Names, Nicknames, and Spelling Errors: Protecting Participant Identity in Learning Analytics of Online Discussions

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ABSTRACT

Messages exchanged between participants in online discussion forums often contain personal names and other details that need to be redacted before the data is used for research purposes in learning analytics. However, removing the names entirely makes it harder to track the exchange of ideas between individuals within a message thread and across threads, and thereby reduces the value of this type of conversational data. In contrast, the consistent use of pseudonyms allows contributions from individuals to be tracked across messages, while also hiding the real identities of the contributors. Several factors can make it difficult to identify all instances of personal names that refer to the same individual, including spelling errors and the use of shortened forms. We developed a semi-automated approach for replacing personal names with consistent pseudonyms. We evaluated our approach on a data set of over 1, 700 messages exchanged during a distance-learning course, and compared it to a general-purpose pseudonymisation tool that used deep neural networks to identify names to be redacted. We found that our tailored approach out-performed the general-purpose tool in both precision and recall, correctly identifying all but 31 substitutions out of 2, 888.

CCS CONCEPTS

• **Applied computing → Collaborative learning**; *Document preparation*; • **Security and privacy → Privacy protections**.

KEYWORDS

anonymisation, pseudonymisation, redaction, personal name, de-identification, learning analytics, ethical issues, privacy

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1 INTRODUCTION

It is common, and even educationally desirable, for contributors in online discussions to refer to one another by name and to sign their own posts [21, 22, 24]. Before using such data for research purposes in learning analytics, it is good ethical practice – and often a strict requirement [4, 10, 13, 18] – that personally identifying information (PII) is removed. The category of PII is not limited to names and also includes email addresses, phone numbers, user names, dates of birth, places of work or study, and other pieces of data that could be used to identify an individual [13]. The *content* of PII is generally of little interest to educational researchers, who have no need for private information such as dates of birth. In fact, removing PII can be beneficial for analysis, since it adds unwanted noise to metrics like word and sentence length, particularly for very short messages.

Personal names require careful handling. While metadata can be removed and other elements of PII can simply be redacted, personal names are often used to indicate the intended recipient of a message and to refer back to points raised by others in earlier messages. Masking, where a single replacement token (*e.g.*, `NAME`) is used to redact all names throughout the data set [13] might be sufficient for some use cases [17, 23], but it discards important information [19] and can harm performance on subsequent analysis tasks [2]. In order to identify the same individual across different messages, personal names must instead be replaced consistently with alternative identifiers, or *pseudonyms*. Additionally, variant forms of the same name must be grouped together, and individuals with similar names must remain distinct.

In other work, the task of tracking mentions of the same individuals throughout a text is often carried out using coreference resolution [20]. Coreference resolution identifies the most likely connections between proper names and references such as pronouns (*e.g.*, *she*) and expressions (*e.g.*, *the author*).[1] In contrast, the approach described in this work does not deal with pronouns or general referring expressions at all. Instead, we focus on full and shortened forms of proper names, along with misspellings. Our approach is not intended to replace coreference resolution but is, instead, a pre-processing step. In particular, pronouns and definite noun phrases (*e.g.*, "the course instructor") are not replaced, since they cannot be used alone to identify specific people. If additional information is made available alongside the transcripts, such as the course title, dates, or time stamps, it might become possible to

[1]For example, in "Robert said that he had read the book", the word *he* is likely to refer to Robert; whereas in "Robert asked if he had read the book", it is more likely that *he* refers to someone else.

re-identify individuals from such descriptive phrases [25]; further anonymisation effort would then be required [13, 25].

The process of manually identifying and replacing personal names can be time-consuming and error-prone [23]. We developed a semi-automated approach to the task of identifying personal names and replacing them with alternative identifiers. We applied it successfully to a data set of messages collected from a distance-learning course. We evaluated the output with reference to the final processed data, in order to determine the importance of handling elements such as misspellings. We found that a relatively simple approach using regular expressions worked better than one that was more computationally demanding, without requiring any additional data to be annotated. Our approach can be adapted easily to handle a wide variety of data sets with differing characteristics.

