

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

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Abstract—Image sharing on online social networks (OSNs) has become an indispensable part of daily social activities, but it has also led to an increased risk of privacy invasion. The recent image leaks from popular OSN services and the abuse of personal photos using advanced algorithms (e.g. DeepFake) have prompted the public to rethink individual privacy needs when sharing images on OSNs. However, OSN image sharing itself is relatively complicated, and systems currently in place to manage privacy in practice are labor-intensive yet fail to provide personalized, accurate and flexible privacy protection. As a result, a more intelligent environment for privacy-friendly OSN image sharing is in demand. To fill the gap, we contribute a systematic survey of ‘privacy intelligence’ solutions that target modern privacy issues related to OSN image sharing. Specifically, we present a high-level analysis framework based on the entire lifecycle of OSN image sharing to address the various privacy issues and solutions facing this interdisciplinary field. The framework is divided into three main stages: local management, online management and social experience. At each stage, we identify typical sharing-related user behaviors, the privacy issues generated by those behaviors, and review representative intelligent solutions. The resulting analysis describes an intelligent privacy-enhancing chain for closed-loop privacy management. We also discuss the challenges and future directions existing at each stage, as well as in publicly available datasets.

Index Terms—Privacy preservation, Online Social Network, Privacy Intelligence, Image Sharing.

I. INTRODUCTION

ONLINE social networks (OSNs) have become a vital component of modern society, facilitating both daily social interactions and information sharing profoundly. The progress in information and communication technologies (ICTs) has boosted the ever-increasing popularity of sharing personal images on OSNs. For example, more than 3 billion images are shared per day on Snapchat [1] and 4.5 billion on WhatsApp [2]. The social experience of OSN users has been dramatically enhanced due to the convenience of image sharing. Photographing and publishing processes can be completed with a few simple clicks anywhere and anytime, allowing OSN users to both express themselves and interact with others lively through sharing photos.

However, the convenience of sharing photos also poses a threat to OSN users’ privacy. The visual content of an image

directly discloses a wealth of sensitive information, which can be further exploited by modern recognition systems or computer vision techniques [3]. For example, the emerging ‘DeepFake’ technique can easily produce a realistic fake media record based on only a single face photo [4]–[6], thus putting individuals at risk. Moreover, with the help of machine recognition, some implicit information such as occupation [7], health condition [8] and even sexual orientation [9] can be revealed from personal photos. In addition to the visual content, affiliated image data (such as metadata or user tags) can also lead to unintended revelations. For example, the camera serial number included in a photo’s metadata can be leveraged to identify user profiles through simple cross-linking [10].

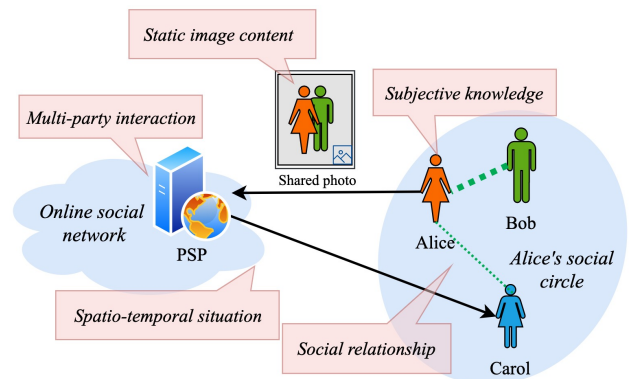


Fig. 1. A simplified OSN image sharing case. Suppose Alice would like to share a photo of her and Bob with a friend (Carol) in her social circle (where the thickness and length of the green dashed line indicates the strength of the social relationship). A relatively ideal privacy management system should take all the variables (shown in the red boxes) into consideration.

Across the globe this privacy crisis has spurred the public to explore effective and practical solutions for privacy management when it comes to OSN image sharing. The numerous recent incidents of photo leaks by some of the most popular online photo service providers (PSPs) such as Facebook [11], iCloud [12] and Snapchat [13] illustrate that the current procedures are insufficient. Present-day privacy management systems face two major obstacles:

1) **The intractability of privacy in OSN image sharing.** Once images interact with the OSN context, the challenge of preserving privacy when sharing images on OSNs involves several factors. Privacy is not only dependent on the static image content but also multiple dynamic factors such as human cognitive ability and contextual dynamics. For example, Figure

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1 shows a simplified scenario of OSN image sharing where three stakeholders are involved. Privacy management can be affected by heterogeneous variables such as subjective knowledge of privacy awareness, the strength of social relationships, the multi-party interactive nature of OSNs and the spatio-temporal situation. As a result, the intractability of privacy in OSN image sharing dramatically increases the difficulties and costs of privacy management.

2) **The labor-intensive status quo.** Currently, the real-world solutions such as privacy laws [14]–[16], user agreements [17]–[19], or oversimplified privacy preference configurations provided by some PSPs [20], [21] either defend users passively or require their self-conscious initiative. They generally require massive labor-intensive operations, which are tedious [22]–[24], error-prone [25], and reduce the ability of users to customize their privacy settings [23]. In addition, they are subject to natural human limitations, such as awareness of privacy issues [22], [26]–[29] and forgetfulness [23], [26].

Satisfying modern privacy needs and addressing the aforementioned challenges facing OSN use will require further explorations and wider adoptions of intelligent solutions and technologies, which we refer to as *privacy intelligence*. This necessitates examining the literature surrounding privacy intelligence published in the recent decade. The intelligent solutions for privacy preservation found there can be used to tackle modern privacy issues in OSN image sharing and fascinate the real-world privacy management, and eventually contribute to building a privacy-friendly OSN image sharing environment for individual users.

A. Comparison of existing surveys

To the best of our knowledge, there does not exist a present-day survey of privacy intelligence with regard to OSN image sharing in the existing literature. However, there are surveys related to this topic for reference:

1) *Surveys on OSN privacy and security:* Fire et al. [30] provided a thorough review of the different security and privacy risks that threaten the well-being of OSN users in general, and presented an overview of existing countermeasures. Abawajy et al. [31] presented a comprehensive survey of privacy risks, attacks and privacy-preserving techniques in general for social network data publishing based on graph modelling methods. Ferrag et al. [32] reviewed the state of the art in privacy-preserving schemes developed for (or applied in the context of) ad hoc social networks, including mobile social networks (MSNs) and vehicular social networks (VSNs).

2) *Surveys on multimedia privacy and security:* Padilla-López et al. [33] provided a comprehensive classification of the protection techniques for image data privacy with an up-to-date review. Ribaric et al. [34] presented a systematic overview of de-identification approaches for non-biometric, physiological, behavioural, and soft-biometric identifiers in multimedia documents. Patsakis et al. [35] outlined the most significant security and privacy issues related to the exposure of multimedia content in OSNs and discussed possible countermeasures (which is particularly relevant to the topic at hand).

While these pioneering surveys were mainly aimed at the privacy and security threats facing static OSN or multimedia data, and summarized some manual operation-dependent solutions, our focus is on the modern privacy issues derived from a dynamic OSN image sharing process from a human-centric perspective, and purely on intelligent solutions with an eye on interdisciplinary influences stemming from recent progress in the domains of artificial intelligence (AI) and computer vision. In addition, we propose a wider range of solutions, including *preventive solutions* (such as privacy risk detection), *protective solutions* (such as access control) and *sustainable solutions* (such as social utility evaluation).

B. Scope of literature for review

To complete a comprehensive survey on privacy intelligence in OSN image sharing, we collected related research articles for review following three steps:

1) Selection. We searched full conference articles published from the year of 2009 using the operator. Considering the interdisciplinary nature of this topic, we selected representative conferences in different areas, including security and privacy, AI, multimedia and computer-human interaction.

2) Exclusion. We reviewed the collected articles and excluded the weakly-relevant topics, such as papers in the field of cloud server security. This survey is closely centered on solutions for privacy issues derived from the general OSN image sharing process. Solutions for security issues related to attacks against e.g. storage [36], computation [37]–[39] or communications [40]–[42] on PSP servers are outside the scope of this survey.

3) Expansion. Taking into consideration of relevance, reputation and influence, we expanded the pool by checking the references in all selected papers for relevance. Lastly, once we distilled our analysis framework (see Section II), we used it to enrich the collection of related research articles by identifying a few additional papers through open searching.

C. Main contributions

- We propose a high-level analysis framework based on the lifecycle of OSN image sharing, which consists of three stages and a series of typical user behaviors. The analyses of privacy issues and corresponding intelligent solutions are then systematically performed based on the stages within the framework.
- We propose a taxonomy of the privacy issues facing OSN image sharing, which can provide an explicit understanding of the targets of privacy intelligence.
- We discuss the outstanding challenges and future directions in each stage of the analysis framework. We also discuss the challenges in the current publicly available datasets.

The remainder of this paper is organized as follows. In Section II, a view of privacy intelligence is presented, including the concept and taxonomy of privacy in OSN image sharing, and the structure of the lifecycle-based analysis framework. In Sections III through V, we identify the modern privacy issues and summarize the corresponding intelligent solutions for each

successive stage of the analysis framework. The challenges and future directions in this field are discussed in Section VI, and Section VII offers a brief conclusion.

II. A VIEW OF PRIVACY INTELLIGENCE

This section discusses the concepts related to privacy intelligence and presents a high-level framework of the OSN image sharing process for further analysis.

A. Privacy taxonomy

There is not a current universal definition of privacy in OSN image sharing. As a starting point, we propose constructing a definition at the intersection of OSN and visual privacy, both of which have been discussed explicitly in the literature. OSN privacy is typically defined as the contextual integrity [43], [44] or visibility [45], [46] of user data in the context of OSN sharing, regardless of the data form or inherent content. Visual privacy generally considers the sensitive visual content depicted in multimedia data [33], [47]–[49] without a particular concern to any contextual constraints. As a result, in our survey we consider privacy in OSN image sharing as the contextual integrity or visibility of sensitive information that can be exposed from the image data throughout the whole OSN propagation process.

According to current literature, we categorized the privacy intelligence regarding OSN image sharing into the following types, as shown in Figure 2.

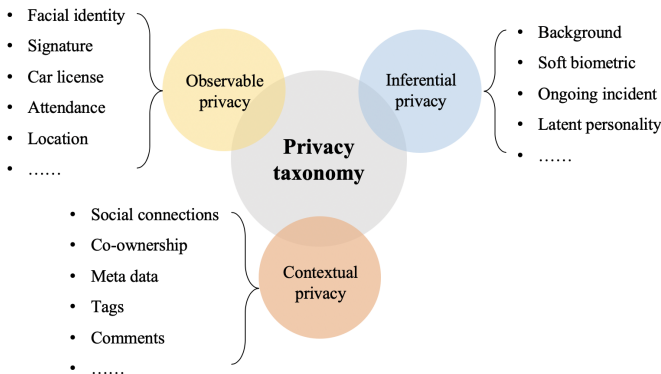


Fig. 2. A taxonomy of privacy in OSN image sharing

- **Observable privacy** refers to the sensitive content which can be viewed directly from the image, such as faces, car licenses and location signs. It is the most common type of privacy regarding OSN image sharing, given that the original intention of OSN image sharing is mainly to convey visual content to others for viewing. In terms of semantic understanding, observable privacy can be further divided into multiple levels from low to high (e.g. pixel level, object level and scene level). Observable privacy is the most vulnerable since sensitive visual content is immediately available once images are accessed maliciously. Moreover, the risks are dramatically amplified by the cutting-edge recognition algorithms, which can facilitate

the semantic processing for image understanding at a very high-level [50]–[54].

- **Inferential privacy** refers to the sensitive information implied in an image that can be inferred through reasoning or association (for example, inferring an event by analyzing location cues and the clothing worn by those in the image). In addition, soft biometric attributes such as facial age and sexual orientation are also considered aspects of inferential privacy, since although these latent attributes are hard to perceive by human viewers, they can be deduced accurately by machines at the abstract feature level [7]–[9].
- **Contextual privacy** refers to the sensitive information associated with an image in the context of the environment. This type of information can be the descriptive texts added by some external actions during the image propagation, such as the metadata recorded by cameras or auxiliary text (e.g., tags or captions) provided by OSN users. The information can also be properties characterized by social interactions. For example, co-ownership of a shared image can be considered as a privacy factor, because it can lead to a conflict of interests when managing multi-party privacy preference configurations.

B. Lifecycle framework for privacy intelligence

Privacy intelligence is a collective concept referring to those intelligent solutions addressing individual privacy issues from multiple perspectives and angles. From the aspect of applied techniques, they can be arbitrarily classified as fully-automated, semi-automated, human-computer interactive, or any mix of them. Due to the complicated nature of privacy issues that emerge as a result of OSN image sharing, a diversified range of intelligent solutions have been proposed. To this end, a high-level analysis framework is needed to systematically identify issues and investigate corresponding solutions, as well as to recognize current challenges and future directions.

As the essence of the OSN image sharing process is a kind of information exchange, we leverage the methodology of information lifecycle management (ILM) [55], [56] to create an analysis framework based on the entire lifecycle of OSN image sharing. We divide the lifecycle of OSN image sharing into three major stages: local management, online management and social experience. Each stage includes a series of user behaviors. Figure 3 shows an overview of the lifecycle of OSN image sharing and the framework we will use in our analysis.

