

## Posts About Students on Facebook: A Data Ethics Perspective

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## **Abstract**

Public schools and districts use social media to share announcements and communicate with parents and the community, but alongside such uses run risks to students' privacy. Using a novel data set of 18 million posts on Facebook by schools and school districts in the United States, we sought to establish how frequently photos of students were shared. Through sequential mixed methods, we estimated that around 4.9 million posts included identifiable images of students and that approximately 725,000 posts included students' first and last names and their approximate location. We discuss the implications of these findings from a data ethics perspective.

## Posts About Students on Facebook: A Data Ethics Perspective

If you search the web for the school district serving the community in which you live, the chances are that one of the first results returned will be that district's Facebook page, a public page on the most-used social media platform—one used daily by around half of American adults (Gramlich, 2021). Scrolling, you may see announcements, among other posts. You may even notice photos highlighting one or more students alongside their names. Importantly, these public Facebook pages are accessible by anyone on the Internet—with or without a Facebook account.

This study examines the posts on these Facebook pages that may reveal the personally identifiable information (PII) of students, information that can be linked to an individual. Guided by two research questions (RQs), we focus on how posting this information may inadvertently risk students' privacy.

*RQ #1:* To what extent do the public Facebook pages of schools and districts depict one or more students in a photo?

*RQ #2:* To what extent do they identify one or more students by both name and photo?

The potential sharing of students' PII is noteworthy for several reasons. Parents have long expressed concerns about *others* sharing the PII of their children (Fox & Hoy, 2019; Plunkett, 2019)—including teachers (Cino & Vandini, 2020). These concerns may be heightened by knowing the potential ease with which companies may access the posts of schools and districts for uses not intended to be accessed by those in schools who have posted. For instance, it is increasingly recognized that predictive policing companies (Hill & Dance, 2020) regularly collect and utilize public social media data.

Furthermore, government agencies, including both the United States (U.S.) and other foreign governments (Cadell, 2021), regularly access public social media data, doing so for purposes ranging from monitoring immigration and predicting crime risk to documenting social connections (Joh, 2016). The potential use of Facebook data by organizations such as the police is noteworthy because secondary use of student-related PII data runs counter to the *Fair Information Processing Standards* (FIPS) that undergird *Family Educational Rights and Privacy Act* (FERPA) protections. Specifically, the FIPS disallows the secondary use of student data (Vance & Waughn, 2021). If schools are aware that third parties access data about students on Facebook, it may run counter to legal protections. We note that media release forms allow parents or guardians to waive protections provided by the Family Educational Rights and Privacy Act (FERPA). This suggests that even if the sharing we have documented is concerning, it may be legal if a media release form has been signed.

There are broader concerns not about the legality but the ethics of using data found on social media. Scholars have increasingly turned to the interdisciplinary field of data ethics to try to make sense of these concerns (Vance & Waughn, 2021). This matters because even if such access is legally allowable, it could cause harm to those the data is about. For instance, child images shared in public posts have reportedly been found on pedophilia websites. According to Battersby (2015), "Innocent photos of children originally posted on social media and family blogs account for up to half the material found on some pedophile image-sharing sites" (p. 1). The unintended secondary data uses, then, suggests that if student photos and PII are shared on social media platforms, there are ethical questions that indicate the need to use not only legal but also ethical lenses to understand the potential harm to students' privacy that may result from posts about students on Facebook.

## Method

**Methodology and data source.** To access Facebook data, we used CrowdTangle<sup>1</sup>, Facebook's platform to provide researchers with access to Facebook data. CrowdTangle permits access to the posts of all public pages and open groups. We used a *public internet data mining* approach to access and record links to Facebook pages from the websites of all of the public districts and schools in the U.S. (Supplementary Material A). This allowed us to access 18,004,024 posts via the CrowdTangle API, with 13,870,211 including one or more images (77%). We note that both the number of posts and the proportion of posts, including photos (by year), increase over time (see Supplementary Material B). Next, we utilized a sequential mixed methods design to address the research question. First, we conducted visual content analysis, qualitatively coding posts for the depiction and identification of students, followed by quantitative analyses, namely, logistic regression, to make inferences about the coded sample—described next.

**Qualitative data analysis.** We developed a coding frame for the number of faces *depicted* (included in a photo) and *identified* (face depicted with an individual's first and last name included) in these photos to qualitatively code 400 posts randomly selected from our full sample of around 18 million posts. Coding was performed by two trained coders who assisted with the development of the coding frame. This process involved six rounds of interrater reliability. At the end, coders demonstrated strong agreement for the depiction (80%;  $K = 0.69$ ) and identification of students (100%;  $K = 1.00$ ). See Supplementary Material C for additional information on the coding and Supplementary Material D for an illustration of the coding process.