The main contributions of this work are 1) to highlight the challenges involved in replacing personal names with pseudonyms in a consistent way across a corpus of informal written messages, when state-of-the-art methods may perform poorly on this type of data; 2) to introduce a semi-automated approach[2] that was developed specifically for online discussion forum messages and has been used successfully to pseudonymise a data set of such messages; and 3) to investigate the relative frequency – and thus importance – of different categories of personal name found in discussion forum messages, including shortened names and misspellings.

2 RELATED WORK

Ethical concerns within learning analytics have tended to focus on avoiding potential harms to learners and other research participants [14]. Learning management systems increasingly employ "anonymity by design" [8], storing learners' personal data separately from system usage data, such as log files, that are commonly exported for use in learning analytics. Statistical disclosure controls preserve privacy by adding random noise to the results of statistical queries, such as counts and averages [10]. However, such measures do not account for elements of personal data that may be present in user-generated content [25]. Valid concerns around participants' privacy mean that discussion forum messages are often excluded from the published data extracted from MOOCs [9]. Such messages may reveal private thoughts and opinions which participants choose to share selectively, with peers, but not with the wider public [7]. Yet, even when researchers have permission to access the raw data in full, it is still necessary to remove personal details before sharing the data with others, such as paid annotators. In the case of student lab reports, for example, simply removing the metadata that links a report document with the author's username would not be sufficient to hide their identity, since learners often refer to themselves and other individuals by name in the body of the text [23].

Much of the work on identifying and removing personal names comes from the medical domain [1] and is focused on anonymisation through redaction. In a study using clinical data, a database of 3.8 million names collected from Social Security data was used to identify and redact personal names from narrative reports written by medical personnel [12]. The size of the database of valid names played an important role in system performance. Competing systems were seen to improve after they were given access to the larger list. However, since many rare names overlap with common dictionary words, between half and two-thirds of all tokens could end up removed from the reports unless the system also made use of frequency counts when deciding whether a word was a name.

Written personal exchanges between individuals, such as email messages, often contain sensitive details that need to be obscured before they can be used for research purposes. A corpus of approximately 2,500 personal email messages was pseudonymised using a hybrid approach combining semi-supervised and manual steps [19]. Words and phrases that were considered to represent sensitive data, including names of people and corporations, were replaced with alternative values. A notable feature of the study [19] was that the replacement names were specifically chosen to preserve the "nature" of the original names – for example, companies of a similar type. Pseudonyms were substituted for sensitive terms consistently across the corpus, indicating that duplicated personal names received no special handling.

Multimodal data poses additional challenges. In a corpus of Dutch Sign Language, names were removed from the textual annotations, but the original video was left unchanged; while in a corpus of German Sign Language, names were also removed from the video, by superimposing black rectangles over the relevant parts of the image [11]. In order to *replace* personal names in audio or video data with alternative names, it would be necessary to re-record the segment. However, text-based transcriptions and annotations can be treated in the same way as other textual corpora.

Named entity recognition (NER) software seems like an obvious choice for detecting names in discussion transcripts, and was used successfully to anonymise a corpus of chat logs in six languages [1]. However, issues like spelling and grammatical errors – common in informal texts – can dramatically reduce its effectiveness [19]. A brute-force approach, which simply looked for the names in the class register, out-performed two different NER implementations, in a study assessing how well the personal names of learners and instructors could be redacted from a data set of 1,000 student lab reports [23]. Another recent study, using a corpus of discussion forum text data from two online courses [4], found that a NER-based approach was not satisfactory for redacting names. Instead, the authors developed bespoke text anonymisation software that used machine learning to classify possible names. Their approach had three main stages:

(1) Identify possible name words.
(2) Classify the words as names or non-names, either manually or using machine learning.
(3) Remove from the text all identified names.