1) *Stage 1: Local management:* At the stage of local management, the images are prepared by the sender in an offline mode. To this end, three typical user behaviors are seen: image capture, image selection and image description.

- **Image capture:** The image is created via a camera device.
- **Image selection:** The sender selects the image from the gallery with an OSN sharing intent.
- **Image description:** For the purposes of self-expression and social interaction, the sender will typically add information (such as a descriptive tag) to the image before sharing.

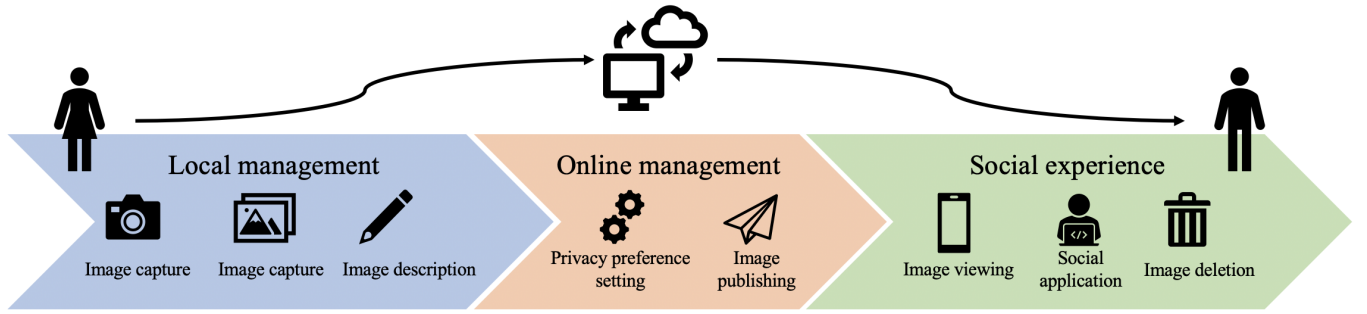


Fig. 3. Lifecycle of OSN image sharing, including three main stages. Each is with multiple sharing-related user behaviors.

2) *Stage 2: Online management:* At the stage of online management, the sender interacts with the PSP, uploading the image to the PSP server and publishing the image online. There are two typical user behaviors at this stage: privacy preference setting and image publishing.

- **Privacy preference setting:** Most current PSPs will provide an interface for the senders to manually specify their privacy preference for sharing uploaded images.
- **Image publishing:** The sender publishes the image to make it accessible to the targeted recipients. This user behavior puts image privacy at high risk due to the combination of direct content disclosure to the outside world while placing the privacy of the image either partially or fully out of the sender's control.

3) *Stage 3: Social experience:* At the stage of social experience, the images have been accessed by the recipient(s). There are three typical user behaviors at this stage: image viewing, social application and image deletion.

- **Image viewing:** The shared image has been received and seen by the authorized recipients (typically human viewers).
- **Social application:** The shared images are applied to some particular PSPs with photo-based services. For example, OSN users might send personal photos to facial age prediction services for fun [57]–[60]. Alternatively, elderly individuals could benefit from photo-based online life logger services which monitor daily actions [61]–[63]. The image recipient is a machine viewer.
- **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.

III. PRIVACY INTELLIGENCE IN LOCAL MANAGEMENT

This section first identifies the possible privacy issues arise from the user behaviors at the local management stage, then provides an investigation on the intelligent solutions targeting each privacy issue. Figure 4 offers an overview of privacy issues and intelligent solutions. Each privacy issue is linked to its user behavior cause and the corresponding intelligent solutions. There are in total 7 kinds of intelligent solutions at this stage.

A. Privacy issues in local management

1) Privacy issues in image capture:

- **Unintended capture.** It is sometimes inevitable when taking a photo to unwittingly capture sensitive information, such as bystanders' faces or military signs. Meanwhile, it is impractical to check images one by one manually to delete this information.
- **In-device leakage.** This kind of leakage may happen when some in-device third-party services attempt to access the captured images. For example, with a coarse camera control permission, many smartphone applications that provide photo-based services easily extract extra information from images that is beyond their actual needs [64].

2) Privacy issues in image selection:

- **Unawareness of privacy.** Privacy should be a crucial consideration influencing the sharing decision (if only to respect the views and values of others). However, it is showed in many previous studies that users often lack a clear awareness of OSN image privacy [22], [26]–[28]. As a result, many images are shared online without any concern for information leakage. Moreover, the complexity of OSN image privacy makes it quite difficult to assess. For example, it nearly impossible for users to distinguish privacy boundaries that incorporate the comprehensive concerns of every perspective. Consequently, users' actions regarding OSN image privacy often deviate from their original intentions [25].

3) Privacy issues in image description:

- **Incautious tagging.** Users might tag images carelessly in ways which disclose individual information. For example, some users name the individuals depicted or describe the location of the captured scene. In addition, some latest camera integrates the functionality of automated recognition to ease the image tagging [65]–[68]. In this way, the information recognized by machines may aggravate privacy leakage

B. Intelligent solutions in local management

1) Solutions for unintended capture:

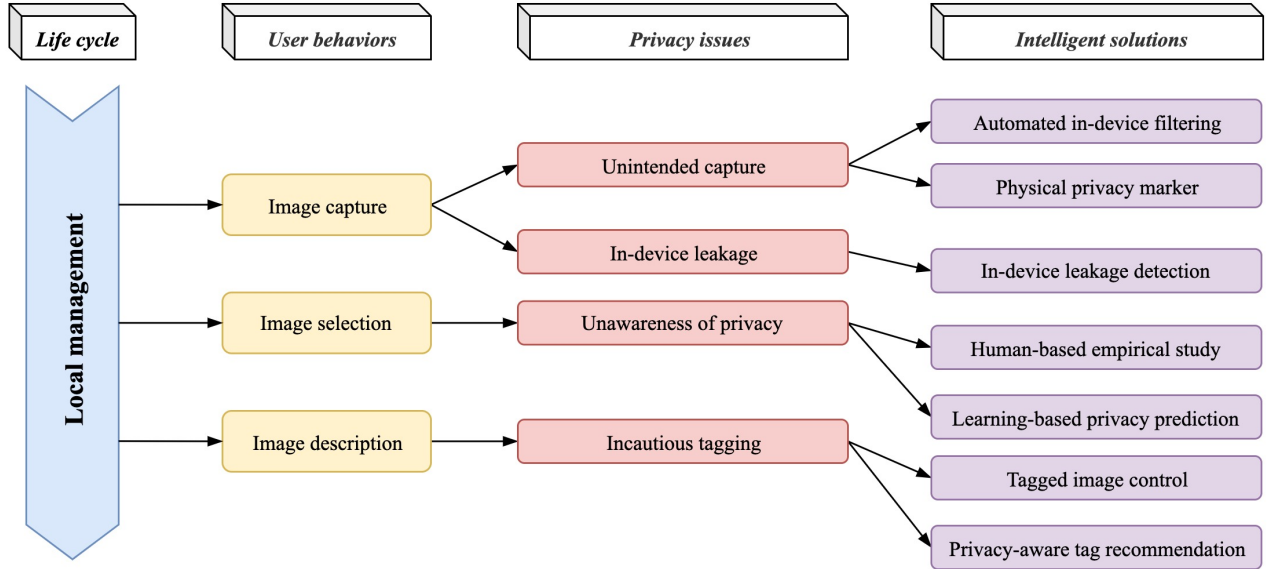


Fig. 4. Overview of privacy issues and corresponding intelligent solutions at the local management stage. Each privacy issue is linked to its user behavior cause and the corresponding intelligent solutions

a) *Automated in-device filtering*: The simplest way to protect the privacy of non-interested parties is to delete the entire image at point of capture. However, this would entail elements of such images recorded for OSN sharing to be lost. A more fine-grained way is to edit the image manually, which is still time-consuming and costly. To address the problem, some automated in-device content filtering methods have been proposed to remove sensitive information from the raw image during real-time photography while retaining the processed image for the user.

Hardware-based methods. Chattopadhyay et al. [69] designed a privacy-enhanced digital signal processor (DSP) for camera devices with an embedded PICO [70] module. The region of interest (ROI) of the captured image (defined as the person entering a static scene by the authors) was extracted through image background subtraction, then encrypted using the public-key Advanced Encryption Standard (AES) [71] technique during the image compression. The secured information was stored inside the image file header to allow revertible decryption by the user.

This DSP-based solution required image processing and encryption after imaging, which might lead to extra computation and power overhead which could affect the camera user experience. In contrast, Pittaluga et al. [72] approached the issue through pre-capture privacy filtering via optical element design. A complementary optic layer was added into the camera sensor that can anonymize sensitive information from the incident light field before sensor imaging. For example, when capturing a face, an electronic display generated $k - 1$ nearest neighbor facial masks corresponding to the real face. Then an alignment sensor performed a pixelwise merger of the real face and the $k - 1$ masks in terms of irradiance to

achieve the k -anonymized face image.

Software-based methods. In addition to the hardware-based solutions, Aditya et al. [73] developed the I-Pic, a software platform for individual policy-compliant content filtering for real-time photography. Users pre-defined privacy policies and broadcasted the policies and their presence to I-Pic via blue-tooth. Then when an I-Pic user took an image, the platform performed a secured visual signature (e.g., facial feature vector) based match between the captured faces and nearby recorded I-Pic users. For those matched users, the platform conformed with their privacy policies and edited the image accordingly.

Shu et al. [47] developed Cardea, a software that can be embedded into camera applications for privacy-respecting photography. Similar to I-Pic, the Cardea users stored their privacy policies and identifiable information in the cloud for subsequent matching and image editing. Compared to I-Pic, Cardea supported users can specify more fine-grained and context-aware privacy policies, which depend on four contextual elements: location, scene, the presence of others, and hand gestures.

b) *Physical privacy marker*: Besides achieving real-time privacy-preserving image capture through in-device filtering solutions, some researchers found solutions based on the physical environment outside the camera through external privacy markers users could employ to express their privacy concerns when being captured.

Privacy visual markers, as proposed by Schiff et al. [74], were a kind of physical hint (such as hats or vests) for people who were not willing to be captured. By embedding a visual color-tracker, cameras were able to identify users wearing visual markers when capturing an image. Then the locations

and sizes of their faces were inferred for anonymization based on the color-space using an Adaptive Boosting (AdaBoost) classifier [75].

Beyond natural visual markers, some studies used artificial visual markers. Pallas et al. [76] proposed a set of four visual symbols representing four elementary privacy preferences, which photo subjects can wear in the form of stickers or badges and are easily recognizable. Taking the badge idea one step further, Bo et al. [77] designed a customized yet compatible QR-code as the privacy marker, which was more easily and accurately recognized by machine processing. Such codes can potentially hold extensive privacy information, allowing users to express their needs in a more nuanced fashion when being photographed.

2) *Solutions for in-device leakage:*

a) *In-device leakage detection:* Access to in-device image data by third-party applications can lead to potential information leakages. To mitigate against this, Srivastava et al. [48] developed an app analysis tool named CamForensics, which can examine an application's execution processing on camera data. The tool simulated photo images with specific types of information such as faces and texts and fed them to software applications as test inputs to monitor the image processing and information extraction executed on the images. The processing of the test images was recorded for further analysis to determine if the application software extracted any in-device data leakage. In addition to the software analysis, the authors also conducted a large-scale user study on Amazon Mechanical Turk (AMT), which is a crowdsourcing marketplace, to understand users' awareness of visual privacy with respect to software applications. According to their investigation on over 600 of the most popular applications with photo-based functionality, 61% of the applications did not provide a clear statement on image processing, and 19% of them defied users' expectations regarding information extraction from camera data.

3) *Solutions for unawareness of privacy:*

a) *Human-based empirical study:* Empirical study is a powerful tool for studying human behavior and group tendencies in complex environments. It has been widely applied both to understand the cognitive abilities of users with respect to OSN image privacy and to help raise privacy awareness in users when selecting images for sharing. The data collected has facilitated current research on the subjectivity of privacy in OSN image sharing from a human-computer-interactive perspective, providing population-based prior knowledge regarding human cognitive ability with respect to privacy. The individual differences regarding privacy concerns discovered from these studies can help raise public privacy awareness as well as benefit some related downstream works (such as personalized privacy recommendations and protections, currently at the study design stage).

Studies on human privacy decision making. To understand how people make privacy decisions in real-world online photo sharing, Ahern et al. [78] conducted a user study enrolling 81 Flickr (a popular photo sharing OSN) users who had uploaded a total of 36915 photos to Flickr using a plugin named ZoneTag [79]. The study illustrated that both the

photo content and the photographed location influenced users' privacy decisions. Specifically, users would make different privacy decisions in different locations and tended to set photos as private in frequently photographed locations. In terms of photo content, the theme of Person was significantly more private to users than other themes including Location, Place, Object, Event, and Activity.

Hoyle et al. [80] carried out another user study that concentrated on users' privacy decision making. It focused on life log images recorded by wearable cameras (given the increasing popularity of using such cameras for OSN sharing). The study involved 36 participants who wore a camera for one week and then indicated a privacy preference for the recorded images. Through this study, the authors found that wearable cameras record many sensitive moments automatically that would not be normally captured by deliberate photography. The camera users tended to make the sharing decision depending on impression management and privacy-protecting concerns of both themselves and bystanders.

