dataset size | Remark |
|----------------|--------------|------------------|-----------------------|--------------|--------|
| PicAlert [138], 2012 | Internet (Flickr) | Image level; Text level | Privacy category (binary); User tags | N = 32106 (4701 private, 27405 public) | 1. Some images are expired; 2. Limited data modality |
| YourAlert [139], 2016 | Local collection (from 27 social network users) | Image level; | Privacy category (binary) | N = 1511 (444 private, 1067 public) | Only image features are released |
| VISPR [140], 2017 | Internet (Flickr and Twitter) | Object level; Privacy attribute (68 types) | N = 22167 (5.22 attributes per image) | Limited data modality |
| VISPR-extension [141], 2018 | Internet (Flickr and Twitter) | Object level; Object level; | Privacy attribute (24 types); Attribute category (3 classes); Privacy region; | N = 22167 (8473 images with region pixel-labeling) |
| VizWiz-Priv [142], 2019 | Local collection (from blind photographers) | Image level; Object level; | Privacy attribute (23 types); Private region; Image/question pairs | N = 13630 (5537 private, 8093 public); 5537 images with region pixel-labeling; 2685 image/question pairs | 1. Collected from a special group; 2. Only masked images are released |

An intuitive solution for disentangling the paradox is to purchase the right to use from the private image owners. Then, privacy would be valued as a commodity and price would become the most important factor in a buyer-seller game. The privacy pricing problem can be motivated by some previous studies [143–146], which provides an auction-based trading mechanisms for private data. Another solution is to use alternative learning fashions such as distributed learning [147, 148] and unsupervised or semi-supervised learning [149–151], which means the raw data does not need to be accessed.

7 CONCLUSION

With a focus on the urgent privacy needs in modern OSN image sharing, we conducted a survey on privacy intelligence in such a sharing context, which is a collective term referring to intelligent solutions to various modern privacy issues derived from sharing-related user behaviors. Specifically, we first introduced the definition and taxonomy of OSN image privacy under the contextual constraints of dynamic OSN image sharing. Then, to analyze multiple privacy issues, solutions and challenges in this interdisciplinary area comprehensively, we
proposed a high-level privacy analysis framework based on the entire lifecycle of OSN image sharing. Using the framework, we systematically identified modern privacy issues induced by OSN users’ behaviors and explored the corresponding intelligent solutions in a stage-based fashion. For the reviewed intelligent solutions at each stage, we elaborated on their methods, advantages and disadvantages, and summarized their common design principles. We also discussed the challenges and future directions in this field.

The privacy intelligence solutions explored in this survey are sufficient to form an intelligent privacy firewall that may contribute to building a more intelligent environment for privacy-friendly OSN image sharing with respecting the privacy of all stakeholders. We hope our work can facilitate current-day privacy management and reconcile the ever-increasing use of OSN image sharing and the modern individual privacy needs.

ACKNOWLEDGMENTS

This paper is supported by an ARC project, LP180101150, from the Australian Research Council, Australia.