**Quantitative data analysis.** Following our qualitative coding, we fit an unconditional logistic regression model<sup>2</sup> to estimate the proportion of photos with one or more students *depicted* or *identified* (as separate models). Then, to interpret the models, we examined the estimate and confidence interval for the intercept. Specifically, to better understand the scale of the issue, we used these estimated coefficients and their confidence intervals to estimate the frequency of depicted and identified students in the larger sample of around 18 million posts.

## Results

The estimates from the logistic regression (Table 1) indicated that 35.40% [30.43% - 40.58%] of photos depicted one or more students, while 5.23% [3.25% - 7.84%] identified students by first and last name. When extrapolated to the full sample, these estimates suggest that around 4.9 million posts depicted one or more students, and just over 725,000 posts identified one or more students.

**Table 1**

*Log odds estimates based on the coded sample and full sample extrapolation for the depiction and identification of students in public Facebook posts*

|  | Depicted             | Identified           |
|--|----------------------|----------------------|
| Estimate Based on the Coded Sample ( $n = 400$ ): $\beta$ [ $SE$ ] | -0.60 [-0.83, -0.38] | -2.90 [-3.39, -2.46] |

<sup>1</sup> <https://crowdtangle.com>

<sup>2</sup> All code needed to reproduce the analysis using the open-source and freely-available statistical software and programming language R is available in anonymized form at the following link: [https://osf.io/bzg5v/?view\\_only=c796b3cc9188423194daded8b01fdb18](https://osf.io/bzg5v/?view_only=c796b3cc9188423194daded8b01fdb18)

|  |   |   |
|--|---|---|
| Extrapolation to the Full Sample ( $n = 13,870,211$ ) [CI] | 4,909,809 students<br>[4,220,891 - 5,629,199] | 725,989 students<br>[451,103 - 1,087,988] |
|--|---|---|

*Note.* The sample estimates are in log odds units, whereas the population point estimates calculated by extrapolation are for the number of posts. The percentages reported in the text result from exponentiating the log odds estimates so that the estimates are in odds units, after which the odds are converted into a probability.

### Discussion

This study revealed how posts about students on Facebook might risk students' privacy. Nearly five million photos depicting students' faces have been shared, with around 725,000 of these photos also identifying students by first and last name. Notably, these findings can be understood in the increasing number of posts and the proportion of posts with images over time: This is a potentially urgent topic to consider. These findings suggest the need for three shifts in present discourse and thinking around student privacy and social media.

The first is a broad shift from legal to ethical considerations. As noted earlier, we think there is a likelihood that posts on Facebook are being accessed by a range of actors, including government agencies, predictive policing companies, and those with nefarious intent. We are not legal experts, so the choice to focus on ethical considerations could be seen as a pragmatic one, but we concur with Vance and Waughn (2021). They argue that many questions about ethical data use and student privacy cannot readily be resolved using existing legal protections. Instead, a data ethics perspective is needed. This perspective highlights the importance of asking questions about who uses data and who benefits and is harmed from its use. If it is legally permissible for schools to post the PII of students whose parents have signed a media release form, knowing about who might access this PII as a form of data and how they may use it, is it right to do so? Such questions take on renewed urgency with companies such as *Clearview AI* applying facial recognition broadly to publicly available media. Even photos without directly attached PII hold the potential to quickly become PII violations in years to come due to expanding facial recognition technology and the use of available photos (Smith & Miller, 2022).

The second shift is from data ethics for researchers to data ethics for educators and educational leaders. Mandinach and Gummer (2021) offer a specific definition that is helpful for considering data ethics for educators: individuals' knowledge, disposition, and skill related to the ethical use of data. This definition emphasizes that these individual characteristics can and must be cultivated. Such a data literacy-focused approach to data ethics could lead to practical benefits, like the revision of media release policies to detail how students' images and information shared on social media can be accessed by a range of actors.

Lastly, although educators and educational leaders can focus to a greater extent on data ethics regarding student privacy, we also need a shift from individual to social and political responsibility. We should thoughtfully and carefully offer regulations and push platforms to make protecting privacy more practical. For instance, might Facebook have the default setting for school and district pages on Facebook to be private rather than public? More broadly, we agree with scholars who argue that data ethics and protecting privacy are not only the responsibility of those of us in education: it is also the responsibility of social media platforms and the wider society (Krutka et al., 2019). We note that at the time of writing this article, the Federal Trade Commission released a policy statement explicitly reminding educational technology companies to comply with the privacy protections included in the Children's Online Privacy Protection Act (COPPA; Federal Trade Commission, 2022)—protections that some

educational technology may not have been followed satisfactorily because COPPA protections have mainly focused on commercial websites.