Privacy decisions depend not only on individual preferences but also social norms and collectively-shared expectations. Hoyle et al. [81] conducted an online factorial vignette study on AMT with 279 participants and found that users shared common expectations about the privacy of online images with socially contingent and multi-dimensional privacy norms, which varied according to differences in social context. The features of social context that influenced privacy decision-making included the number of people in the photo, the presence of sensors or monitors, and the users' role in relation to the photo. The authors concluded that while some measures of individual privacy preferences mattered, social privacy norms for online images were robust to differences in individual preferences, demonstrating the sociological nature of privacy in contrast to privacy as merely an individual preference.

Studies on human privacy awareness. In comparison to the visual content of an image, the affiliated metadata is more likely to be neglected and even unknown by OSN users [82]. Therefore, when users share images online, the privacy threats posed by the exposure of metadata are often underestimated. To study the gap in user awareness of metadata, Xu et al. [10] conducted a data-driven investigation to assess the potential privacy risks arising from metadata at different stages during the online propagation process. The authors identified several; for example, the camera serial number field in the metadata could be used as an attack vector to re-identify the photographer via cross-linking websites.

To understand users' ability in identifying and resolving the problem of multi-party privacy conflicts (MPCs), Such et al. [83] conducted a questionnaire-based survey study on AMT designed using the guidelines for the critical incident technique (CIT) [84]. A total of 1033 questionnaires from 496 uploaders and 537 co-owners were included. According to the user feedback, the authors identified the primary characteristics of photo MPCs were over prevalence, context and severity. They also examined the frequency and effectiveness of different communication and resolution strategies applied by users to address MPCs. This study also showed a significant divergence in perceptions regarding privacy awareness between individu-

als the uploader role and the co-owner role.

b) Learning-based privacy prediction: Even if users are aware which images should be considered private information, manual selection is still error-prone and time-consuming. A more efficient way would be to discriminate the images automatically. To examine this solution, some studies formulated the task as a classification problem and addressed it intelligently. Two essential procedures are involved: first, private features have to be determined; and second, a classifier has to be trained to discover the privacy pattern based on the features. These types of solutions can assist OSN users to make proper privacy decisions from a data-driven aspect. Using machine learning to discover and model privacy patterns from data can help eliminate individual bias in privacy decisions caused by human cognitive diversity and provide more personalized recommendations.

Predictions from content. Considering that the privacy of a visual image is likely tied to its content, Tran et al. [85] proposed an end-to-end framework that extracted hierarchical features from the visual content of images for privacy classification. The hierarchical features consisted of two components: the object feature extracted by an object detection convolutional neural network (CNN) and the CNN features extracted by a generic CNN. A support vector machine (SVM) classifier was then developed based on hierarchical features to make the final decision. This framework was able to not only identify private images with a high degree of accuracy but also infer which objects made the image private from the output probabilities of the object detection CNN.

Yu et al. [86] proposed another study about learning object-privacy relatedness using deep multi-task learning. In this study, the semantic objects were first segmented from the image and then aligned automatically with different privacy settings based on an object-privacy relevance score via random walk. Then privacy-sensitive objects were detected using a deep multi-task learning algorithm (constructed by joining a deep CNN to a tree classifier). This allowed the privacy decision to be improved from the coarse image level to a fine-grained object level.

Predictions from context. As OSN image privacy depends not only on the content but also the associated context (such as tags), some authors explored the capacity of utilizing multi-modality feature fusion for privacy prediction. Zerr et al. [87] developed a method to fuse hand-crafted visual feature vectors and textual feature vectors. The visual features, including the edge feature (Edge Direction Coherence Vector or EDCV), object feature (Scale-Invariant Feature Transformation or SIFT) and color feature (color-histograms), implied the multi-level visual nature of an image. The textual features were constructed as the term frequencyinverse document frequency (tfidf) of tags. Squicciarini et al. [88] applied a similar feature fusion method. In addition, the authors investigated the effectiveness of privacy prediction in different feature combination sets and identified the smallest set performing the best was the combination of SIFT feature and tag feature.

In contrast to the hand-crafted features, some researchers applied deep feature encoding for privacy-related feature extraction, taking advantage of the progress in deep learning.

Tonge et al. [89] studied the usefulness of deep visual features extracted from various layers of a deep CNN named AlexNet [90], as well as the deep tags annotated as the top k objects recognized by AlexNet when classifying image privacy. In a follow-up study by the authors [91], they proposed a dynamic feature fusion algorithm for multiple modalities including image objects, scenes and tags. Given an image, the algorithm would first identify two groups of neighborhood images using visual similarity and sensitive content similarity. Then a competence estimator was developed based on the neighborhood images to rank the competence of each base model trained from a single modality. Voting on the decisions of the most competent modalities eventually predicted the privacy label of the image.

Another concern specified for OSN image privacy prediction is the social group tendentiousness with regard to privacy, i.e., the same image may result in different privacy decisions by different groups according to the group preferences. Looking at this problem, Zhong et al. [92] proposed a stochastic group-based personalized model (GBPM) for OSN image privacy classification. The concept of a privacy group was defined as referring to a group of users who shared a finite set of patterns for privacy decisions. For each user, the group membership, which meant the user belonged to a certain group, was regarded as a latent variable. The personalized model then estimated the probabilities for a user associated with each group to label a photo as private based on the labeled image patches provided by the user and the user's demographics info. Given an unseen image, the user-specific probability that the image is private is then an average of the privacy posteriors in each group.

4) Solutions for incautious tagging:

a) Tagged image control: Incautious or unauthorized tagging easily violates privacy of the tagged subjects. For example, tagging names on others' faces will make the faces easy to recognize, and may lead to a social impression suppression if the scene recorded in the tagged image is embarrassing. Some PSPs like Facebook provide an untagging mechanism by which tagged users can delete their tags. However, this mechanism can result in a continuous competition cycle of retagging and untagging until one party compromises, leading to a social ownership tension between the image owner and tagged user.

To alleviate the problem, Besmer et al. [93] first conducted a user study among 18 undergraduates to analyze the privacy needs and concerns of tagged photos, through which a set of design considerations were identified for tagged photo privacy. Based on these design considerations, the authors then developed a tagged photo control tool allowing tagged users to send specific sharing requests to the owner that the tagged photo should be hidden from certain people. As a result, tagged photos can be collaboratively controlled by both parties rather than the image owner only, easing the social ownership tension.

b) Privacy-aware tag recommendation: Manual tagging at the sole discretion of human users is likely to inadvertently inflict privacy invasion. Tonge et al. [94] proposed a privacy-aware tag recommendation approach that could provide high-

quality privacy-aware tags for each target image automatically. Specifically, the approach first identified the top k similar neighboring images for a target image based on both visual content similarity and tag similarity. Then for each candidate tag in the target image, a privacy-aware ranking algorithm was performed based on the sum of similarities between the target image and its neighboring images and the probability likelihood that the tag belonged to the privacy class (e.g., public or private). Tags likely correlated to different image privacy patterns could therefore be identified, and tags were finally recommended according to the ranking scores.

C. Discussion

Table I provides a breakdown of the reviewed solutions at this stage. The images are held and controlled by the owners and the owners have few online interactions with others. Therefore, the main privacy concern is the limitation of the owner's cognitive capabilities regarding privacy. As a result, the behaviors of the image owners sometimes unwittingly violate the privacy desires of themselves or others.

The major target of privacy intelligence at this stage is to automatically identify the risk of privacy leakage in order to help improve human cognition of privacy. Most of the solutions are performed in a human-computer-interactive fashion, where the computer alerts the image owner of risks prior to sharing and leaving the ultimate decision to be made by humans. The privacy intelligence at this stage can be viewed as *preventive intelligence*.

In addition, there are some overarching tasks for some intelligent solutions from the technical perspective. For example, for those solutions involving unintended capture and in-device leakage detection, the capacity for real-time processes with a power overhead is required, given the limited computational resources in camera devices. For the solutions involving privacy unawareness, the core task is to find out the factors that influence the privacy pattern. To this end, privacy awareness empirical studies often attempt to conduct large-scale user studies to eliminate demographic bias in privacy cognition, while learning-based prediction solutions normally leverage feature engineering to discover the relevance of privacy. For the solutions involving incautious tagging, preserving contextual privacy while providing tags with high-quality and social usability is a crucial design goal.

From the perspective of practical implementation, all the reviewed solutions at this stage can be performed in an offline mode. This offers the chance to integrate these solutions locally in a modular manner, which can be embedded into end devices in the case of cameras or implemented in the user interfaces of OSN services.

IV. PRIVACY INTELLIGENCE IN ONLINE MANAGEMENT

In this section, we first identify the possible privacy issues that arise from user behaviors at the online management stage. Then the intelligent solutions aiming at addressing each issue are investigated in detail. Figure 5 offers an overview of privacy issues and corresponding intelligent solutions at this stage. Each privacy issue is linked to its user behavior cause

and the corresponding intelligent solutions. There are in total 6 kinds of intelligent solutions at this stage.

A. Privacy issues in online management

1) Privacy issues in privacy preference setting:

- **Coarse-grained setting.** Currently, the privacy preference setting configurations provided by most PSPs only allow coarse-grained options, e.g., whether an image is public, private or visible to their family members or friends, which is far from meeting practical privacy needs given the complexity of OSN image privacy. Moreover, the manual settings are error-prone and tedious, inflicting additional burdens on users. Given the large amount of shared information and the lack of privacy-related knowledge, users normally struggle to set up and maintain such settings to achieve desired levels of privacy protection [22], [95]–[97].
- **Multi-party privacy conflicts.** The other privacy issue in privacy preference setting is the MPCs problem, arising from shared content which is closely related to multiple stakeholders. As users behave differently regarding the ways they disclose information [98], they may have different perceptions regarding what content is sensitive, resulting in different privacy needs. Issues occur when the choices of the sender go against those of other stakeholders, or the privacy setting of one owner overrides those of other co-owners. However, the current privacy preference setting mechanisms cannot effectively handle cases where the stakeholders have conflicting settings: the configuration is fully controlled by the sender whereas other stakeholders are not granted any say in the matter, and the sender is not required to solicit the opinions of all the other stakeholders before publishing the image.

2) Privacy issues in image publishing:

- **Undesirable visual exposure.** Undesirable visual exposure is a common concern in OSN image sharing. Users do not want to expose sensitive image content to unwanted viewers, given that it may cause impression suppression and economic losses. Yet there are numerous ways of incurring undesirable visual exposure. Although the PSPs provide basic access control mechanisms for image visibility via privacy preference settings, it is impractical to expect users to configure every shared image. And sensitive images can still be exposed even with well-chosen privacy configurations. For example, images can be accessed by unauthorized hackers by-passing PSPs' access control [11]–[13], or passed on by authorized recipients to other viewers counter to the privacy preferences of the original sender.
- **Malicious inference.** Nowadays, the pervasive use of recognition systems in OSN image sharing brings with it the increased risk of malicious inference which violates privacy. The rich semantic knowledge contained in the image data can convey high-level sensitive information beyond the direct visual content. Previous studies showed that using ML models, implicit information such as occupation [7], health condition [8], dating relationship

TABLE I
A SUMMARY OF PRIVACY ISSUES AND CORRESPONDING INTELLIGENT SOLUTIONS AT THE LOCAL MANAGEMENT STAGE

User behavior	Privacy issues	Intelligences	Paper & Year	Techniques	Summary
Image capture	Unintended capture	In-device content filtering	[69] 2007	Hardware engineering	Performed in-device filtering in static environment
			[72] 2015	Hardware engineering	Performed in-device face anonymization in real-time
			[73] 2016	Software engineering	Developed a platform for individual privacy policy-compliant content filtering in camera
		[47] 2018	Software engineering	Developed a camera app add-on enabling privacy-respecting photographing	
		Physical privacy marker	[74] 2009	Machine learning	Designed a visual color-tracker for camera tracking physical privacy hints
			[76] 2014	Protocol design	Designed a set of visual symbols for elementary privacy preferences expression
	[77] 2014		Protocol design	Designed a QR-code for physical privacy concern expression	
Information leakage	In-device leakage detection	[48] 2017	Software engineering	Analyzed camera data leakage in popular OSN apps with photo-based functionality	
Image selection	Unawareness of privacy	Human-based empirical study	[78] 2007	Quantitative survey	Studied how people make their instinctive privacy decisions in real-world online photo sharing
			[80] 2015	Follow-up user study	Studied the privacy concerns of wearable camera users towards lifelogging photos
			[81] 2020	Online factorial vignette study	Studied the dependence of privacy on social norms and collectively-shared expectations
			[10] 2015	Data-driven investigation	Assessed the privacy risks arising from metadata during the online propagation process
			[83] 2017	Qualitative survey	Studied users' ability in identifying and resolving the multiparty privacy conflicts (MPCs) problem
		Learning-based privacy prediction	[85] 2016	Deep learning	Proposed an end-to-end framework using visual content for privacy classification
			[86] 2017	Deep multi-task learning	Predicted privacy by learning the object-privacy relatedness from social images
			[87] 2012	Feature engineering	Predicted privacy by fusing the hand-crafted visual feature and the textual feature
			[88] 2014	Feature engineering	Identified the smallest feature fusion set that performed the best at privacy prediction
			[89] 2019	Deep learning	Studied the usefulness of the deep visual features combined with deep textual features for privacy prediction
			[91] 2019	Deep learning	Developed a dynamic feature fusion algorithm for recognizing privacy patterns using multi-modality information
			[92] 2017	Statistical learning	Predicted privacy according to social group tendentiousness
Image description	Incautious tagging	Tagged image control	[93] 2010	Protocol design	Analyzed users' privacy needs regarding tagged photos and developed a tagged photo control tool
		Privacy-aware tag recommendation	[94] 2018	Feature engineering	Developed an automated system for high-quality and privacy-aware tag recommendation

[99] and sex orientation [9] can be derived from the OSN images. However, compared with undesirable visual exposure, malicious inference is normally inconspicuous, and guarding against it is challenging since it is associated with latent features underlying the image data, which are hard to recognize and filter out by naive visual image processing.