REFERENCES

[1] NIXINTEL. Using flight tracking for geolocation - quiztime 30th October 2019, November 2019.
[2] Shane Ahern, Dean Eckles, Nathaniel S. Good, Simon King, Mor Naaman, and Rahul Nair. Over-exposed?: Privacy patterns and considerations in online and mobile photo sharing. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’07, pages 357–366, New York, NY, USA, 2007. ACM.
[3] Roberto Hoyle, Luke Stark, Qatrunnada Ismail, David Crandall, Apu Kapadia, and Denise Anthony. Privacy norms and preferences for photos posted online. ACM Transactions on Computer-Human Interaction, March 2020.
[4] Phillip Nyoni and Mthulisi Velemepini. Privacy and user awareness on Facebook. South African Journal of Science, 114:1 – 5, 06 2018.
[5] Benjamin Henne and Matthew Smith. Awareness about photos on the web and how privacy-privacy-tradeoffs could help. In Andrew A. Adams, Michael Brenner, and Matthew Smith, editors, Financial Cryptography and Data Security, pages 131–148, Berlin, Heidelberg, 2013. Springer Berlin Heidelberg.
[6] Alessandro Acquisti, Laura Brandimarte, and George Loewenstein. Privacy and human behavior in the age of information. Science, 347(6221):509–514, 2015.
[7] Sunil Hazari and Cheryl Brown. An empirical investigation of privacy awareness and concerns on social networking sites. Journal of Information Privacy and Security, 9(4):31–51, 2013.
[8] Jose M. Such, Joel Porter, Sören Preibusch, and Adam Joinson. Photo privacy conflicts in social media: A large-scale empirical study. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, CHI’17, pages 3821–3832, New York, NY, USA, 2017. ACM.
[9] Changxing Ding and Dacheng Tao. A comprehensive survey on pose-invariant face recognition. ACM Trans. Intell. Syst. Technol., 7(3):37:1–37:42, February 2016.
[10] Wei-Ta Chu and Chih-Hao Chiu. Predicting occupation from images by combining face and body context information. ACM Trans. Multimedia Comput. Commun. Appl., 13(1):7:1–7:21, December 2016.
[11] M. Shamim Hossain and Gulam Muhammad. Cloud-assisted speech and face recognition framework for health monitoring. Mobile Networks and Applications, 20(3):391–399, Jun 2015.
[12] Yilun Wang and Michal Kosinski. Deep neural networks are more accurate than humans at detecting sexual orientation from facial images. Journal of Personality and Social Psychology, 114:246–257, 02 2018.
[13] Lynn M. Marvin and Yohance Bowden. Conducting u.s. discovery in asia: An overview of e-discovery and asian privacy laws. In 21 Rich. J.L. & Tech, 2015.
[14] Jacob Victor. The eu general data protection regulation: Toward a property regime for protecting data privacy. In 123 Yale Law Journal 513, 2013.
[15] M. Fire, R. Goldschmidt, and Y. Elovici. Online social networks: Threats and solutions. IEEE Communications Surveys Tutorials, 16(4):2019–2036, Fourthquarter 2014.
[16] J. H. Abawajy, M. I. H. Ninggal, and T. Herawan. Privacy preserving social network data publication. IEEE Communications Surveys Tutorials, 18(3):1974–1997, thirdquarter 2016.
[17] J Alemany, E Del Val, and A Garcia-Fornes. A review of privacy decision-making mechanisms in online social networks. ACM Computing Surveys (CSUR), 55(2):1–32, 2022.
[18] José Ramón Padilla-López, Alexandros Andre Chaaraoui, and Francisco Flórez-Revuelta. Visual privacy protection methods: A survey. Expert Systems with Applications, 42(9):4177 – 4195, 2015.
• Sergej Zerr, Stefan Siersdorfer, Jonathon Hare, and Elena Demidova. Privacy-aware image classification and search. In Proceedings of the 1st Workshop on Privacy and Security in Online Social Media, pages 1–8, 2012.

• Jinpeng Chen, Pinguang Ying, Xiangling Fu, Xiaopeng Luo, Hao Guan, and Kaimin Wei. Automatic tagging by leveraging visual and annotated features in social media. IEEE Transactions on Multimedia, 2021.

• Lihong Tang, Wanlun Ma, Marthie Grobler, Weizhi Meng, Yu Wang, and Sheng Wen. Faces are protected as privacy: An automatic tagging framework against unpermitted photo sharing in social media. IEEE Access, 7:75556–75567, 2019.

• A. Chattopadhyay and T. E. Boult. Privacycam: a privacy preserving camera using uclinux on the blackfin dsp. In 2007 IEEE Conference on Computer Vision and Pattern Recognition, pages 1–8, June 2007.

• F. Pittaluga and S. J. Koppal. Privacy preserving optics for miniature vision sensors. In 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 314–324, June 2015.

• Paarjaat Aditya, Rijurekha Sen, Peter Druschel, Seong Joon Oh, Rodrigo Benenson, Mario Fritz, Bernt Schiele, Bobby Bhattacharjee, and Tong Tong Wu. I-pic: A platform for privacy-compliant image capture. In Proceedings of the 14th Annual International Conference on Mobile Systems, Applications, and Services, MobiSys ’16, pages 235–248, New York, NY, USA, 2016. ACM.

• Jiayu Sha, Rui Zheng, and Pan Hui. Cardea: Context-aware visual privacy protection for photo taking and sharing. In Proceedings of the 9th ACM Multimedia Systems Conference, MMSys ’18, pages 304–315, New York, NY, USA, 2018. ACM.

• Jeremy Schiff, Marcii Meingast, Deirdre K. Mulligan, Shankar Sastry, and Ken Goldberg. Respectful Cameras: Detecting Visual Markers in Real-Time to Address Privacy Concerns, pages 65–89. Springer London, London, 2009.

• Frank Pallas, Max-Robert Ulbricht, Lorena Jaume-Palasi, and Ulrike Höppner. Offlinetags: A novel privacy approach to online photo sharing. In CHI ’14 Extended Abstracts on Human Factors in Computing Systems, CHI EA ’14, page 2179–2184, New York, NY, USA, 2014. Association for Computing Machinery.

• Cheng Bo, Guobin Shen, Jie Liu, Xiang-Yang Li, YongGuang Zhang, and Feng Zhao. Privacy.tag: Privacy concern expressed and respected. In Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems, SenSys ’14, pages 163–176, New York, NY, USA, 2014. ACM.