As social media data and data mining methodologies allow new ways to examine student and family education rights issues and current data use practices, research has the potential to reveal potential harms to students; even relatively low proportions of posts that reveal the PII of students mean that the privacy of hundreds of thousands of students may be risked. Therefore, we encourage educational leaders and researchers to offer a vision of what it might mean to use digital and educational technologies in ways that honor the privacy of students while still accomplishing the goal of communicating with parents and the community.

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### **Supplementary Material A: Additional Information on Accessing Facebook Data**

To access the Facebook data, we used a public data mining methodology (Kimmons et al., 2018), which is distinguished by the use of (largely unstructured) publicly available data, such as data from websites and social media platforms (Fischer et al., 2020). Specifically, we used CrowdTangle, Facebook's platform for providing academics and journalists access to data about public content on Facebook, including the content of posts and information about them. CrowdTangle allows its users to access (a) the content of all pages with more than 50,000 likes and (b) the content of public pages that are manually uploaded.

Because many school and district pages had fewer than 50,000 likes, we created a collection of school and district Facebook pages using a novel method to access pages to manually upload. Specifically, we used the statistical software R (R Core Team, 2021) to programmatically access (or web scrape) their homepages using data provided by the Common Core of Data (CCD; National Center for Education Statistics, 2021). We recorded all links to Facebook pages from their home pages with that method. When schools linked to their district's Facebook page, we considered the corresponding Facebook page as a "district page." Our data sampling resulted in 8,112 out of 9,949 (81.54%) districts and 5,634 out of 99,603 (5.66%) public schools listed by NCES to be represented in our data sample. Once we had this collection of 15,583 districts and schools, we manually uploaded the list of links to district and school pages to CrowdTangle. We then used the "historical data access" function in CrowdTangle to access all of the posts from Jan 1, 2005, to December 31, 2020. The total study population included 18,004,024 million posts shared from 2005 to 2020, with 13,870,211 of these posts (77.03%) including at least one photo. See Author (2022) for more information on using CrowdTangle.

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## Supplementary Material B: Post Activity by Year

### Supplementary Table B1

*Yearly development of the number of posts, posts with images, and their relative share among all posts in our database.*

| Year  | # Posts  | %<br>(Cumulative) | # Posts with<br>Images | %<br>(Cumulative) | % Posts with<br>Images |
|-------|----------|-------------------|------------------------|-------------------|------------------------|
| 2005  | 18       | 0.00 (0.00)       | 12                     | 0.00 (0.00)       | 0.67                   |
| 2006  | 19       | 0.00 (0.00)       | 8                      | 0.00 (0.00)       | 0.42                   |
| 2007  | 33       | 0.00 (0.00)       | 21                     | 0.00 (0.00)       | 0.64                   |
| 2008  | 204      | 0.00 (0.00)       | 154                    | 0.00 (0.00)       | 0.75                   |
| 2009  | 15951    | 0.00 (0.00)       | 4974                   | 0.00 (0.00)       | 0.31                   |
| 2010  | 97761    | 0.01 (0.01)       | 27578                  | 0.00 (0.00)       | 0.28                   |
| 2011  | 240885   | 0.01 (0.02)       | 70868                  | 0.01 (0.01)       | 0.29                   |
| 2012  | 403428   | 0.02 (0.04)       | 145461                 | 0.01 (0.02)       | 0.36                   |
| 2013  | 578760   | 0.03 (0.07)       | 222830                 | 0.02 (0.04)       | 0.39                   |
| 2014  | 843634   | 0.05 (0.12)       | 425635                 | 0.03 (0.07)       | 0.50                   |
| 2015  | 1449125  | 0.08 (0.20)       | 988729                 | 0.07 (0.14)       | 0.68                   |
| 2016  | 2014235  | 0.11 (0.31)       | 1552170                | 0.11 (0.25)       | 0.77                   |
| 2017  | 2458027  | 0.14 (0.45)       | 1978142                | 0.14 (0.39)       | 0.80                   |
| 2018  | 2819174  | 0.16 (0.61)       | 2344186                | 0.17 (0.56)       | 0.83                   |
| 2019  | 3262617  | 0.18 (0.79)       | 2814209                | 0.20 (0.76)       | 0.86                   |
| 2020  | 3820153  | 0.21 (1.00)       | 3295234                | 0.24 (1.00)       | 0.86                   |
| Total | 18004024 |                   | 13870211               |                   | 0.77                   |

### Supplementary Material C: Additional Information on the Coding Procedure

A depicted student was one for whom three out of four of the following features were visible without enlarging the image: a) eyes, b) nose, c) ears, and d) mouth. An identified student was one whose full name could easily be matched with a face depicted in the photo. First, the two coders trained on the coding frame by discussing each code and identifying examples of the code. Our coding process included multiple inter-rater reliability checks. At the conclusion of six rounds of inter-rater reliability checks of around 20 posts in each round, after which the coders met to discuss disagreements and, occasionally, make revisions to the coding frame. The results of the inter-rater coding process are presented in Supplementary Table C1 below. We note that by conventional interpretation, these values range from perfect or almost perfect to substantial (Landis & Koch, 1977).