B. Intelligent solutions in online management

1) Solutions for coarse-grained setting:

a) *Personalized policy generation:* The default privacy preference setting options applied by most of PSPs can provide personalized sharing policies for individual OSN users. Therefore, some researchers studied intelligent policy generation which can mine fine-grained privacy policies according to the context of social image sharing and user profiles.

Policy recommendation. The descriptive information of OSN images such as tags and captions can be used to generate effective privacy policies for users. In an 18-participant laboratory study, Klemperer et al. [100] found that the tags

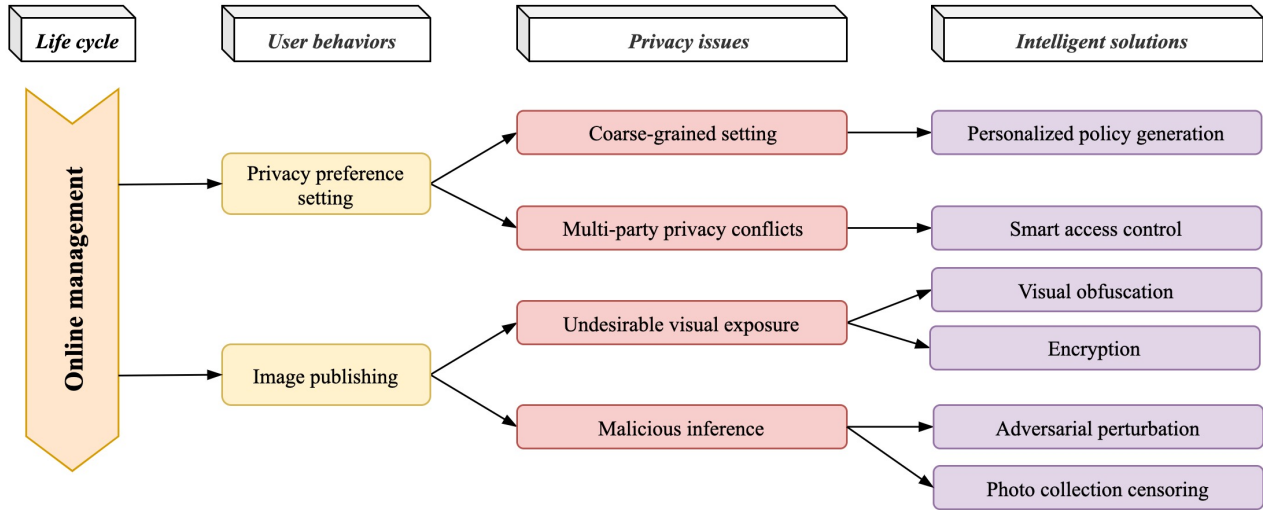


Fig. 5. Overview of privacy issues and corresponding intelligent solutions at the local management stage. Each privacy issue is connected to the inducing user behaviors and the corresponding intelligent solutions by arrows.

added for organizational purposes by photo owners can be repurposed to help them create more efficient and relatively accurate sharing rules, especially when they tagged photos with access control in mind. Yeung et al. [101] developed a policy recommendation mechanism using both tags and linked data provided by Semantic Web. The core idea is to assist users in matching different groups in their social circles to specific tags. For example, a photo tagged as 'birthday' can only be accessed by friend group. Their mechanism was implemented as a browser plug-in prototype using several Web technologies, including the OpenID protocol [102] for authentication, the Tag Ontology [103] for tagging activity representation, the AIR Policy Language [104] for access control policies creation, and the Tabulator [105] for user interface design.

Policy inference. Compared with policy recommendations created by pre-defined rules, some researchers explored intelligent policy inference, which creates more efficient and accurate privacy policies automatically with computer assistance. Squicciarini et al. [106] proposed a two-level policy inference framework called A3P (Adaptive Privacy Policy Prediction). The first-level component, A3P-core, focused on inferring individual privacy policy. It first classified the newly uploaded image into categories associated with similar policies based on image content and metadata, then decided the privacy policy by hierarchical association rule mining and user tendency-based prediction. The second-level component, A3P-social, aimed at adaptively adjusting users' privacy policies over time, by adopting a multi-criteria inference approach to improve policies with regard to users' historical social context and general attitude toward privacy. The A3P simultaneously took the social context, image content, and metadata into policy consideration.

Another study on intelligent policy inference from Yu et al.

[107] considered that content sensitivity and user trustworthiness were inseparable for determining privacy policy. To this end, the authors proposed a tree classifier-like policy generator that was trained on the basis of the seamless integration of the image content sensitivity and the user trustworthiness. The image content sensitivity was represented at both the deep feature level and the privacy-sensitive object level. The user trustworthiness was represented by social group clustering based on users' social behaviors (such as closeness of the relationship and matching scores of interests).

2) *Solutions for multi-party privacy conflicts:*

a) *Smart access control:* The personalized policy generation can be seen as an individual-based access control mechanism which recommends policy automatically while leaving the final decision to the image sender. Despite meeting the individual privacy needs of the sender, this mechanism fails to address the problem of conflict of interests due to senders likely being isolated from other stakeholders when setting local policies. In contrast, the smart access control mechanisms which are centralized on the PSPs' servers can manage the image sharing process from a global privacy perspective for all OSN users.

Personal identity-based access control. One approach for centralized access control is to leverage personal identifiable information (PII) in the shared image to perform permissions from all stakeholder sides rather than just the sender side. When a viewer posts an access request, the server determines the access level of the viewer by matching the PII of the depicted stakeholders and their access control list. For example, Ilija et al. [108] used faces as PII and designed a 3D matrix access control model based on the subjects (users), object groups (photos) and objects (faces) to manage multi-owner control policy. The owner (defined as the subjects depicted in the photo) identified by face recognition set their specific

permissible viewer lists denoted as entries in the matrix. Then when an access request arrived, the system decided which face should be hidden according to the matrix. Similarly, Li et al. [109] developed HideMe, a framework that granted the control rights to every depicted user. The difference from Ilia et al. [108] is that HideMe provides an automated access control mechanism instead of setting policies photo-by-photo by users themselves. The mechanism identified each depicted user and associated the corresponding scenarios with this photo, including temporal, spatial, interpersonal, and attribute factors, to establish a scenario-based access control. In addition, the author also designed a photographic distance-based algorithm to identify and protect the privacy of bystanders.

Social norm-based access control. Another approach for centralized access control is to leverage social norms to regularize image propagation. This type of approach normally formulates the access control mechanism on the entire social graph $G \triangleq \langle V, E \rangle$, where V is the set of users in this social network and E the set edges connecting pairs of users with a certain relationship.

Xu et al. [110] designed a trust-based access control mechanism in a global incentive fashion instead of collecting permissions. This mechanism was built on the maintainability of the mutual trustworthiness between OSN users, which could prompt a dynamic social ecosystem where the participants were incentivized to respect others' privacy actively when sharing images. Specifically, aiming at preserving the privacy of photo stakeholders who can be identified in the shared photo, the authors formulated the privacy loss of one stakeholder as negatively correlated with the trust between the stakeholder and the recipient and positively correlated with the user-specific sensitivity of the photo. In each photo propagation round, the PSP utilized privacy loss to perform anonymization for each stakeholder and updated the trust between the sender and the stakeholder for the next propagation round according to the stakeholders' feedback. As a consequence, users were encouraged to pay attention to others' privacy in OSN photo sharing activities to gain more trust from others continuously and improve the social relationship.

A photograph may easily bypass the pre-defined privacy setting and eventually reach a wider audience through unanticipated channels of disclosure if re-shared via other social connections by the recipients. Lin et al. [111] proposed an access control mechanism to alleviate this problem by estimating the privacy risk of unwanted image disclosure through the social graph. Specifically, based on the big data regarding image sharing history possessed by PSPs, the authors built a sophisticated probability model that aggregated the image disclosure probabilities along different propagation channels. The model calculated the probability that different users will be able to view an image if one particular user decided to share it within social networks of varying sizes. If the computed disclosure probability indicated high risks of a privacy breach, e.g., if the image was likely to be disclosed to unwanted users who were not included in the original sharing list, then the privacy policy was adjusted accordingly. This mechanism offered a direct and quantitative view of the risk of sharing.

3) Solutions for undesirable visual exposure:

a) *Visual obfuscation:* Visual obfuscation is widely used to prevent shared images from exposure to potential viewers through hiding or removing sensitive visual content via direct image modification. Figure 6 shows examples of different visual obfuscation methods. The traditional visual obfuscation methods such as blurring, pixelation, cartooning and abstracting have been well summarized in previous surveys [33], [35].

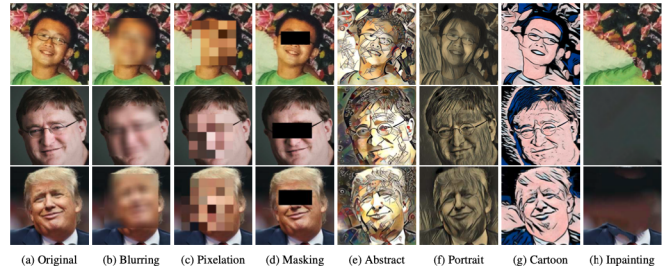


Fig. 6. Different visual obfuscation methods. Reprinted from [112].

Obfuscation with natural inpainting. One major concern of visual obfuscation is how to fill in the region that remains naturally after the object is removed to make the image realistic; otherwise, the user experience will be damaged in terms of social sharing purpose and malicious viewers could easily perceive that the image has been edited (and therefore could potentially recover the hidden region [113], [114]). The images processed by the aforementioned traditional methods suffer from a considerable loss of visual integrity. In contrast, some novel visual obfuscation methods that benefit from modern computer vision techniques show promise power in disentangling the problem. Recently, the generative adversarial net (GAN)¹-based [115] image inpainting technique, which can seamlessly blend the inpainting patches into the surrounding scene context of the targeted region, has attracted the attention of the research community given the remarkable performance of GAN in synthesizing authentic-looking images [116]–[119].

Uittenbogaard et al. [120] proposed an image inpainting framework for object removal to protect the privacy of pedestrians and vehicles in street-view imagery. The framework leveraged a set of consecutive images of the same streetview scene for the detection and segmentation of objects to remove by exploiting consistencies in depth across these images. Then a multi-view GAN was developed with the multi-view information serving as a prior to guide the region reconstruction for final inpainting.

Sun et al. [121] proposed a head replacement approach using GAN-based inpainting. The challenge of realistic head replacement is that heads depicted in social media photos normally appear in diverse activities and orientations. The author addressed this problem by adopting GAN in two stages. First, a deep convolutional generative adversarial network (DCGAN) [122] was constructed to generate facial landmarks from image context (e.g. body pose) to sensibly represent the head pose.

¹Generative adversarial net is a kind of generative machine learning model that learns to map from a latent space (e.g., random noise) to a data distribution of interest (e.g., targeted images) by contesting with a discriminative model via adversarial learning [115].

Then another DCGAN was developed as the head generator conditioned by the generated facial landmark. In a subsequent article, the authors [123] improved the head generator from facial landmarks to rendering faces with controllably different identities. Specifically, the identity-related component of the original face was abstracted as a semantic parameter vector using 3D Morphable Model (3DMM) [124]. Then the semantic parameters were modified and clustered into different identity groups, providing an explicit manipulation of identity. Finally, the rendering faces were synthesized based on the identity groups using the Model-based Face Autoencoder (MoFA) [125] for the subsequent inpainting.

Obfuscation with measurable privacy. Another concern of visual obfuscation is that most solutions protect image privacy in an intuitionistic manner and fail to provide rigid and provable privacy guarantees. To alleviate this drawback, Fan et al. [126] proposed a visual obfuscation solution based on metric privacy [127] which was generalized from differential privacy [128], [129]. The solution contained two main steps: First the sensitive ROI was transformed into a k -dimensional feature vector using Singular Value Decomposition (SVD), which could support invertible transformation by preserving image perceptual similarity in the transformed domain [130]. Then a sampling mechanism satisfying the metric privacy was performed on the feature vector according to certain probability distributions. The sampled vector was then transformed inversely to replace the original region in the image.