• Lam Tran, Deguang Kong, Hongxia Jin, and Ji Liu. Privacy-cnhs: A framework to detect photo privacy with convolutional neural network using hierarchical features. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, AAAI’16, pages 1517–1523. AAAI Press, 2016.

• Yahui Han, Yonggang Huang, Lei Pan, and Yunbo Zheng. Learning multi-level and multi-scale deep representations for privacy image classification. Multimedia Tools and Applications, 81(2):2259–2274, 2022.

• Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. Advances in neural information processing systems, 30, 2017.

• J. Yu, B. Zhang, Z. Kuang, D. Lin, and J. Fan. iprivacy: Image privacy protection by identifying sensitive objects via deep multi-task learning. IEEE Transactions on Information Forensics and Security, 12(5):1005–1016, May 2017.

• Guang Yang, Juan Cao, Zhineng Chen, Junbo Guo, and Jintao Li. Graph-based neural networks for explainable image privacy inference. Pattern Recognition, 105:107360, 2020.

• Guang Yang, Juan Cao, Qiang Sheng, Peng Qi, Xirong Li, and Jintao Li. Drag: Dynamic region-aware gen for privacy-leaking image detection. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, AAAI’22. AAAI Press, 2022.

• Sergej Zerr, Stefan Siersdorfer, Jonathon Hare, and Elena Demidova. Privacy-aware image classification and search. In Proceedings of the 35th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’12, pages 35–44, New York, NY, USA, 2012. ACM.

• Anna C. Squeciarini, Cornelia Caragea, and Rahul Balakavi. Analyzing images’ privacy for the modern web. In Proceedings of the 25th ACM Conference on Hypertext and Social Media, HT ’14, pages 136–147, New York, NY, USA, 2014. ACM.

• Haoti Zhong, Anna Squeciarini, David Miller, and Cornelia Caragea. A group-based personalized model for image privacy classification and labeling. In Proceedings of the 26th International Joint Conference on Artificial Intelligence, IJCAI’17, pages 3952–3958. AAAI Press, 2017.
Privacy Intelligence: A Survey on Image Privacy in Online Social Networks • 29

[44] Ashwini Tonge and Cornelia Caragea. On the use of “deep” features for online image sharing. In Companion Proceedings of the The Web Conference 2018, WWW ’18, pages 1317–1321, Republic and Canton of Geneva, Switzerland, 2018. International World Wide Web Conferences Steering Committee.

[45] Ashwini Tonge and Cornelia Caragea. Dynamic deep multi-modal fusion for image privacy prediction. In The World Wide Web Conference, WWW ’19, pages 1829–1840, New York, NY, USA, 2019. ACM.

[46] Chi Liu, Zongyuan Ge, Mingguang He, and Xiaotong Han. A label uncertainty-guided multi-stream model for disease screening. In 2022 IEEE 19th International Symposium on Biomedical Imaging (ISBI), pages 1–5. IEEE, 2022.

[47] Ashwini Tonge, Cornelia Caragea, and Anna Squicciarini. Privacy-aware tag recommendation for image sharing. In Proceedings of the 29th on Hypertext and Social Media, HT ’18, pages 52–56, New York, NY, USA, 2018. ACM.

[48] Bart P. Knijnenburg, Alfred Kohsa, and Hongxia Jin. Dimensionality of information disclosure behavior. International Journal of Human-Computer Studies, 71(12):1144 – 1162, 2013.

[49] Ching-man Au Yeung, Lalana Kagal, Nicholas Gibbs, and Nigel Shadbolt. Providing access control to online photo albums based on tags and linked data. In Social Semantic Web: Where Web 2.0 Meets Web 3.0, Papers from the 2009 AAAI Spring Symposium, Technical Report SS-09-08, Stanford, California, USA, March 23-25, 2009, pages 9–14, 2009.

[50] Peter F. Klemperer, Yuan Liang, Michelle L. Mazurek, Manya Sleeper, Blase Ur, Lujo Bauer, Lorrie Faith Cranor, Nitin Gupta, and Michael K. Reiter. Tag, you can see it!: using tags for access control in photo sharing. In CHI Conference on Human Factors in Computing Systems, CHI ’12, Austin, TX, USA - May 05 - 10, 2012, pages 377–386, 2012.

[51] Anna Cinzia Squicciarini, Dan Lin, Smitha Sundareswaran, and Joshua Wede. Privacy policy inference of user-uploaded images on content sharing sites. IEEE Trans. Knowl. Data Eng., 27(1):193–206, 2015.