Recent advances in the area of Natural Language Processing (NLP) have led to the widespread use of pre-trained language models such as BERT [5] for many tasks. Model training makes use of enormous data sets and large amounts of computing power to train on low-level tasks such as predicting the missing word in a sentence. The models can then be fine-tuned in different ways to tackle higher-level downstream tasks, using a much smaller amount of training data. In service of text anonymisation, the Textwash tool [15] used a BERT model, fine-tuned on annotated data from the British National Corpus [3], the Enron email corpus [16], and Wikipedia, in order to

[2] https://github.com/efarrow/nicknames

identify PII entities. In addition to names, Textwash also redacted locations, occupations, dates and times, and many other classes of information that could be used to identify someone. The evaluation of Textwash was unusually robust, focusing on the likelihood of de-anonymisation of individuals in a realistic setting. Famous people could often by re-identified based on small pieces of information such as roles they had played in movies, while less famous people were almost never de-anonymised.

The present work aims to address several weaknesses of earlier approaches, while presenting a novel process that can be used to pseudonymise messages from asynchronous online discussion forums without requiring additional data annotation. There is growing interest within learning analytics in the analysis of online discussions [4, 6]; but valid ethical concerns remain, relating to protecting the identities of participants, even where studies are conducted in-house. Additionally, restrictions on data sharing frequently hamper the reproduction of results. Many of these concerns could be alleviated by reliable pseudonymisation methods. Our first research question was thus:

RQ1: *How well can regular expressions identify the personal names in discussion forum messages and connect them to the correct participants, compared to using the class list or a deep neural network?*

We also explored the many-to-many relationship between people and names, an aspect that is often overlooked, leading tools to treat every instance of a given name as a reference to the same individual. Nicknames, misspellings, and similar artefacts are common in informal written texts but tend not to appear in the curated sources on which many NLP tools are trained. For this reason, standard tools may not handle informal texts well. The second research question addressed in the present study was therefore:

RQ2: *What is the impact of non-standard names, such as nicknames and misspellings, on the task of pseudonymising discussion forum messages?*

3 SCOPE OF STUDY: CATEGORIES OF PERSONAL NAMES

Personal names can take many forms. It will generally be impossible to predict all possible name variations that could be used in an informal online discussion, even when a full list of participants is available. Instead, it is necessary to take a data-driven approach. This section addresses some of the common issues we encountered that made personal name identification difficult. The example discussion in Figure 1 illustrates how the personal names used in messages should be replaced consistently with pseudonyms, despite spelling errors and other variations.

Full names of participants may be available, particularly where the data is collected during a course of education. This is a useful starting point for pseudonymisation, but will directly cover only a few cases in an informal discussion forum. Students will often be registered under their legal names but they may use a different name in everyday situations. Full names often have several parts (*e.g.*, first, middle, last), of which a subset might be used in messages – perhaps just the given name, which could be a middle name. Some given names have more than one word (*e.g.*, *Mary Jane*) but must be replaced with a single copy of the pseudonym (*e.g.*, `[U43]`).[3]

Shortened forms of names can exhibit a lot of variation. For example, an individual whose first name is *Robert* might sign messages as *Robbie*, *Rob*, *Bert*, or *Bob* (among others). Another common choice is to use initials (*e.g.*, *MJ* or *R-J*). Nicknames may not be related to any of the parts of the participant's full name, but must nevertheless be redacted to preserve the privacy of the participant. Depending on the research goal, shortened names and nicknames might be allocated their own, related, pseudonyms.

Misspelled names are common in informal text-based discussions. Some misspellings are simple typos (*Margret* for *Margaret*), mistaken capitalisation (*RObert* for *Robert*), or using only part of a multi-part name (*Mary* for *Mary Jane*). Common alternative spellings may be substituted (*Elizabeth* for *Elisabeth*). Stylised forms of names may be used to sign messages, such as alternating letters and spaces (*R o b e r t*), or surrounding initials with dashes (*-RG-*). Misspellings should normally be replaced in the same way as the correct name (*e.g.*, using `[U12]` for both *Arthur* and *Arhtur*).