Li et al. [112] proposed a privacy-preserving attribute selection algorithm for facial image obfuscation, which provided measurable privacy by selecting facial attributes for anonymization with privacy guarantees. First, 40 facial attributes were selected by a combination of GoogLeNet [131] and random forest classifier [132] to construct an attribute set. Then each attribute belonging to the attribute set was modified with the constraint that the distribution of any attribute would be close to its real-world distribution subject according to t -closeness [133]. Moreover, a stochastic perturbation was imposed on the edited attribute set to satisfy ϵ -differential privacy. The final anonymized attributes were reconstructed into a new face using StarGAN [134] (a variation of GAN) to achieve natural obfuscation.

b) Encryption: Encryption is another method widely applied for preventing visual exposure end-to-end. There are two major technical design goals in OSN image encryption. One is to maintain recoverability of encryption conditioned on the OSN image transformation. Most of OSN PSPs convert the uploaded images to a uniform format for better storage and communication needs, regardless of the original format. For instance, Facebook converts all photos to JPEG with certain quality settings. Therefore, the encryption/decryption mechanism is expected to be resilient to OSN format transformations, such that the recipient is able to retrieve the original image from the OSN-transformed version. The other goal is to perform more personalized and fine-grained encryption. Rather than encrypting the entire image, this would allow partial or hierarchical encryption in accordance with the content of the image or the identity of the recipient.

Encryptions focusing on recoverability. Tierney et al.

[135] proposed an end-to-end encryption system, Cryptagram, that considers recoverability when factoring encryption robustness to lossy OSN image compression such as JPEG transformation. With the goal of preserving data confidentiality and probabilistic data integrity for lossy images, the authors defined a notion of q, p -Recoverability that given a minimum quality level q of the transformed image, an authorized recipient can decode the original image with a high probability p . To attain the q, p -Recoverability property for different levels of JPEG compression, the system first encrypted a to-be-shared image using the standard block cipher algorithm AES with a secret key to produce a byte sequence. Then the authors designed a class of JPEG embedding protocols that can operate completely in the encrypted bit space by embedding cryptographic primitives. Cryptagram can be implemented as a browser extension integrating seamlessly with preexisting OSNs, including Facebook and Google+.

Another work from Sun et al. [136] further propelled the exploration on encryption robustness for OSN image transformation under the condition that the lossy manipulations by OSNs are usually unknown and free of user control, resulting in the design of a secure, robust, high-fidelity and storage-efficient image sharing scheme over Facebook. The authors first investigated the operations that Facebook applied to the uploaded images and found that four types of operations were performed, including format conversion, resizing, JPEG compression, and enhancement filtering. With prior knowledge of the manipulations, the authors estimated the parameters employed in these operations through an offline training procedure to develop a DCT-domain image encryption scheme that was robust against these particular lossy operations.

Image steganography [137], a cluster of techniques that hide cryptographic data in the original image, provides another potential avenue for recoverable encryption. For example, Fu et al. [138] proposed a reversible data hiding scheme in encrypted images based on an adaptive encoding strategy. Specifically, the original image content was encoded by block permutation and stream cipher. By analyzing the distribution of most significant bits (MSB) [139], embeddable blocks were first decided, followed by the generation of auxiliary data. Then the MSB layers are encoded with occurrence frequency to create room for the embedding of additional data into an encrypted image with reversed Huffman codewords. Based on the availability of encryption key and data hiding key, the recipient can efficiently perform data extraction, image decryption and image recovery separately.

Encryptions focusing on personalization. Compared with the aforementioned techniques which secured the whole image, some studies attempted to partially encrypt the image to provide more personalized solutions propagated via different communication channels. For instance, Ra et al. [140] proposed an image sharing system that separated an image into a public part and a private part by a component-based threshold. Then the private part was encrypted in the Discrete Cosine Transform (DCT) domain while preserving the public part as a standards-compatible plaintext form. These two parts were shared independently according to the authorization of the recipient.

He et al. [141] proposed similar work on partial encryption of shared images named PUPPIES. There were two major differences. First, PUPPIES provided a more personalized separation of the image which leveraged a ROI detection and recommendation mechanism to identify the private part and allowed users to customize their privacy-sensitive regions. Second, PUPPIES designed several DCT coefficient preserving methods to perturb images, which were transparent to image transformation techniques and could support most image processing libraries without any extra cost.

4) Solutions for malicious inference:

a) *Adversarial perturbation*: Intuitively, visual obfuscation may prevent malicious inference indirectly because the original sensitive visual content has been removed or edited from the image. However, in most cases the privacy infringed by malicious inference is at a higher level, depending more on the implicit semantic relevance of the global image content than partial visual objects or regions. In fact, some studies have found that some ML systems can still make correct inferences using a partially obfuscated image [142], [143]. Visual obfuscation solutions are therefore viewed as insufficient to prevent adverse inferences, and more specific solutions are needed to prevent inferences from latent attributes. Recently, inspired by the evolving techniques of generative adversarial attack [144]–[146], which add human-imperceptible noises to the raw image to encroach on the decisions of ML models, some scholars designed adversarial perturbation mechanisms for inferential privacy protection.

Chhabra et al. [147] explored the possibility of anonymizing certain attributes for privacy preservation and fooling automated attribute inference systems. The authors proposed a general adversarial perturbation framework inspired by k -anonymity [148]. The proposed framework embedded imperceptible noise in an image such that ML systems yielded incorrect classification results for the selected attributes. The key idea was to design appropriate adversarial objective functions for adversarial learning. The objective functions anonymize targeted latent attributes selectively in line with users' desires while preserving the visual quality of images. The proposed algorithm enabled a user control mechanism where users can select single or multiple attributes to be surpassed while preserving identity information and visual content.

Another work from Shen et al. [149] further pushed forward the level of human imperceptibility in adversarial perturbation. The key idea was the novel design of a sensitivity map. The authors conducted a series of human studies to empirically explore human sensitivity to visual changes of multi-level image features. The results revealed that human sensitivity was influenced by multiple factors, from low-level features such as illumination and texture to high-level attributes like object sentiment and semantics. Based on the findings, a new concept sensitivity map was proposed, which indicated different levels of human sensitivity within an image. Using the sensitivity map, the authors designed a sensitivity-aware perturbation model that was able to modify the sensitive image attributes while keeping other attributes unaltered. By integrating the image sensitivity map, the proposed perturbation model was able to reach a high degree of human imperceptibility.

b) *Photo collection censoring*: Different from the attribute inference from a single image, photo collection can also reveal some inferential clues when aggregating information. For example, even without geotags, location information can be leaked from photo collections created in the same location.

To overcome this problem, Yang et al. [150] considered how to limit associated inadvertent geolocation privacy disclosure by carefully pruning select photos from photo collections before publishing, i.e., selecting a minimal set of images to delete from a given collection such that the true location was not included in the most likely locations predicted from the remaining images. The authors formulated collection censoring as a combinatorial optimization problem in the context of geolocation prediction facilitated by deep learning. They first demonstrated computational complexity both by showing that a natural greedy algorithm can be arbitrarily sub-optimal and by proving that the problem is NP-Hard (since the optimal deletion set should not just censor the images that were most indicative of the true location but also maintain the likelihood of plausible alternatives). They proposed a mixed-integer linear programming (MILP) formulation for the NP-Hard problem to allow the use of standard MILP solvers.

C. Discussion

Table II provides a breakdown of the reviewed solutions at this stage. The images are mutually controlled by both the owners and the PSP in interim interactions, and going to be released presently. Therefore, the major privacy concern is the risk of information disclosure to unwanted recipients. Accordingly, the main target of privacy intelligence here is to provide differentiated and personalized methods to protect images from unwanted disclosures at different levels. In this way, the privacy intelligence at this stage can be seen as *protective intelligence*.

From the technical perspective, two kinds of techniques are widely adopted in the intelligent solutions reviewed at this stage: facial identity recognition and adversarial learning. Facial identity recognition technique ensures the automated recognition of identity, which is an influential factor in social relationship-based privacy management, and thus has been extensively applied in personalized solutions to privacy policy inference and smart access control. Adversarial learning technique optimizes for the specific objective using conditional constraints by converging towards an equilibrium among multiple competing objectives. It can create powerful generative models for visual obfuscation and adversarial perturbation which generate images with manipulated content from the raw visual data.

From the perspective of practical implementation, all the reviewed solutions at this stage can be implemented and integrated into the PSP server as a cloud-based control engine. The centralized schedule of the server can ensure multiple protective solutions to be activated in an orderly and efficient manner, as well as free from users' perception and intervention.

TABLE II
A SUMMARY OF PRIVACY ISSUES AND CORRESPONDING INTELLIGENT SOLUTIONS AT THE ONLINE MANAGEMENT STAGE

User behavior	Privacy issues	Intelligences	Paper & Year	Techniques	Summary	
Privacy preference setting	Coarse-grained setting	Personalized policy generation	[108] 2015	Rule design	Assisted users in matching different groups in their social circles to specific tags	
			[106] 2014	Machine learning	Developed an Adaptive privacy policy prediction model using social context, image content and metadata simultaneously	
			[107] 2017	Machine learning	Intelligent policy generation based on content sensitivity and user trustworthiness	
	Multi-party privacy conflicts	Smart access control	[108] 2015	Mechanism design	Designed a 3D matrix access control model among subjects, object groups and objects	
			[109] 2019	Mechanism design	Designed an access control mechanism based on the temporal, spatial, interpersonal, and attribute factors in an OSN context	
			[110] 2019	Mechanism design	Designed an access control mechanism based on the mutual trustworthiness between OSN users	
			[111] 2020	Probability model	Designed an access control mechanism based on the image disclosure probabilities along different propagation channels	
Image publishing	Undesirable visual exposure	Visual obfuscation	[120] 2019	Generative model	An image inpainting framework for object removal in street-view imagery	
			[121] 2018	Generative model	GAN-based head replacement approach for heads with diverse activities and orientations	
			[123] 2018	Generative model	Head replacement using a GAN-based head generator with controllable different identities	
			[126] 2019	Anonymization	Visual obfuscation with rigid and provable privacy guarantees based on the metric privacy	
			[112] 2019	Anonymization	A privacy-preserving attribute selection algorithm for facial image obfuscation with differential privacy guarantees	
			Encryption	[135] 2013	Bit encryption	Designed an image encryption system which is tolerant to standard image transformations applied by PSPs
				[136] 2018	DCT-domain encryption	Proposed a DCT-domain image encryption/decryption framework that was robust against lossy operations
				[138] 2019	Image steganography	Proposed a reversible data hiding scheme in encrypted images based on the adaptive encoding strategy
				[140] 2013	DCT-domain encryption	Encrypted a part of the photo and shared it separately from the remaining public part
	[141] 2016	DCT-domain encryption		A dynamic encryption system allowing users to encrypt specific private image regions for given receivers		
	Malicious inference	Attribute perturbation	[147] 2018	Adversarial learning	Proposed a general adversarial perturbation framework anonymizing k -facial attributes	
			[149] 2019	Adversarial learning	Designed a sensitivity map to enhance the level of human imperceptibility in adversarial perturbation	
		Photo collection censoring	[150] 2020	Mixed-integer linear programming	Limited associated inadvertent geolocation privacy disclosure by pruning photo collections	

V. PRIVACY INTELLIGENCE IN SOCIAL EXPERIENCE

This section identifies the possible privacy issues arising from the user behaviors at the social experience stage and then provides an investigation of the intelligent solutions targeting each privacy issue. Figure 7 offers an overview of privacy issues and corresponding intelligent solutions. Each privacy issue is linked to its user behavior cause and the corresponding intelligent solutions. There are in total 8 kinds of intelligent solutions at this stage.