[52] Jun Yu, Zhenzhong Kuang, Baopeng Zhang, Wei Zhang, Dan Lin, and Jianping Fan. Leveraging content sensitivity and user trustworthiness to recommend fine-grained privacy settings for social image sharing. IEEE Trans. Information Forensics and Security, 13(5):1317–1332, 2018.

[53] Ricard L Fogués, Jose M Such, Agustín Espinosa, and Ana García-Fornes. Bff: A tool for eliciting tie strength and user communities in social networking services. Information Systems Frontiers, 16(2):225–237, 2014.

[54] Trung Dong Huynh, Nicholas R Jennings, and Nigel R Shadbolt. An integrated trust and reputation model for open multi-agent systems. Autonomous Agents and Multi-Agent Systems, 13(2):119–154, 2006.

[55] Panagiotis Ilia, Jasonas Polakis, Elias Athanassopoulos, Federico Maggi, and Sotiris Ioannidis. Face/off: Preventing privacy leakage from street-view panoramas using depth and multi-view imagery. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

[56] Qianru Sun, Liqian Ma, Seong Joon Oh, Luc Van Gool, Bernt Schiele, and Mario Fritz. Natural and effective obfuscation by head inpainting. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2018.
[67] Qianru Sun, Ayush Tewari, Weipeng Xu, Mario Fritz, Christian Theobalt, and Bernt Schiele. A hybrid model for identity obfuscation by face replacement. In The European Conference on Computer Vision (ECCV), September 2018.

[68] Zhenzhong Kuang, Zhiqiang Guo, Jinglong Fang, Jun Yu, Noboru Babaguchi, and Jianping Fan. Unnoticeable synthetic face replacement for image privacy protection. Neurocomputing, 457:322–333, 2021.

[69] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134, 2017.

[70] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pages 234–241. Springer, 2015.

[71] Tianqing Zhu, Dayong Ye, Wei Wang, Wanlei Zhou, and Philip Yu. More than privacy: Applying differential privacy in key areas of artificial intelligence. IEEE Transactions on Knowledge and Data Engineering, 2020.

[72] L. Fan. Practical image obfuscation with provable privacy. In 2019 IEEE International Conference on Multimedia and Expo (ICME), pages 784–789, July 2019.

[73] Jinao Yu, Hanwu Xue, Bo Liu, Yu Wang, Hsibing Zhu, and Ming Ding. Gan-based differential private image privacy protection framework for the internet of multimedia things. Sensors, 21(1):58, 2021.

[74] Matt Tierney, Ian Spiro, Christoph Bregler, and Lakshminarayanan Subramanian. Cryptagram: photo privacy for online social media. In Conference on Online Social Networks, COSN’13, Boston, MA, USA, October 7-8, 2013, pages 75–88, 2013.

[75] Weiwei Sun, Jiantao Zhou, Shuyuan Zhu, and Yuan Yan Tang. Robust privacy-preserving image sharing over online social networks (osns). TOMM, 14(1):14:1–14:22, 2018.

[76] Abbas Cheddad, Joan Condell, Kevin Curran, and Paul McKeivitt. Digital image steganography: Survey and analysis of current methods. Signal Process., 90(3):727–752, 2010.

[77] Yujie Fu, Ping Kong, Heng Yao, Zhenjun Tang, and Chuan Qin. Effective reversible data hiding in encrypted image with adaptive encoding strategy. Information Sciences, 494:21 – 36, 2019.

[78] Yoo-Bryong Ra, Ramesh Govindan, and Antonio Ortega. P3: toward privacy-preserving photo sharing. In Proceedings of the 10th USENIX Symposium on Networked Systems Design and Implementation, NSDI 2013, Lombard, IL, USA, April 2-5, 2013, pages 515–528, 2013.

[79] Jianping He, Bin Liu, Dequang Kong, Xuan Bao, Na Wang, Hongxia Jin, and George Kesidis. PUPPIES: transformation-supported personalized privacy preserving partial image sharing. In 46th Annual IEEE/IFIP International Conference on Dependable Systems and Networks, DSN 2016, Toulouse, France, June 28 – July 1, 2016, pages 359–370, 2016.

[80] Vahid Mirjalili and Arun Ross. Soft biometric privacy: Retaining biometric utility of face images while perturbing gender. In 2017 IEEE International joint conference on biometrics (IJCB), pages 564–573. IEEE, 2017.

[81] Richard McPherson, Reza Shokri, and Vitaly Shmatikov. Defeating image obfuscation with deep learning. ArXiv, abs/1609.00408, 2016.

[82] Sheng-Hua Zhong, Yan Liu, and Kien A. Hua. Field effect deep networks for image recognition with incomplete data. ACM Trans. Multimedia Comput. Commun. Appl., 12(4), August 2016.