#### Supplementary Table C1

*Inter-rater reliability statistics over six coding rounds*

| Code         | <i>n</i> | Agreement | Kappa | Round |
|--------------|----------|-----------|-------|-------|
| First Names  | 15       | 100       | 1.00  | 1     |
| Last Names   | 15       | 100       | 1.00  | 1     |
| Detectable   | 15       | 71.43     | 0.59  | 1     |
| Identifiable | 15       | 100       | 1.00  | 1     |
| First Names  | 20       | 95        | 0.82  | 2     |
| Last Names   | 20       | 95        | 0.82  | 2     |
| Detectable   | 20       | 95        | 0.88  | 2     |
| Identifiable | 20       | 100       | 1.00  | 2     |
| First Names  | 20       | 100       | 1.00  | 3     |
| Last Names   | 20       | 100       | 1.00  | 3     |
| Detectable   | 20       | 100       | 0.83  | 3     |
| Identifiable | 20       | 95        | 0.78  | 3     |
| First Names  | 20       | 85        | 0.35  | 4     |
| Last Names   | 20       | 100       | 1.00  | 4     |
| Detectable   | 20       | 75        | 0.60  | 4     |
| Identifiable | 20       | 85        | -0.03 | 4     |
| First Names  | 21       | 95.24     | 0.90  | 5     |

|              |    |       |      |   |
|--------------|----|-------|------|---|
| Last Names   | 21 | 95.24 | 0.83 | 5 |
| Detectable   | 21 | 76.19 | 0.68 | 5 |
| Identifiable | 21 | 95.24 | 0.83 | 5 |
| First Names  | 20 | 100   | 1.00 | 6 |
| Last Names   | 20 | 100   | 1.00 | 6 |
| Detectable   | 20 | 80    | 0.69 | 6 |
| Identifiable | 20 | 100   | 1.00 | 6 |

Supplementary Material C Reference

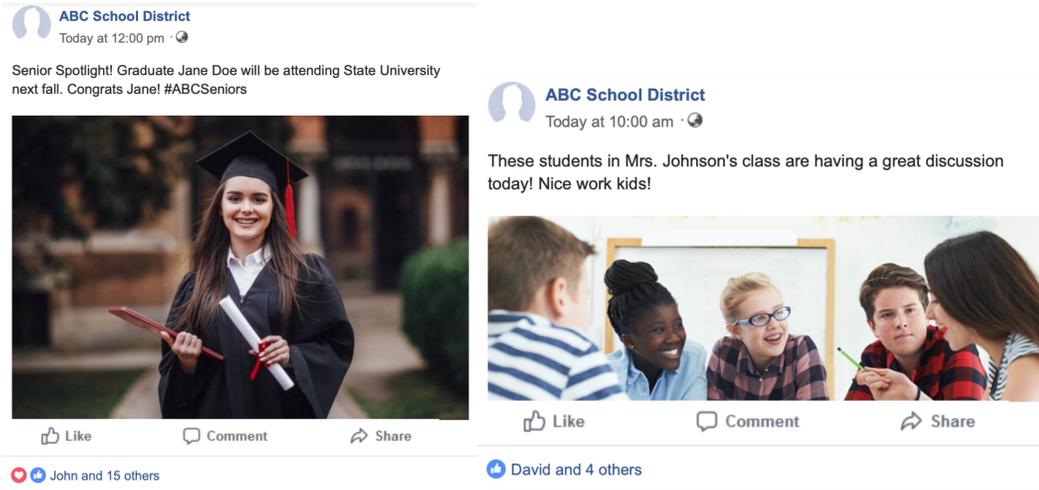
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## Supplementary Material D: Illustration of the Coding Process

The post on the left contains one student's name in the text of the post (Jane Doe) and one student's face in the image. This post would be coded as having one identifiable face because there is only one name and one face; thus, they can be identified together. The post in the right panel contains no student names in the text of the post but one staff last name (Johnson).

### Supplementary Figure D1.

#### Example Posts.



The image would be coded as having three student faces, despite there being five individuals pictured because only three of the student's faces are the eyes, nose, mouth, and/or ears clear and visible. This post would be coded as having zero identifiable faces because none of the pictured students are named in the text of the post, and there is no staff face in the image to be identified with the listed name.