A. Privacy issues in social experience

1) Privacy issues in image viewing:

- **Utility loss.** As the original purpose of OSN image sharing is to convey information to authorized recipients, it is expected that the visual integrity of the shared images will be preserved when viewed by recipients. However, many solutions such as visual content obfuscation and partial encryption require processing the visual content. The images therefore might suffer from utility loss. This prompts the desire to find solutions that balance privacy-preserving effectiveness and the utility of image applications.
- **Image tampering.** When images are received by recipients, control over them by both the sender and PSP is lost. The recipients are able to store, edit and reuse the image

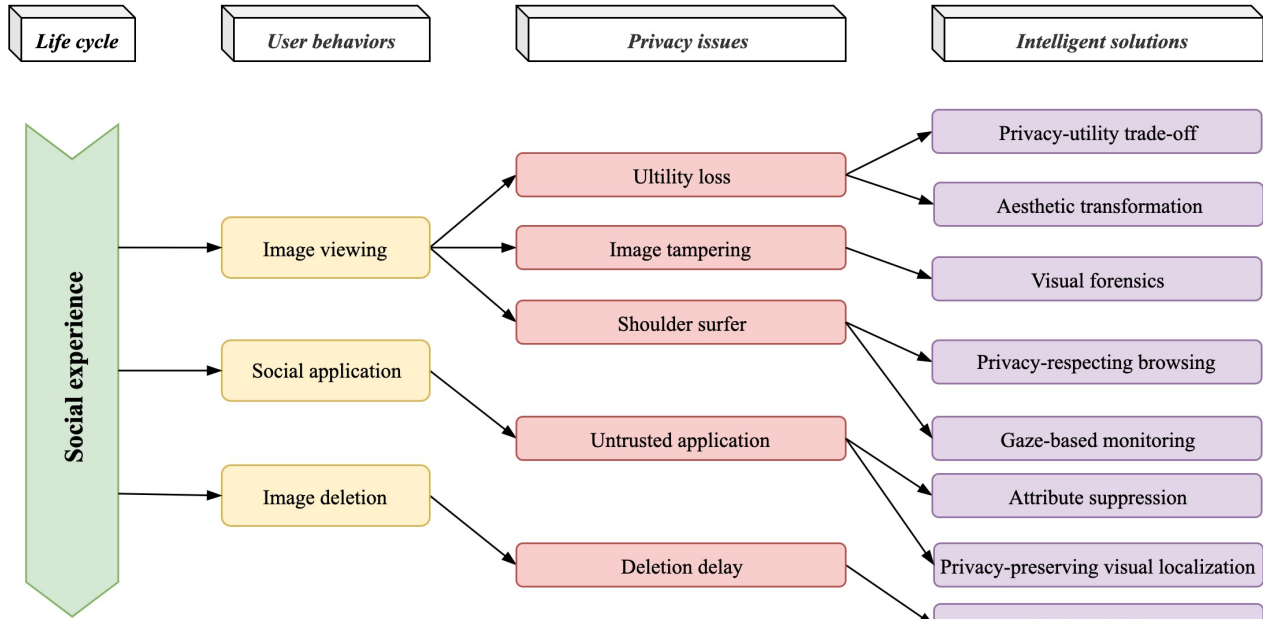


Fig. 7. Overview of privacy issues and corresponding intelligent solutions at the social experience stage. Each issue is connected to the inducing user behaviors and the corresponding intelligent solutions by arrows.

freely, resulting in the potential for image tampering. Although digital watermarking techniques are widely adopted to ensure the copyright of the image owner [151]–[153], this set of techniques is vulnerable to various removal and geometrical attacks [154]–[156]. In addition, it is difficult to prevent the original visual content from being tampered with. For example, an emerging set of image tampering techniques called DeepFake can synthesize fake yet realistic media records from the original visual content (such as a human face) [4]. This novel image tampering technique has led to heightened public concern due to its powerful counterfeiting capability and the difficulty of defending against such measures [5], [6].

- **Shoulder surfer.** Shoulder surfing refers to unauthorized viewers who access visual content by uninvited looking at a recipient’s screen. The convenience of mobile devices in viewing images anywhere and anytime easily leads to such leakages.

2) Privacy issues in social application:

- **Untrusted application.** Another purpose for modern OSN image sharing is to employ some social applications that rely on photo-based services, such as entertaining age estimation applications or ancillary life-loggers. This kind of applications normally require the use of an automated recognition system with remote deployment in the cloud, where the image owner exercises little if any control [157]–[161]. This may harbor the risk that a dishonest application may perform excessive recognition procedures outside of the user’s authorization, in effect

stealing information for commercial benefit from the photo.

3) Privacy issues in image deletion:

- **Deletion delay.** A satisfactory privacy management system in modern OSN image sharing should seriously respect the users’ right to be forgotten, which is required by the European General Data Protection Regulation (GDPR) [162]. In other words, once the sharing purposes are completed the image should be removed from OSN by certain strategies to avoid the possibility of malicious use. However, at present OSN image sharing easily suffers from an issue of deletion delay [163], which means the image exists much longer online than expected by the user, even after a clear deletion request from the user has been activated. For example, it had been reported that the user-deleted photos on Facebook were still accessible online after many years [164] and images deleted from Snapchat could be recovered by hackers [13].

B. Intelligent solutions in social experience

1) Solutions for utility loss:

a) *Privacy-utility trade-off:* Given that a lot of powerful privacy protection techniques will lead to a certain visual utility loss which goes against the original purpose of social sharing, some scholars have made efforts to find out the trade-off between privacy and utility.

Some studies conducted human-centric investigations from the perspective of human-computer interaction. For example, Li et al. [165] studied the effectiveness and human viewers’

attitudes of applying two partial obfuscation techniques (blurring and blocking images) as a privacy-enhancing technology. The author reported results from an online experiment with 53 participants that explored users' perceptions of these obfuscations in terms of image satisfaction, information sufficiency, enjoyment, and social presence. Their results showed that although blocking is more effective at de-identification than blurring, users' attitudes towards blocking are the most negative. In a subsequent online experiment [166] with 271 participants conducted by the same authors, they found blurring, pixelating, inpainting, and avatar (which replaces content with a graphical representation) were preferable from a viewer experience perspective while inpainting and avatar were the most effective in privacy-enhancing obfuscation. Similarly, in another online experiment with 570 participants, Hasan et al. [167] studied five different image transformations applied to obfuscate twenty different objects and attributes, and evaluated how effectively they protect privacy and preserve image quality for human viewers from both the aspects of visual aesthetics and user satisfaction. Their results showed that in some scenarios a high degree of privacy can be attained while retaining utility.

Some other studies tried to probe the trade-off by automation. For instance, Raval et al. [168] built upon the adversarial learning framework to design a perturbation mechanism that jointly optimizes both privacy and utility objectives, with a primary focus of empirically quantifying privacy or utility guarantees achieved by the mechanism. The authors designed two competing networks for adversarial learning. One was an attacker network that learned to identify secrets in the obfuscated images. The other was an obfuscator network that attempted to fool the attacker by learning the correct transformation. When the competition reached the equilibrium, the obfuscator generated obfuscated images whose privacy was maximally preserved while minimizing the visual utility loss. (In addition, the authors discussed whether the adversarial perturbation approach could become a basis for formally defining privacy in images.)

b) Aesthetic transformation: A plausible solution for utility loss is to restore viewer satisfaction by boosting or enhancing the aesthetics of an obscured image, thereby compensating for the negative effects of a privacy transformation. Using a between-subjects online experiment, Hasan et al. [169] studied the effects of three artistic transformations on images that had objects obscured using three popular obfuscation methods. A path model was leveraged to study the interdependencies of the utility variables. The results offered evidence that using artistic transformations can mitigate some negative effects of obfuscation methods.

2) Solutions for image tampering:

a) Visual forensics: Visual forensics is a set of solutions targeting to detect statistical or physical artifacts to verify the authenticity of visual media without evidence from an embedded security mechanism [170]–[173]. In the past decade, two techniques have been widely studied for visual forensics, namely digital fingerprints [174], [175] and digital watermarking [151]–[153]. The former leverages the unique and stable digital marks attributed to manufacturing imper-

fections of camera devices to identify the source of images, while the latter involves embedding artificial watermarks in images as complementary forensics for image authentication. These two techniques are powerful to ensure the traceability and ownership of images so as to protect the copyright. However, they are insufficient to detect the further abuse of the original visual content, such as the emerging image tampering technique named DeepFake [5], [6]. To cop with the modern threats brought by visual content tampering, a number of solutions for image manipulation detection have been proposed.

Forensics based on self-consistency. This set of solutions detect tampering by determine whether an image is self-consistent, i.e., whether its content could have been produced by a single imaging pipeline. For example, Bondi et al. [176] proposed a forensic algorithm for image tampering detection and localization based on characteristic digital footprints. The authors considered that that all pixels of a pristine image should be identified created by the same camera device. Conversely, forged images were those with composing regions taken from pictures shot with other different camera models. The proposed method was devised to examine the coherence of image portions to estimate the camera attribution of all image patches. The proposed algorithm exploited a CNN model to extract characteristic camera model features from image patches. These features were then analyzed by means of iterative clustering techniques in order to detect the manipulation and localized the alien region.

Similarly, Huh et al. [177] proposed to use the EXIF metadata to detect the self-consistency. The EXIF metadata, which was recorded automatically by a camera device, was a free and plentiful supervisory signal for learning self-consistency. The authors trained a classification model which was self-supervised in that only real photographs and their EXIF meta-data were used for training. A consistency classifier was learned for each EXIF tag separately using pairs of photographs, and the resulting classifiers were combined together to estimate self-consistency of pairs of patches in a novel input image. Therefore, the model can be trained without the need of any annotated splice or hand crafted detection cues.

Forensics based on tampering artifacts. This set of solutions examine the tampering artifacts, i.e., the abnormality of the image content to determine whether it had been manipulated. For instance, Bappy et al. [178] employed a hybrid multi-task deep learning model to detect and localize manipulated image regions by capturing discriminative features between manipulated and non-manipulated regions. The discriminative features were exhibited as spatial structures in boundaries shared with neighboring non-manipulated pixels. The model was built on a CNN along with long-short term memory (LSTM) [179] cells to end-to-end learn the boundary discrepancy, represented as the patch labels (manipulated vs non-manipulated), and pixel-wise segmentation jointly. The overall framework was capable of detecting different types of image manipulations, including copy-move, removal and splicing.

Zhou et al. [180] proposed a two-stream Faster R-CNN network [181] and trained it end-to-end to learn rich features

to detect the tampered regions. The intuition behind the two-stream framework was that when an object was removed from an image and pasted into another, the noise features between the two images were unlikely to match. Therefore, one of the two streams was an RGB stream whose purpose was to extract features from the RGB image to find tampering artifacts, such as strong contrast difference and unnatural tampered boundaries. The other was a noises stream that leveraged the noise features extracted from a steganalysis rich model filter layer to discover the noise inconsistency between authentic and tampered regions. The features from the two streams were fused through a bilinear pooling layer to further incorporate spatial co-occurrence of the two modalities. The two-stream framework outperformed the individual stream framework based on each single modality.

Forensics based on implicit pattern. Some studies detect DeepFake tampering by recognizing and authenticating the facial pattern of an individual. For example, Agarwal et al. [182] described a forensic technique that models facial expressions and movements that typify an individual's speaking pattern. The motivation was that when individuals are speaking, they exhibit relatively distinct patterns of facial and head movements [183]. As these correlations were often violated by the nature of how DeepFake videos were created, the authors exploited these regularities to build a soft biometric models of high-profile individuals to detect DeepFake videos. They first tracked facial and head movements and extracted the presence and strength of specific action units. Then they built a SVM detection model that distinguished an individual from other individuals as well as DeepFake impersonators. The proposed approach was resilient to laundering because it relied on relatively coarse measurements that were not easily destroyed, and was able to detect three common forms of DeepFake attacks, including face-swap [4], puppet-master [184] and lip-sync [185].

Note that given the DeepFake has received increasing public concerns [186]–[189], the DeepFake detection has become a booming research area and numerous solutions have been proposed. Despite the brief investigation made here, we refer the reader with interests to those meritorious surveys specific on DeepFake attack and detection [5], [6].

3) Solutions for shoulder surfer:

a) Privacy-respecting browsing: It has been shown that humans are able to recognize images and especially faces when they know or have seen them before, even when the images were highly distorted [190]. This ability is known to be stronger if users themselves created or captured the image [191]. Some studies exploited this ability to design mechanisms to prevent strangers from surreptitiously viewing images at the end device.

Tajik et al. [192] proposed an image transformation strategy based on the format-preserving encryption scheme [193] named Thumbnail-Preserving Encryption (TPE). In TPE, a ciphertext was an image that shared the same thumbnail with the plaintext image but leaked nothing about the plaintext beyond its thumbnail. Users who knew the original images were able to identify TPE-encrypted images using thumbnails with low enough resolutions, which were difficult for others

and even recognition systems to recognize. In addition, by controlling the resolution of the thumbnail preserved by the ciphertext, users can achieve a good balance between usability and privacy.

Zeuschwitz et al. [194] designed an approach to protect photos on smartphones from unwanted observations. The proposed method distorted images in a way that made the visual content hard or impossible to recognize for an onlooker who did not know the photographs. On the other hand, due to how the photos were distorted, the device owners who knew the original images had no problem recognizing them.

b) Gaze-based monitoring: Gaze monitoring has been studied by tracking eye or motion movements. It has become a promising area for privacy protection in public for digital devices, which can be applied to prevent photos by shoulder surfing [195]. Gaze-based privacy protections were investigated from two perspectives. One is active protection of image viewing by hiding content that the viewer may not care to share. The other one is to raise the user's awareness by detecting the gaze direction of bystanders.

Zhou et al. [196] designed a detector for mobile shoulder surfing which used motion tracking sensors to locate and orient an onlooker relative to a tablet. When the shoulder surfer was detected, the system resulted in multiple interfaces that raise the user's awareness of shoulder surfers through visual and auditory notifications. The authors also designed content and related scenarios to elicit privacy behaviors and gather feedback in an experimental simulation, and found that the most suitable notification technique varied with both context and content attributes.

Ragozin et al. [197] proposed Private Reader, an eye-tracking approach towards maintaining privacy while rendering visible the portion of text that is being read. The author also conducted a user study by evaluating (for both the reader and observer) privacy, reading comfort, and reading speed for different reading modes, and determined that the scrambled text mode performed best in terms of perceived effort and thwarting shoulder surfing.

4) Solutions for untrusted application:

a) Attribute suppression: The solution of attribute suppression for untrusted applications is superficially reminiscent of the aforementioned solution of adversarial attribute perturbation, in that both aim to suppress the sensitive attributes from machine perception while retaining the utility of other attributes. However, there is a significant difference in the purpose of attribute retention. Adversarial perturbation normally preserves visual utility to maximize the social experience of human viewers, while the solutions for dishonest application aim to retain features to satisfy certain functionalities of the targeted applications.