[83] Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, Omar Fawzi, and Pascal Frossard. Universal adversarial perturbations. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1765–1773, 2017.

[84] Shawn Shan, Emily Wenger, Jiayun Zhang, Huiying Li, Haitao Zheng, and Ben Y Zhao. Fawkes: Protecting privacy against unauthorized L. Fan. Practical image obfuscation with provable privacy. In 2019 IEEE International Conference on Multimedia and Expo (ICME), pages 784–789, July 2019.

[85] Zhiqi Shen, Shaojing Fan, Yongkang Wong, Hongbo Jiang, Haowen Chen, and Yonghe Liu. Gender-adversarial networks for face privacy preserving. IEEE Internet of Things Journal, 2022.

[86] Qianru Sun, Ayush Tewari, Weipeng Xu, Mario Fritz, Christian Theobalt, and Bernt Schiele. A hybrid model for identity obfuscation by face replacement. In The European Conference on Computer Vision (ECCV), September 2018.

[87] Zhenzhong Kuang, Zhiqiang Guo, Jinglong Fang, Jun Yu, Noboru Babaguchi, and Jianping Fan. Unnoticeable synthetic face replacement for image privacy protection. Neurocomputing, 457:322–333, 2021.

[88] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134, 2017.

[89] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pages 234–241. Springer, 2015.

[90] Tianqing Zhu, Dayong Ye, Wei Wang, Wanlei Zhou, and Philip Yu. More than privacy: Applying differential privacy in key areas of artificial intelligence. IEEE Transactions on Knowledge and Data Engineering, 2020.

[91] L. Fan. Practical image obfuscation with provable privacy. In 2019 IEEE International Conference on Multimedia and Expo (ICME), pages 784–789, July 2019.

[92] Jinao Yu, Hanwu Xue, Bo Liu, Yu Wang, Hsibing Zhu, and Ming Ding. Gan-based differential private image privacy protection framework for the internet of multimedia things. Sensors, 21(1):58, 2021.

[93] Matt Tierney, Ian Spiro, Christoph Bregler, and Lakshminarayanan Subramanian. Cryptagram: photo privacy for online social media. In Conference on Online Social Networks, COSN’13, Boston, MA, USA, October 7-8, 2013, pages 75–88, 2013.

[94] Weiwei Sun, Jiantao Zhou, Shuyuan Zhu, and Yuan Yan Tang. Robust privacy-preserving image sharing over online social networks (osns). TOMM, 14(1):14:1–14:22, 2018.

[95] Abbas Cheddad, Joan Condell, Kevin Curran, and Paul McKeivitt. Digital image steganography: Survey and analysis of current methods. Signal Process., 90(3):727–752, 2010.

[96] Yujie Fu, Ping Kong, Heng Yao, Zhenjun Tang, and Chuan Qin. Effective reversible data hiding in encrypted image with adaptive encoding strategy. Information Sciences, 494:21 – 36, 2019.

[97] Yoo-Bryong Ra, Ramesh Govindan, and Antonio Ortega. P3: toward privacy-preserving photo sharing. In Proceedings of the 10th USENIX Symposium on Networked Systems Design and Implementation, NSDI 2013, Lombard, IL, USA, April 2-5, 2013, pages 515–528, 2013.

[98] Jianping He, Bin Liu, Dequang Kong, Xuan Bao, Na Wang, Hongxia Jin, and George Kesidis. PUPPIES: transformation-supported personalized privacy preserving partial image sharing. In 46th Annual IEEE/IFIP International Conference on Dependable Systems and Networks, DSN 2016, Toulouse, France, June 28 – July 1, 2016, pages 359–370, 2016.

[99] Vahid Mirjalili and Arun Ross. Soft biometric privacy: Retaining biometric utility of face images while perturbing gender. In 2017 IEEE International joint conference on biometrics (IJCB), pages 564–573. IEEE, 2017.

[100] Richard McPherson, Reza Shokri, and Vitaly Shmatikov. Defeating image obfuscation with deep learning. ArXiv, abs/1609.00408, 2016.

[101] Sheng-Hua Zhong, Yan Liu, and Kien A. Hua. Field effect deep networks for image recognition with incomplete data. ACM Trans. Multimedia Comput. Commun. Appl., 12(4), August 2016.

[102] Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, Omar Fawzi, and Pascal Frossard. Universal adversarial perturbations. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1765–1773, 2017.

[103] Shawn Shan, Emily Wenger, Jiayun Zhang, Huiying Li, Haitao Zheng, and Ben Y Zhao. Fawkes: Protecting privacy against unauthorized L. Fan. Practical image obfuscation with provable privacy. In 2019 IEEE International Conference on Multimedia and Expo (ICME), pages 784–789, July 2019.