Duplicate names arise when two or more participants in a discussion forum share a name. Where the downstream research tasks require individuals to be traced across messages, it will be necessary to disambiguate such duplicate names so that the correct pseudonym can be assigned. Often this can be achieved automatically, simply by paying attention to scope and context, *e.g.*, whether the two participants joined the course in different years. If the participants contribute to the same thread, one or both of them may (temporarily) alter the way they sign messages to avoid ambiguity, increasing the overall number of names in use.

Glued words can disguise names. Names should generally only be replaced when they appear as full words, to avoid phrases like "a summary report" becoming "a sum[U43] report". However, care needs to be taken to check for words that have been accidentally glued together, for example, "thanksMary". This issue is often encountered when sentences are run together, if the tokenisation relies on white space.[4]

Unwanted matches arise where a personal name does not refer to a conversation participant and should thus not be replaced; for example, names of public figures. Leaving the names of public figures unchanged is often desirable – for example, so that they can be discovered by a named entity recogniser in subsequent research tasks. It would be wrong to substitute the pseudonym `[U12]`, relating to the participant named *Arthur*, in a reference to the author *Arthur C. Clarke*. Such a substitution would increase the risk that the mapping from the pseudonym to the real name could be deduced and the participant's identity revealed.

4 METHOD

Our approach to redacting personal names followed a similar three-step approach to earlier work by Bosch and colleagues [4]:

[3]For clarity, in the examples in this paper we use identifiers of the form `[U43]` as replacements – *categorisation*, rather than true pseudonymisation [11, 19]. A second substitution step could replace the identifiers with alternative names, if desired.

[4]One of the sample outputs from Textwash demonstrates how easily names can be missed when the input text is not well-formed according to the assumptions of the tokenisation tool: "a really good song NAME did with NAME swift.i like NAME…" [15, p. 12].

Message ID: 12 Parent ID: 10 User ID: U12
Hi ***Mary*** Interesting presentation. I have to disagree with one of the statements you made though: [. . .] In fact, I was reminded of a science fiction novel by Arthur C. Clarke! What do you think? ***Arthur***

Message ID: 14 Parent ID: 12 User ID: U43
Hi ***Arhtur*** I am not sure if I understand what you mean. Can you explain a bit more? Thanks ***Mary Jane***

Message ID: 15 Parent ID: 14 User ID: U01
Hello ***MJ*** - I think I understand what our friend ***Arthr*** was trying to say. [. . .] Hope that helps! ***R o b e r t***

Message ID: 12 Parent ID: 10 User ID: U12
Hi **[U43]** Interesting presentation. I have to disagree with one of the statements you made though: [. . .] In fact, I was reminded of a science fiction novel by Arthur C. Clarke! What do you think? **[U12]**

Message ID: 14 Parent ID: 12 User ID: U43
Hi **[U12]** I am not sure if I understand what you mean. Can you explain a bit more? Thanks **[U43]**

Message ID: 15 Parent ID: 14 User ID: U01
Hello **[U43]** - I think I understand what our friend **[U12]** was trying to say. [. . .] Hope that helps! **[U01]**

Figure 1: Fictionalised Example of a Threaded Conversation, Before and After Pseudonymisation

(1) Automatically identify candidate name words.
(2) Filter out non-names and add missing names.
(3) Perform the substitution.

There are two main differences between the approach of Bosch and colleagues [4] and ours. First, the goal of the earlier work was basic anonymisation, so all confirmed names were simply redacted. In contrast, our aim was to track individuals across messages and replace their names with (unique) pseudonyms, to support later analysis of the conversations. Second, the prior work used a set-theoretic approach to identify all possible name words in their corpus, by removing any dictionary word that was not also a known name or location. However, a name identified in isolation would not be immediately useful for our task. Instead, we used regular expressions to collect candidate names for each participant (Section 4.2) and maintained a mapping between the names identified in the data and the participants who used those names. Our approach allowed for both manual and automated refinement of the mapping before the substitution step. Figure 2 shows a schematic diagram of the three-step process.