From the perspective of application functionality, solutions can be divided into identification-oriented suppression and recognition-oriented suppression.

Identification-oriented suppression. Some studies considered the problem of perturbing a face image to defend against biometric attributes such as age, gender and race being recognized yet preserve attributes such that the image can be used for automatic face identification. For example, Othman

et al. [198] proposed a face fusion method that combined another face with the targeted face via a morphing scheme. The combining process can be used to progressively modify the candidate face such that gender information is progressively suppressed while the modified images can still be used for identification. In a subsequent study [199], the authors improved the fusion method from the morphing scheme to an adversarial learning scheme to achieve a precise and natural face alignment.

Recognition-oriented suppression. Action recognition, which leverages machine to detect and understand human actions from visual media, is now a popular function in some OSN applications such as life-logger for daily health management. While seeking to ensure that the recognition system detects important events to assist human daily lives while not intruding on the privacy of individuals, Ren et al. [200] proposed an adversarial training setting with two competing systems. One is an anonymizer that modified the original image to remove privacy-sensitive information while still trying to maximize spatial action detection performance. The other is a discriminator that tried to extract privacy-sensitive information from the anonymized images. The competition result was an anonymizer that performed pixel level modifications to anonymize each human face with minimal effect on action detection performance.

Another series of studies focus on the privacy risk in facial expression recognition applications which are widely used for social enjoyment. For example, Rahulamathavan et al. [201] proposed an efficient algorithm to perform privacy-preserving facial expression classification in a client-server model. The server held a database and offered clients a classification service to identify the facial expression of subjects. The authors assumed that the client and server were mutually untrusted parties and they wanted to perform the classification without revealing their inputs to each other. They proposed a lightweight algorithm that projected the image onto a lower-dimensional space in private based on a randomization technique. Their method achieved classification accuracy equivalent to the accuracy of the conventional algorithm while preserving privacy, effectively hiding the client's input image and the classification result from the server.

Comparably, Wu et al. [202] provided a more general adversarial learning framework without specifying the recognition task of the social application. The reason was that the privacy budget, often defined and measured in task-driven contexts, cannot be reliably represented by any single performance model. Strong privacy protection had to be sustainable against any possible model that tried to hack privacy information. The author explicitly developed a degradation transformation for the original image and proposed two strategies (budget model restarting and budget model ensemble). The strategies not only enhanced the generalization of the learned degradation on protecting privacy against unseen hacker models, but also optimized the trade-off between target task performance and the associated privacy budgets on the degraded data.

b) Privacy-preserving visual localization: Image based localization services have become increasingly popular and are widely used for augmented/mixed reality games or live navigation.

Such services require users to share images such that camera pose estimations can be made on a server. Structure-based camera pose estimation methods, which match feature points in a query image to a pre-computed 3D point cloud of the scene to generate geometric constraints [203]–[206], have been adopted by many industrial products such as Microsoft HoloLens [207] and Google Maps AR [208]. However, 3D point clouds and descriptors can be inverted to recover the original scene in detail [209], leading to privacy infringement.

To address the problem, Speciale et al. [210] proposed the first privacy-preserving camera pose estimation system, which transformed 3D point clouds into 3D line clouds by a novel map representation. The map representation obfuscated the underlying scene geometry while retaining sufficient geometric constraints to enable robust and accurate camera pose estimation in many settings. Their solution made it possible to enable privacy-preserving localization on a local device at the client side. In a subsequent study [211], the authors improved their work by providing privacy-preserving localization for cloud-based services at the server side, which was more robust against the 'man-in-the-middle' attacks and needless trust in the server. The key insight was to replace the 2D image feature points in the image with randomly oriented 2D lines passing through the original point positions. This approach required uploading only the 2D lines and associated feature descriptors to the server, making it not feasible to invert the features. Meanwhile, it still provided sufficient geometric constraints from 2D line to 3D point correspondences to enable effective camera pose estimation.

5) Solutions for deletion delay:

a) Digital oblivion: The wide acceptance of OSNs' free dissemination of personal information, and the availability of cheap, massive and perfect online digital storage has led the Internet to 'remember' shared images even if the users have proactively deleted the images from their own OSNs. To address this problem, some studies provided solutions for automated OSN image deletion.

Self-destruction-based methods. Some digital oblivion solutions were built on data self-destruction mechanisms [212], [213]. For example, Backes et al. [214] developed a system called X-pire!, which allowed users to set an expiration date for images in OSNs. The expiration configuration information was embedded as encrypted information within JPEG files in a way that adapted JPEG compression. Using X-pire!, the images became unavailable once the expiration date was reached, without any requirement of additional interaction with the PSPs for users. Moreover, the image owner can dynamically adjust the expiration dates, including lengthening, shortening, or immediately activating the self-destruction mechanism.

Collaboration-based methods. Some studies leveraged collaborative mechanisms for digital oblivion. Domingo-Ferrer et al. [215] designed a set of protocols based on game theory to encourage users who received information from an individual to rationally help the individual enforce his/her oblivion policy. Specifically, the content owner embedded an expiration date in the image and published it. Then different fingerprints for different receivers were added to the content so that the owner can trace the unlawful usage or spread of the image

after the expiration date had passed. The protocols motivated each entity to collaborate in finger-printing the content they forwarded to others and used rewards and punishments to achieve oblivion enforcement collaboratively.

Stokes et al. [216] designed a system enabling the peer-to-peer (P2P) agent community to assist in digital oblivion within OSNs. The P2P community was formed by participants who agreed to protect the privacy of individuals who requested images be forgotten. The system distributed and maintained up-to-date information on oblivion requests, and implemented filtering functionality based on the authentication of user-to-content relations that were particularly relevant for digital oblivion. To this end, a family of protocols was designed leveraging a combination of digital signatures, watermarking, image tags, and trust management that guided digital oblivion with respect to these user-to-content relations within the community implementing the protocol. No collaboration was required from the PSP, although the system could also be incorporated as a standard function of OSNs.

C. Discussion

Table III provides a breakdown of the reviewed solutions at this stage. The images have been already accessed and controlled by the recipients for social usages and out of the control of the original owner. Given the uncertainty of the recipients' behaviors, the privacy issues here are more open than at the previous two stages. At this stage, the major privacy concern is to maintain the social utility of the shared images while preserving privacy. From a dynamic perspective, as strong measures regarding privacy have been taken at the previous stage, the main target of privacy intelligence here is to further intensify the image privacy in the context of social experience.

From the technical perspective, the main design goals with regard to privacy concerns differ according to whether the recipients are trusted or not. For the former group, the main design goal is to maintain social utility, such as the visual integrity for human viewers or attribute availability for social applications, while protecting the targeted privacy. For the latter group, as the images have been already accessed by the recipients, the main design goal is to identify and thwart further privacy leakage.

From the perspective of practical implementation, the reviewed solutions at this stage can be implemented at either the PSP side or the recipients' end devices, depending on whether the image is shared for human viewing or social application.

In looking back over the wide array of intelligent solutions, we find that most of them provided an available prototype in the practice phase (such as a plug-in for browsers or OSN apps) that remains backwards compatible with existing OSN user interface designs. This indicates the potential to design a centralized scheme integrating the aforementioned three types of privacy intelligence in line with the logic of the lifecycle framework, resulting in an intelligent privacy-enhancing chain for closed-loop privacy management in practice, as shown in Figure 8

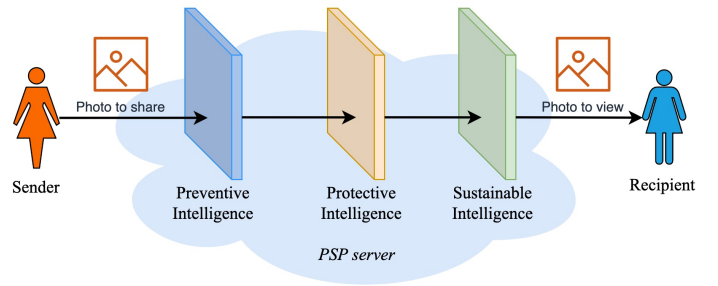


Fig. 8. The conceptual structure of the intelligent privacy-enhancing chain, which can be fully deployed in the PSP server.

VI. CHALLENGES AND FUTURE DIRECTION

In Sections III-V, we have discussed the existing intelligent solutions towards privacy issues derived from typical user behaviors at each stage of the OSN image sharing lifecycle. Although these solutions can plausibly cover the entire OSN image sharing lifecycle, we are aware that there are still some challenges to be addressed. In this section, we discuss the challenges lurking at each stage and propose some future direction to motivate additional research.

A. Challenges in local management

1) *Privacy pattern modelling*: For privacy intelligence in local management, a crucial task is to help users understand privacy in OSN image sharing. To this end, using automated methods to discover the privacy pattern from the image in the context of OSN sharing has been a trend. This kind of solution leverages a learning model to map the input factors relevant to privacy to the output privacy decision. There are some challenges at both the input side and output side of the current models.

On the input side, two significant factors are often overlooked in privacy pattern modelling. One is the spatio-temporal factor, reflecting the dynamic of privacy needs changing with time and location in different environments or situations [217]. 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). In conclusion, for privacy pattern modelling, images should be interpreted at higher understanding levels. The emerging techniques of social image understanding [48][50], [189], [190] powered by deep learning techniques, offer a promising direction to alleviate this problem.

At the output side, the existing models generally formulated the privacy decision as a simple classification problem, i.e., to classify the degrees of sensitivity into entirely private, partially private, and public. However, since different users' awareness of privacy is subjective and cognitively different, making it quite difficult to measure quantitatively, there is not a distinct cut-off for measuring the degree of privacy sensitivity. It is challenging to define the output decision in a progressively smooth manner. Using ranking score or probability-based measurement may potentially help, which is worth further investigation.

TABLE III
A SUMMARY OF PRIVACY ISSUES AND CORRESPONDING INTELLIGENT SOLUTIONS AT THE SOCIAL EXPERIENCE STAGE

User behavior	Privacy issues	Intelligences	Paper & Year	Techniques	Summary
Image viewing	Utility loss	Privacy-utility trade-off	[165] 2017	Online user study	Studied the effectiveness and viewers' attitudes of two partial obfuscation techniques, blurring and blocking.
			[166] 2017	Online user study	Studied the preference of 11 obfuscation techniques from a viewer experience perspective
			[167] 2018	Online user study	Studied viewer preference of 5 obfuscation techniques from both aspects of visual aesthetics and user satisfaction of the image
			[168] 2017	Adversarial learning	Designed a perturbation mechanism that jointly optimized privacy and utility objectives with quantifiable guarantees
		Aesthetic transformation	[169] 2019	Between-subjects study	Studied the effects of three artistic transformations on images that had objects obscured
	Image tampering	Visual forensics	[176] 2017	Deep learning	A forensic algorithm for image tampering detection and localization based on characteristic digital footprints
			[177] 2018	Self-supervised learning	Used the EXIF metadata to detect the self-consistency for visual forensics
			[178] 2017	Deep multi-task learning	Employed a CNN-LSTM model to detect and localize manipulated image regions by detecting boundary discrepancy
			[180] 2018	Deep multi-stream learning	Proposed a two-stream Faster R-CNN network to find tampering artifacts and the noise in-consistency for tampering detection
			[182] 2019	Machine learning	Modelled facial expressions and movements that typify an individual's speaking pattern to detect DeepFake attack
	Shoulder surfer	Privacy-respecting browsing	[192] 2019	Format-preserving encryption	Proposed a thumbnail-preserving encryption strategy to balance usability and privacy in privacy-respecting browsing
			[194] 2016	Distortion	Distorted images in a way that made the visual content hard or impossible to recognize for an onlooker who did not know the photographs
		Gaze-based monitoring	[196] 2016	Motion tracking	Designed a detector for mobile shoulder-surfing which used motion tracking sensors to locate and orient an onlooker relative to the tablet
			[197] 2019	Eye gaze tracking	Designed an eye-tracking approach towards maintaining privacy while rendering the portion of text that is reading by the reader
Social application	Untrusted application	Attribute suppression	[198] 2014	Face morphing	Proposed a face fusion method that combined another face with the targeted face to suppress gender while retaining identification information
			[199] 2017	Adversarial learning	Proposed a face fusion method using an adversarial learning scheme to achieve a natural face alignment for gender suppression
			[200] 2018	Adversarial learning	Designed an anonymizer that performed pixel-level modifications to anonymize face with minimal effect on action detection performance
			[201] 2017	Feature randomization	Proposed an efficient algorithm to perform privacy-preserving facial expression classification in a client-server model
			[202] 2018	Adversarial learning	Provided a more general adversarial learning framework for attribute suppression without specifying the recognition task of the social application
	Privacy-preserving visual localization	[210] 2019	Feature projection	Proposed a privacy-preserving camera pose estimation system, which transformed 3D point clouds to 3D line clouds by a novel map representation	
		[211] 2019	Feature projection	Proposed a privacy-preserving camera pose estimation system which replaced 2D feature points with randomly oriented 2D lines	
Image deletion	Deletion delay	Digital oblivion	[214] 2011	Protocol design	Developed a system allowing users to set an expiration date for images in OSNs and embedded the expiration configuration within JPEG files
			[215] 2011	Protocol design	Designed a game theory-based protocols to encourage users who received information from an individual to help him/her enforce the oblivion policy
			[216] 2013	Cryptographic primitives	Designed a system enabling the peer-to-peer agent community for digital oblivion in OSNs.