[104] Zhiqi Shen, Shaojing Fan, Yongkang Wong, Hongbo Jiang, Haowen Chen, and Yonghe Liu. Gender-adversarial networks for face privacy preserving. IEEE Internet of Things Journal, 2022.

[105] Qianru Sun, Ayush Tewari, Weipeng Xu, Mario Fritz, Christian Theobalt, and Bernt Schiele. A hybrid model for identity obfuscation by face replacement. In The European Conference on Computer Vision (ECCV), September 2018.
Refereed conference papers and journal articles:

- Zhenyu Wu, Zhangyang Wang, Zhaowen Wang, and Hailin Jin. "Towards privacy-preserving visual recognition via adversarial training." *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018, Stockholm, Sweden*, pages 656–662, 2018.

- Latanya Sweeney. "k-anonymity: A model for protecting privacy." *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 10(5):557–570, 2002.

- H. Alshamsi, V. Kepuska, H. Alshamz, and H. Meng. "Automated facial expression and speech emotion recognition app development on smart phones using cloud computing." In *2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, pages 730–738, 2018.

- Binbin Yong, Gaofeng Zhang, Huaming Chen, and Qingguo Zhou. "Intelligent monitor system based on cloud and convolutional neural networks." *The Journal of Supercomputing*, 73(7):3260–3276, 2017.

- Animesh Srivastava, Puneet Jain, Soteris Demetriou, Landon P. Cox, and Kyu-Han Kim. "Camforensics: Understanding visual privacy leaks in the wild." In *Proceedings of the 15th ACM Conference on Embedded Network Sensor Systems*, SenSys ’17, pages 30:1–30:13, New York, NY, USA, 2017. ACM.

- Kaitai Liang, Joseph K. Liu, Rongxing Lu, and Duncan S. Wong. "Privacy concerns for photo sharing in online social networks." *IEEE Internet Comput.*, 19(2):58–63, 2015.

- Richard L. Gregory. "Knowledge in perception and illusion." *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 352(1358):1121–1127, 1997.

- Emanuel von Zeeschitz, Sigrid Ebbinghaus, Heinrich Hussmann, and Alexander De Luca. "You can’t watch this!: Privacy-respectful photo browsing on smartphones." In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA, USA, May 7-12, 2016*, pages 4329–4334, 2016.

- Kimia Tajik, Aksithum Gunasekaran, Rhea Dutta, Brandon Ellis, Rakesh B. Bobba, Mike Rosulek, Charles V. Wright, and Wu-chi Feng. "Balancing image privacy and usability with thumbnail-preserving encryption." In *26th Annual Network and Distributed System Security Symposium, NDSS 2019, San Diego, California, USA, February 24-27, 2019, 2019.

- Christina Katsini, Yasmeen Abdrabou, George E. Raptis, Mohamed Khamis, and Florian Alt. "The role of eye gaze in security and privacy applications: Survey and future HCI research directions, 2020.

- Huiyuan Zhou, Khalid Tearo, Aniruddha Waje, Elham Alghamdi, Thamara Alves, Vinicius Ferreira, Kirstie Hawkey, and Derek Reilly. "Enhancing mobile content privacy with proxemics aware notifications and protection." In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA, USA, May 7-12, 2016*, pages 1362–1373, 2016.

- Kirill Ragozin, Yun Suen Pai, Olivier Augereau, Koichi Kise, Jochen Kerdels, and Kai Kunze. "Private reader: Using eye tracking to improve reading privacy in public spaces." In *Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services, MobileHCI 2019, Taipei, Taiwan, October 1-4, 2019*, pages 18:1–18:6, 2019.

- Zhongzheng Ren, Yong Jae Lee, and Michael S. Ryoo. "Learning to anonymize faces for privacy preserving action detection." In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part I*, pages 639–655, 2018.

- Zhenyu Wu, Zhangyang Wang, Zhaowen Wang, and Hailin Jin. "Towards privacy-preserving visual recognition via adversarial training: A pilot study." In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XVI*, pages 627–645, 2018.

- Yogachandran Rahulmathavan and Multukrishnan Rajarajan. "Efficient privacy-preserving facial expression classification." *IEEE Trans. Dependable Sec. Comput.*, 14(3):326–338, 2017.

- Kazuaki Nakamura, Naoko Nitta, and Noboru Babaguchi. "Encryption-free framework of privacy-preserving image recognition for photo-based information services." *IEEE Transactions on Information Forensics and Security*, 14(5):1264–1279, 2018.