We evaluated our approach on a data set of messages collected from a distance-learning course. Similar to the lab reports in earlier work [23], the messages in the present study contained both personal names, to be pseudonymised, and names of cited authors, to be left unchanged. We conducted a *post hoc* evaluation of our approach with reference to the complete list of personal names found in the data set.[5] The evaluation metrics included recall, precision, and F_1 scores; the number of individuals where all names used for them were replaced; and the total number of missed connections between an individual and a name. These metrics were computed for the candidate names identified by regular expressions and compared to a baseline using only names derived from the official class list. A second comparison used the set of names identified by the supervised machine learning model from the Textwash system. Textwash can identify several different classes of PII. The evaluation included only the tokens that Textwash labelled as `PERSON_FIRSTNAME` or `PERSON_LASTNAME`.

The rest of this section is organised as follows. The data set we used for evaluation contained examples of personal names in each of the categories described in Section 3. We briefly describe the data and the course from which it was collected in Section 4.1. The three stages of our approach are presented in detail: identifying possible names in the data (Section 4.2); filtering out non-names and adding missing names (Section 4.3); and performing the substitution (Section 4.4). The *post hoc* evaluation we carried out in order to answer our research questions is outlined in Section 4.5.

[5]The complete list of names was the result of careful and comprehensive manual review.

4.1 Data Used in the Study

The data we used was collected across 6 sessions of a Masters-level distance-learning course run by a Canadian university (Table 1). We needed to remove the personal names before sharing the discussion messages with annotators who were not part of our core research group. There were 84 unique participants in the data set and the *post hoc* evaluation revealed that they used 148 unique personal names between them, including multi-word names. Since some names were shared by multiple people, the total number of valid connections between a person and a name was 163.

The participation instructions for the discussion assignment indicated that every student should start a new thread, in which they would share a video presentation and field questions and comments from their peers. Course instructors rarely took part in the discussions. The user interface allowed messages to be added as replies to previously posted messages; thus, conversations were arranged in nested threads. Messages were written in English and were extracted for analysis as unformatted text. Consent was obtained to collect and analyse the data, in accordance with the requirements of our institution, but we do not have permission to share the data; example sentences in this work are illustrative.

The metadata associated with each message included the time stamp when the message was posted, along with numerical identifiers for the following:

- the session in which the course ran;
- the thread within the session;
- the participant who posted the message;
- the message itself; and
- the parent message, if any (zero for the top-level messages that started each thread).

We augmented the metadata by adding a derived field to indicate the identity of the participant who posted the parent message, if any, since that individual was the person most likely to be addressed by name in a reply. The value of the derived field was set to zero for top-level messages with no parent.