In conclusion, despite the various models that have been proposed to satisfy various specific scenarios, a more generalized modelling method still has appeal in the future. Such a method can not only benefit the privacy pattern recognition tasks themselves but also contribute to upstream public dataset development and downstream privacy protection tasks. The prior knowledge needed for generalized modelling can be identified by determining privacy boundaries [218]. Three boundaries typically exist with respect to privacy in OSN image sharing:

- **Disclosure boundary**, which manages the tension between private and public, i.e., the degree of disclosure of individual information from OSN image sharing in subjective self-cognition.
- **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.
- **Spatio-temporal boundary**, which manages the tension of privacy decisions changing over time and in different locations.

The identified privacy boundary can help discover the interactional decisive factors for privacy pattern modelling in the context of OSN image sharing, as shown in Figure 9.

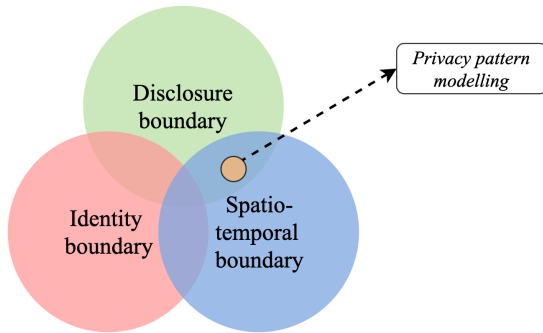


Fig. 9. Modelling privacy based on privacy boundaries. The yellow dot denotes a sample modelling which is determined by the factors and features discovered from the interdependent spaces of the disclosure and spatio-temporal boundaries.

B. Challenges in online management

1) *Barriers of access control mechanisms*: In rethinking the access control mechanisms for privacy preference settings, a challenge is how to handle the privacy of all involved stakeholders to ensure everyone’s privacy can be respected at their desired level. Since the identity of stakeholders can be multiple (either interdependent or independent with the sender and the recipient), the complexity of the social connection graph rises exponentially, making the problem of multi-party conflicts appear intractable.

Another challenge of the current access control mechanisms is a common neglect of one social norm: the social relationship strength. According to the literature, most of the solutions simply managed the social relationships into different arbitrary groups such as family, friends and colleagues, and allocated

a uniform and static privacy policy to each group. However, it is more rational in the real-world OSN that the relationship strengths vary in different user pairs, and may change dynamically. Therefore, it is logical to include the property of relationship strength in access control mechanisms and set appropriate update rules correspondingly. From this perspective, the trustworthiness-based access control mechanism designed by Xu et al [110], which built a dynamic OSN ecosystem from a global viewpoint, can be seen as an initial step in this direction. Further inspiration for improvements can be found in studies focusing on relationship strength modelling in traditional OSN interactions [219]–[222].

2) *Advanced computer vision techniques*: Computer vision techniques have permeated the field of privacy intelligence in OSN image sharing. For example, most solutions involving visual obfuscation or adversarial perturbation adopted automated recognition systems to accurately differentiate object level or attribute-level properties in advance. Undoubtedly, progress in computer vision techniques, especially the deep learning-based methods [90], [131], [223], [224], indirectly boost the improvement of privacy-enhancing techniques in OSN image sharing. However, from the reverse side, the accessibility of advanced computer vision techniques can also pose serious threats if they are implemented to invade someone’s privacy. For example, previous studies had showed that some naive means for visual obfuscation and attribute perturbation are vulnerable against the elaborate recognition systems [142], [225], [226], as the hidden information can be easily inferred or recovered.

To avoid such threats from malicious recognition systems, more targeted image processing-based protections are needed. However, a challenge is that in the vast majority of cases, most attacks are from black-box attackers, i.e., the recognition systems adopted by malicious viewers are usually unknown. The potential strategies for this problem can be borrowed from the previous studies conducting black-box attacks against recognition systems [227]–[230]. Alternatively, game theory can provide Another promising lens to solve this problem. As inspired by Oh et al. [231], the behaviors of the protector and the recognizer can be described as a two-person game [232], where each player has its own strategy space unknown to the opponent. Once the game converges to Nash Equilibrium, the optimal combination set of image processing strategies for privacy protection can be always derived by the protector irrespective of what countermeasures are adopted by the recognizer.

3) *Privacy of by-standers*: We also focus on the privacy needs of bystanders incidentally depicted in OSN images. These individuals are considered as the weakest group in terms of exercising individual privacy preferences among all the involved entities in OSN image sharing, since they have almost no chance to take any preemptive measures against the sharing process and their privacy rights are often ignored by image owners. Therefore, when designing privacy intelligence for OSN image sharing, we argue that this group should be concerned particularly by the practitioner. Nevertheless, according to the literature, only a few solutions raised such concerns [77], [109], [233]. The technical challenge is how

to differentiate strangers from acquaintances who are willing to share photos of themselves online. Traditional methods normally apply face matching in line with the identity lists provided by the OSN user. This kind of method requires a prior knowledge base of the allowable faces and may cause additional computational overhead. A possible direction is to recognize the relationship directly from the image based on the visual cues, such as physical distance and direction of eye gaze [234]. This may take advantage of the works on image depth estimation, which measure the view depth by understanding the 3D scene geometry of images [235]–[238].

C. Challenges in social experience

1) *DeepFake: challenging the real-world*: We pay special attention to the emerging facial image tampering technique known as DeepFake [4], given that in most cases human faces are supposed to be highly sensitive. Powered by GAN, DeepFake can effectively generate natural and realistic fake faces from a real face photo, and blend them into other media records seamlessly. This technology is a double-edged sword for privacy in OSN image sharing. It can be applied for hiding original faces to protect facial privacy, or inversely to forge media records for malicious usage which leads to a privacy threat to the victim. It is an understatement to say that there is widespread concern about the malicious application of this technology.

DeepFake has received extensive public attention in terms of its potentially disruptive consequences to visual security, laws, politics, and society in general [186]–[189], [239]. The research community has become an influential force to motivate the studies on DeepFake detection. Multiple large-scale DeepFake detection datasets have been released [240]–[245]. In 2019, Facebook in cooperation with several companies and universities, had launched a 'Deepfake Detection Challenge' (DFDC) competition with more than \$10 million for awards and grants [246]. However, the detection solutions are somewhat reactive for preventing individuals from DeepFake attacks, as the attack may have occurred already. It is extremely challenging to prevent the abuse of DeepFake once malicious viewers have thoroughly accessed face photos since by that time they are capable of fully controlling the data. Therefore, we believe more effort is needed on solutions that forestall and prevent malicious viewers from getting the data, such as identifying malicious viewers ahead of publishing images according to historical internet trails. In short, preventing and protecting against DeepFake attacks involves a long-term arms race, requiring researchers in this field to be keenly aware of emerging trends.

2) *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 [162], should be guaranteed in a privacy-friendly environment for OSN image sharing.

Currently, the digital oblivion solutions for the right to be forgotten normally 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 supports 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 [247]. Future intelligent digital oblivion designs may be inspired by consensus-based mechanisms, e.g., a blockchain-based deletion scheme [248], which leverages the blockchain technique to build a trusted P2P chain for data deletion.

Another challenge to ensure the right to be forgotten is that the shared images are normally associated with multiple information sources. On 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 erase the sensitive information thoroughly. 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 the GPS recorder (shared in the VSN domain). Such cross-domain relations [249] pose intractable challenges to achieving the right to be forgotten by only deleting image data from the OSN domain.

D. Dataset challenges

1) *Paradox of privacy dataset publishing*: Most of the intelligent solutions that leverage machine learning algorithms, such as learning-based privacy prediction and personalized policy generation, are essentially data-driven. They heavily depend on the image datasets with privacy knowledge, such as the annotations of privacy or not. According to the literature, currently there are only five publicly available datasets:

- **PicAlert** [250]: This is the first image dataset with privacy pattern annotations that was made public. A total of 37535 images were collected from Flickr and labeled as private and public by 81 users. In addition, PicAlert also provided at least one user tag per image.
- **YourAlert** [251]: This dataset includes 1511 image feature vectors gathered from 27 OSN users. The users were asked to provide binary privacy annotations for their personal photos. To reduce privacy leakage, only the visual and semantic features (VLAD [255], CNN [223] and SemFeat [256]) were collected and released to the public.
- **VISPR** [252]: This dataset provides object-level annotation instead of image-level annotation. A total of 22167 images were gathered from Flickr and Twitter and 68 kinds of privacy attributes such as nudity, signature and face were identified from these images.
- **VISPR-extension** [253]. This is an extension version of VISPR. The privacy attributes were reduced to 24 classes and divided into three categories including Textual, Visual

TABLE IV
DETAILS OF PUBLICLY AVAILABLE DATASETS PROVIDING PRIVACY KNOWLEDGE

Dataset & Year	Image source	Annotation level	Available annotations	Dataset size	Remark
<i>PicAlert</i> [250], 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
<i>YourAlert</i> [251], 2016	Local collection (from 27 social network users)	Image level;	Privacy category (binary)	N = 1511 (444 private, 1067 public)	Only image features are released
<i>VISPR</i> [252], 2017	Internet (Flickr and Twitter)	Object level	Privacy attribute (68 types)	N = 22167 (5.22 attributes per image)	Limited data modality
<i>VISPR-extension</i> [253], 2018	Internet (Flickr and Twitter)	Object level; Pixel level	Privacy attribute (24 types); Attribute category (3 classes); Private region;	N = 22167 (8473 images with region pixel-labeling)	
<i>VizWiz-Priv</i> [254], 2019	Local collection (from blind photographers)	Image level; Object level; Pixel level; Text 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

and Multimodal. More importantly, VISPR-extension is the first privacy dataset available for pixel-level annotation, including 8473 images with private regions labeled by polygons.

- **VizWiz-Priv** [254]. This dataset is similar to VISPR-extension. However, all the images of this dataset were from blind photographers. For privacy concerns, the images were released with visual masks.

Table IV provides an overview of the five privacy datasets. Confronting the increasing research interests in this field, the current data resources are insufficient. Adding to this predicament is the paradox of privacy dataset publishing, which means that the privacy datasets must contain certain sensitive information naturally, and thus should not be fully released to the public. Although in some existing datasets only the representative contents such as feature vectors or masked images were published, it would compromise the performance of models using incomplete data. The original contents can still be recovered from the representative contents by some image reconstruction techniques [257]–[260]. Moreover, the traditional privacy-persevering data publishing methods using differential privacy mechanisms [261], [262] are hard to apply to image visual content.

There might be some potential solutions to address this challenge. An intuitive solution is to purchase private data from data owners. In this way, privacy is valued as a commodity, and price becomes the most important factor in the buyer-seller game. The privacy pricing problem can be motivated from some previous studies [263]–[266], which provided various pricing mechanisms to build into an auction-based trading market for private data.

Another solution is to use alternative learning algorithms or frameworks which can avoid accessing the raw data. The distributed learning frameworks such as collaborative learning

[267]–[269] and federated learning [270] may be candidates, as they develop independent models locally without data sharing, then aggregate the local models together to attain a global model. As a pioneering instance, Xu et al. [271] adopted distributed learning to train a face recognition model for the access control of co-owned images in OSN sharing. Another candidate learning algorithm is unsupervised or semi-supervised learning. For example, some studies applied GAN to transform the raw images into synthesized alternatives while preserving the privacy pattern in data [272]–[274]. The synthesized images were then annotated with privacy labels and released freely. Other methods include unsupervised learning-based on deep feature clustering for image privacy classification, instead of learning directly from original images [275].

VII. CONCLUSION

With a focus on the urgent privacy needs in modern OSN image sharing, we conducted a survey on the privacy intelligence in such a sharing context, which is a collective term referring to the intelligent solutions devoted to addressing various modern privacy issues derived from sharing-related user behaviors. Specifically, we first analyzed the privacy concept and taxonomy within the contextual constraints of OSN image sharing to provide a conceptual view of privacy intelligence. To cope with multiple privacy issues, solutions and challenges with regard to the interdisciplinary nature of this area, we then proposed a high-level analysis framework based on the entire lifecycle of OSN image sharing. Using the framework we systematically identified privacy issues and explored the corresponding intelligent solutions in a stage-based fashion. For every intelligent solution reviewed at each stage, we elaborated on its methods or strategies and summarized their technical features. 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-enhancing chain from the perspectives of prevention, protection, and social application, which may contribute to building a more intelligent environment for privacy-friendly OSN image sharing where the privacy of all stakeholders are respected. We hope our work can facilitate current-day privacy management and address the gap between the increasing use of OSN image sharing and individual privacy needs.

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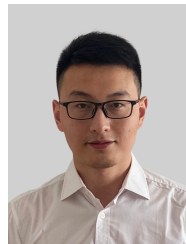
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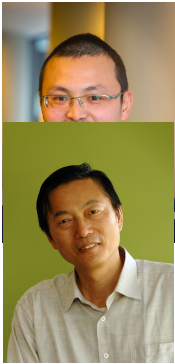
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