- Zhihua Xia, Lan Wang, Jian Tang, Neal N Xiong, and Jian Weng. "A privacy-preserving image retrieval scheme using secure local binary pattern in cloud computing." *IEEE Transactions on Network Science and Engineering*, 8(1):318–330, 2020.

- Zongye Zhang, Fucai Zhou, Shiyue Qin, Qiang Jia, and Zifeng Xu. "Privacy-preserving image retrieval and sharing in social multimedia applications." *IEEE Access*, 8:66828–66838, 2020.

- Julian Backes, Michael Backes, Markus Dürmuth, Sebastian Gerling, and Stefan Lorenz. "X-pire! - A digital expiration date for images in social networks." *CoRR*, abs/1112.2649, 2011.

- Jinghan Yang, Ayan Chakrabarti, and Yevgeniy Vorobeychik. "Protecting geolocation privacy of photo collections." *CoRR*, abs/1912.02085, 2019.

- Josep Domingo-Ferrer. "Rational enforcement of digital oblivion." In *Proceedings of the 2011 International Workshop on Privacy and Anonymity in Information Society, PAIS 2011, Uppsala, Sweden, March 2011*, page 2, 2011.

- Klara Stokes and Niklas Carlsson. "A peer-to-peer agent community for digital privacy in online social networks." In *2013 Eleventh Annual Conference on Privacy, Security and Trust*, pages 103–110. IEEE, 2013.

- Alexander Novotny and Sarah Spiekermann. "Oblivion on the web: an inquiry of user needs and technologies." In *22nd European Conference on Information Systems, ECIS 2014, Tel Aviv, Israel, June 9-11, 2014*, page 31.
[116] Changsong Yang, Xiaofeng Chen, and Yang Xiang. Blockchain-based publicly verifiable data deletion scheme for cloud storage. *Journal of Network and Computer Applications*, 103:185 – 193, 2018.

[117] Irwin Altman. Privacy regulation: Culturally universal or culturally specific? *Journal of Social Issues*, 33(3):66–84, 1977.

[118] Z. Li, J. Tang, and T. Mei. Deep collaborative embedding for social image understanding. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(9):2070–2083, Sep. 2019.

[119] Somak Aditya, Yezhou Yang, and Chitta Baral. Integrating knowledge and reasoning in image understanding. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019*, Macao, China, August 10-16, 2019, pages 6252–6259, 2019.

[120] Leyisia Palen and Paul Dourish. Unpacking “privacy” for a networked world. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI ’03, pages 129–135, New York, NY, USA, 2003. ACM.

[121] Wenxiu Ding, Rui Hu, Zheng Yan, Xinren Qian, Robert H Deng, Laurence T Yang, and Mianxiong Dong. An extended framework of privacy-preserving computation with flexible access control. *IEEE Transactions on Network and Service Management*, 17(2):918–930, 2019.

[122] Yifang Li, Nishant Vishwanmitra, Bart P. Kuijnenburg, Hongxin Hu, and Kelly Caine. Blur vs. block: Investigating the effectiveness of privacy-enhancing obfuscation for images. In *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 1343–1351, 2017.

[123] Yifang Li, Nishant Vishwanmitra, Bart P. Kuijnenburg, Hongxin Hu, and Kelly Caine. Effectiveness and users’ experience of obfuscation as a privacy-enhancing technology for sharing photos. *Proc. ACM Hum.-Comput. Interact.*, 1(CSWC), December 2017.

[124] Rakibul Hasan, Eman T. Hassan, Yifang Li, David J. Crandall, Roberto Hoyle, and Apu Kapadia. Viewer experience of obscuring scene elements in photos to enhance privacy. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, CHI 2018, Montreal, QC, Canada, April 21-26, 2018*, page 48, 2018.

[125] Rakibul Hasan, Yifang Li, Eman T. Hassan, Kelly Caine, David J. Crandall, Roberto Hoyle, and Apu Kapadia. Can privacy be satisfying?: On improving viewer satisfaction for privacy-enhanced photos using aesthetic transforms. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, CHI 2019, Glasgow, Scotland, UK, May 04-09, 2019*, page 367, 2019.

[126] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, *European Conference on Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II*, volume 9906 of *Lecture Notes in Computer Science*, pages 694–711. Springer, 2016.

[127] Nisarg Raval, Ashwin Machanavajjhala, and Landon P. Cox. Protecting visual secrets using adversarial nets. In *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 1329–1332, 2017.

[128] Samuel Greengard. Will deepfakes do deep damage? *Commun. ACM*, 63(1):17–19, December 2019.

[129] Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez, Aythami Morales, and Javier Ortega-Garcia. Deepfakes and beyond: A survey of face manipulation and fake detection, 2020.