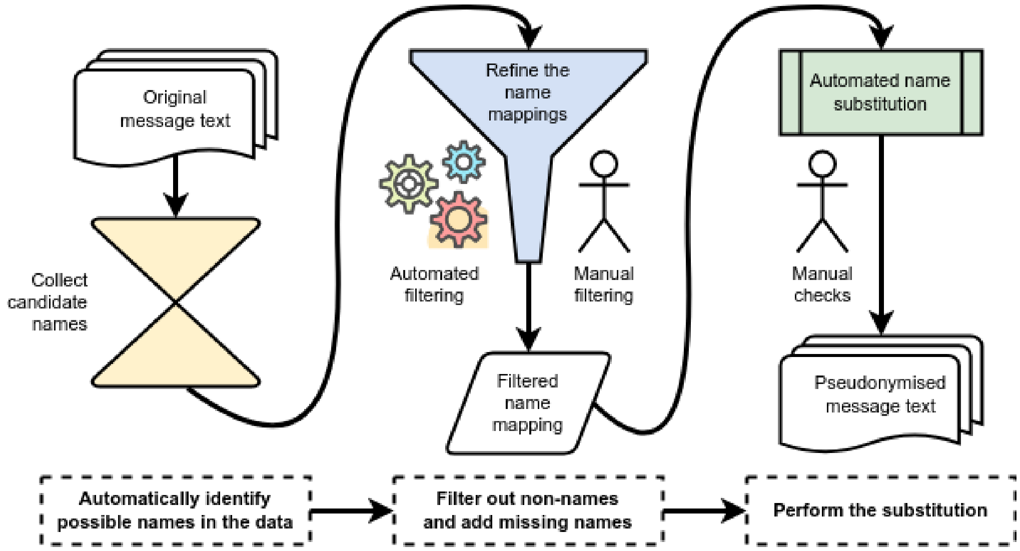

Figure 2: Schematic of Three-Step Approach to Replacing Names with Pseudonyms

Table 1: Statistics for the Data Set

Session	Participants	Threads	Messages	Message Length (words)		
				Mean	SD	Median
1	16	15	212	107.6	99.7	78.5
2	24	23	633	137.6	124.5	104.0
3	12	11	243	147.9	95.8	126.0
4	9	8	63	123.0	74.5	107.0
5	15	14	359	133.1	85.0	117.0
6	13	13	237	148.4	123.6	124.0

The steps we took to process the data and replace the personal names with alternative identifiers using our three-step approach (Figure 2) are presented next.

4.2 Step 1: Identifying Candidate Names

The first step towards replacing personal names with pseudonyms consistently across the data set was to identify a collection of strings that were likely to be personal names that needed to be replaced. After looking at a sample of our data, we chose to use regular expressions to collect candidate names from the messages. Note that we did not need to collect every *instance* of a name, but only the set of names used for each participant. We also did not need to collect *every* name, since many names referred to the authors of published research papers that were being discussed, rather than to the participants themselves.

To identify possible names used by the **sender** of the message, we looked at the end of each message for the regular expression `(\w+(-\w+)?(\s+\w\.?)?)$`. This can be expanded for ease of reading as '`WORD CHAR.`', '`WORD CHAR`', or '`WORD`', where `CHAR` indicates a Unicode word character and `WORD` indicates a sequence of one or more consecutive `CHAR`s, with an optional hyphen in the middle. We hoped that this regular expression would capture sufficiently many examples of participants signing their messages, while at the same time avoiding excess noise. All sequences of text that matched the regular expression were treated as potential names. The trailing punctuation, if any, was stripped off, and any match that contained a decimal digit was discarded.

To find candidate names for message **recipients**, we looked at the start of each message for the case-insensitive phrase 'Hi `WORD`', using the regular expression `^[hH][iI]\W+(\w+(-\w+)?)`. The text that matched `WORD` was returned as the search result, and we again dropped any result containing a digit. We made the working assumption that every reply was addressed to the participant who posted the parent message, and connected candidate names with individuals on that basis.

A single set of candidate names was generated for each participant, combining the names identified in their roles as sender and (assumed) recipient of messages. We kept track of how many messages contained each name – a lower bound on the total number of instances of each name in the data, since it ignored multiple uses of the same name within one message. These counts allowed us to rank the names identified for each participant by their frequency of use.

We generated two additional name mappings to support the evaluation of our approach. For our baseline, we used the names from the class list and generated additional candidate names by splitting each full name into shorter forms composed of subsets of its parts (*e.g.*, first and last, first and middle, each part alone). Names from the class list that did not appear anywhere in the data were removed. For a more challenging comparison, we collected the personal names that were identified by the Textwash model and connected them to both the sender and (assumed) recipient of the message in which they appeared.

4.3 Step 2: Filtering and Refining the Names

In order to allow the mapping from participants to names to be filtered and refined, it was written out to a text file in a simple, human-readable format (Figure 3). The mapping file was designed to be edited, manually or automatically, before being used to replace the names in the data. Obvious **non-names** can be removed and additional entries can be added. For example, for participant `[U01]`, both *Thanks Robert* and *html* would be removed. In future, the removal of non-names could perhaps even be automated, using a machine learning approach like that in earlier work [4].

Mistaken connections between participants and names also need to be removed. Sometimes participants add their messages at the wrong level in the nested thread structure. For example, a reply addressed to one participant might appear nested under an earlier reply sent by another participant. In cases like that, the simple heuristic used to identify the likely recipient of a message would connect the name with the wrong participant (*e.g.*, the name *Maggie* in the list for participant `[U03]`). If a class list is available, it can be used to identify names that are out of place. Shared cultural knowledge might also suggest that some names belong together (grouping *Maggie* with *Margaret*). Our system tracked how often each name was connected to an individual and displayed the names in frequency order. In the absence of a class list, frequency information could be used to determine which names were most likely to relate to each participant.