[130] Thanh Thi Nguyen, Cuong M. Nguyen, Dung Tien Nguyen, Duc Thanh Nguyen, and Saeid Nahavandi. Deep learning for deepfakes creation and detection. *CoRR*, abs/1909.11573, 2019.

[131] Chi Liu, Huanjie Chen, Tianqiang Zhu, Jun Zhang, and Wanlei Zhou. Making deepfakes more spurious: evading deep face forgery detection via trace removal attack. arXiv preprint arXiv:2003.11433, 2022.

[132] Andreas Rössler, Davide Cozzolino, Luisa Verdeliiva, Christian Riess, Justus Thies, and Matthias Nießner. Faceforensics++: Learning to detect manipulated facial images. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 1–11, 2019.

[133] Yuezun Li, Xin Yang, Pu Sun, Honggang Qi, and Siwei Lyu. Celeb-df: A large-scale challenging dataset for deepfake forensics, 2019.

[134] Shiang-Feng Tzeng, Shi-Jinn Horng, Tianrui Li, Xian Wang, Po-Hsian Huang, and Muhammad Khurram Khan. Enhancing security and privacy for identity-based batch verification scheme in vanets. *IEEE Transactions on Vehicular Technology*, 66(4):3235–3248, 2015.

[135] Sergey Zerr, Stefan Siersdorfer, and Jonathon Hare. Picaclet!: A system for privacy-aware image classification and retrieval. In *Proceedings of the 21st ACM International Conference on Information and Knowledge Management, CIKM ’12*, pages 2710–2712, New York, NY, USA, 2012. ACM.

[136] Eleftherios Spyromitros-Xioufis, Symeon Papadopoulos, Adrian Popescu, and Yiannis Kompatsiaris. Personalized privacy-aware image classification. In *Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval, ICMR ’16*, pages 71–78, New York, NY, USA, 2016. ACM.
[140] Tribhuvanesh Orekondy, Bernt Schiele, and Mario Fritz. Towards a visual privacy advisor: Understanding and predicting privacy risks in images. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.

[141] T. Orekondy, M. Fritz, and B. Schiele. Connecting pixels to privacy and utility: Automatic redaction of private information in images. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8466–8475, June 2018.

[142] Danna Gurari, Qiqi Li, Chi Lin, Yinan Zhao, Anhong Guo, Abigale Stangl, and Jeffrey P. Bigham. Vizwiz-priv: A dataset for recognizing the presence and purpose of private visual information in images taken by blind people. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

[143] Chao Li, Daniel Yang Li, Gerome Miklau, and Dan Suciu. A theory of pricing private data. *Commun. ACM*, 60(12):79–86, 2017.

[144] Wenqiang Jin, Mingyan Xiao, Ming Li, and Linke Guo. If you do not care about it, sell it: Trading location privacy in mobile crowd sensing. In *2019 IEEE Conference on Computer Communications, INFOCOM 2019, Paris, France, April 29 - May 2, 2019*, pages 1045–1053, 2019.

[145] Arpita Ghosh and Aaron Roth. Selling privacy at auction. *Games Econ. Behav.*, 91:334–346, 2015.

[146] Aaron Roth. Buying private data at auction: the sensitive surveyor’s problem. *SIGecom Exchanges*, 11(1):1–8, 2012.

[147] K. Xu, Y. Guo, L. Guo, Y. Fang, and X. Li. My privacy my decision: Control of photo sharing on online social networks. *IEEE Transactions on Dependable and Secure Computing*, 14(2):199–210, March 2017.

[148] Ting Li, Wei Liu, Shangsheng Xie, Mianxiong Dong, Kaoru Ota, Neal N Xiong, and Qiang Li. Bpt: a blockchain based privacy information preserving system for trust data collection over distributed mobile edge network. *IEEE Internet of Things Journal*, 2021.

[149] Sean Augenstein, H. Brendan McMahan, Daniel Ramage, Swaroop Ramaswamy, Peter Kairouz, Mingqing Chen, Rajiv Mathews, and Blaise Agüera y Arcas. Generative models for effective ML on private, decentralized datasets. *CoRR*, abs/1911.06679, 2019.

[150] Sen-Ching Samson Cheung, Herb Wildfeuer, Mehdi Nikkhah, Xiaojing Zhu, and Wai-tian Tan. Learning sensitive images using generative models. In *2018 IEEE International Conference on Image Processing, ICIP 2018, Athens, Greece, October 7-10, 2018*, pages 4128–4132, 2018.

[151] Sola Shirai and Jacob Whitehill. Privacy-preserving annotation of face images through attribute-preserving face synthesis. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops 2019, Long Beach, CA, USA, June 16-20, 2019*, page 0, 2019.