When a **glued word** appears in the list of candidate names (*e.g.*, *thanksMary*), the glued part of the word (*thanks*) will be dropped during the substitution. Alternatively, a separate entry could be added, connecting the glued word with a composite output (*e.g.*, *thanks* `[U43]`). A third option is to delete the glued word from the mapping and edit the corpus data file directly.

It may be desirable to replace **multi-word names** with a single token, for the benefit of later analysis. The name *Mary Jane* would otherwise become `[U43] [U43]`, while the shortened form *MJ* would become `[U43]`. In addition, the likelihood of encountering duplicate names within the same context is lower for multi-part names like *Mary Jane* than for single word names like *Robert*. Since the regular expressions described in Section 4.2 return only single words as candidate names, or a word followed by a single letter, we augmented the mapping file by adding all the candidate names generated from the class list. Additional full names could also be added manually; for example, the name *Robbie Jones* might be added for participant `[U01]`, based on the high frequency of occurrence of those names individually.

By comparison, the Textwash system automatically concatenates adjacent words found in the text, creating multi-word tokens from consecutive words that are identified as being the same type of entity. A multi-part first name like *Mary Jane* would thus be recognised as a single name. However, since Textwash uses different entity types for first names and last names, full names are never completely rejoined. This limitation means that a system relying on Textwash to identify possible names would replace a single mention of the name *Elisabeth Brown* with two consecutive instances of the token `[U03]`. In addition, names that are in common use as both first and last names, such as *Arthur*, may not be merged as expected.

Rather than adding multi-word names to the mapping file, an alternative approach would be to use only single-word names in the initial substitution and then to compress consecutive instances of the same token into a single instance in a post-processing step. While simpler in some ways, the resulting increase in duplicate names requiring manual resolution might make such a two-step approach undesirable.

4.4 Step 3: Substituting Personal Names

The filtered mapping file was used to replace the identified names with their associated pseudonyms consistently across the full data set. A regular expression was generated from each candidate name: `\b{NAME}\b`, where `NAME` was the properly escaped form of the name. Wrapping the name in this way ensured that only full words were replaced. The names were sorted and substituted longest-first, so that multi-part names would be found before their constituent parts and could be replaced with a single instance of the correct pseudonym.

To deal with duplicate names shared by two or more individuals, we experimented with different ways of grouping the messages while carrying out the substitution step: one discussion thread at a time, one course session at a time, and the full data set at once. Where the same candidate name was connected to multiple participants within the same group (*e.g.*, the name *Robert* for both `[U01]` and `[U04]`), a warning message was generated by the system so that the conflict could be resolved manually. It is worth noting that the same name mapping file was used in every case – there is no need to create specific mappings for subsets of the data.

4.5 *Post Hoc* Evaluation

After the name replacement step had run, the substitutions were reviewed by the research team. Names shared by multiple participants (*e.g.*, *Robert*) and flagged by the system as ambiguous were manually assigned to the correct individual. During the review, the team discovered a small number of examples of personal names that had been missed. It was easy to add additional entries to the mapping file to connect the names with appropriate identifiers and then rerun the name substitution step to catch all instances of the same name.

Unwanted substitutions were reverted, such as *Arthur C. Clarke* in the example described in Section 3. While it would be possible to identify some public figures automatically from sources such as Wikipedia, the non-participant names we encountered were more often those of authors of scientific papers, most of whom are unlikely to be listed in Wikipedia. If desired, names that should be

```
U01 | Robbie | Jones | Robert | Thanks Robert | R o b e r t | RObert | html
U02 | Margaret | Maggie | Smith | Margret | Again | all | S
U03 | Brown | E | Elisabeth | E Brown | Elisabeth Brown | Elizabeth | Maggie
U04 | Bob | RG | Bert | Robert Grey | Cheers | Robert | Grey | Rob
U12 | Arthur | Arhtur | Arthr | Arthur von Trapp | Artur | Arthur Trapp | von Trapp
U43 | Mary Jane | Mary | MJ | Mary Jane Poe | Jane | Poe | thanksMary
```

Figure 3: Example Mapping File, Connecting Participants with Candidate Names

left unchanged could be added to the mapping at the review stage, and the substitution algorithm updated to handle them accordingly.

For the evaluation, we referred to the final, corrected version of the data set and created a gold-standard mapping file, connecting all the personal names found in the data with the correct participant identifiers. This gold-standard mapping was used to evaluate the mapping generated using regular expressions and to compare it against a baseline that only used the class list, and against the mapping generated using the Textwash model, addressing **RQ1**.

Recall is arguably the most important metric for this task [2], since it indicates what proportion of the personal names in the data were correctly identified. Missing even one name means that the identity of the individual could be revealed [23]. Where the missed name in a message is a single character, the risk of re-identification is low, but the direct link is nonetheless broken between that message and others where the same individual is mentioned. Precision indicates what proportion of the suggested mappings are correct. Precision can be improved by removing non-names and mistaken connections (Section 4.3). If left uncorrected, low precision in the mapping will lead to a higher incidence of wrong substitutions that need to be reverted. The F_1 score, which is defined as the harmonic mean of recall and precision, is included for completeness.

In addition to these standard metrics, we defined two more, specific to the pseudonymisation task: missed connections and coverage. Since some names were used by multiple people (like *Robert* in the example), simply counting the found names could miss cases where a name was correctly connected to one individual but not to another. Instead, we counted the number of **missed connections** between a person and a name, compared to the total number of valid connections in the gold-standard mapping. Similarly, we calculated the **coverage** given by a mapping as the proportion of participants where every name used for that individual was correctly identified in the mapping.

The complexity of the name replacement task in general depends to a large extent on the number of unique names used for each individual and the difficulty in identifying those names in the text. Addressing **RQ2**, we used the gold-standard data set to discover the distribution of personal names across the major categories from Section 3:

- Full names,
- Subsets of full names (*e.g.*, first and last),
- Nicknames, initials, and other shortened forms,
- Misspelled names.

We counted the number of unique names in each category, the number of connections between those names and different individuals, and the number of substitutions made for names of that type. We note that the same name can be a valid name for one participant and a misspelled name for another; for example, variants like *Elisabeth* and *Elizabeth*.

The *post hoc* evaluation concluded with further system comparisons. We looked at the manual edits and deletions required in the filtering step for both the regular expressions and for Textwash. We carried out an error analysis on the missed connections. Finally, we identified the optimal scope to use while grouping messages in the substitution step – session, thread, or whole data set – in order to capture names shared by multiple individuals.

5 RESULTS

5.1 Initial Mapping from Participants to Candidate Names

We compared the gold-standard mapping from participants to candidate names against the mapping generated by using regular expressions, a baseline mapping using names from the class list, and the mapping generated using the Textwash model (Table 2). The table also includes results for the mappings generated by combining the class list with the other two approaches, for cases where a class list is available. Many of the incorrect connections in the initial mapping were removed during the filtering step (Section 4.3); they are included in the results in this section to allow a fair comparison of the candidate identification methods.

On inspection of the missed connections, there were several examples where the target was a multi-word name and the mapping correctly contained all the individual words; for example, a participant signing a message as *Robbie Jones*. We therefore carried out a further comparison after splitting the multi-word tokens in all the mappings into single words (Table 3). The splitting operation resulted in 153 unique single-word names and 169 connections between individuals and names.

In answer to **RQ1**, the regular expressions performed better on every metric compared with the deep neural network model from Textwash. The regular expressions achieved better coverage and higher recall and F_1, compared to using the class list alone, but at the expense of lower precision. The best coverage and recall scores were achieved by adding the names from the class list to the mappings extracted using regular expressions; this combination also gave the best F_1 score in Table 2, but there was a reduction in precision compared to the regular expressions alone. When only single-word names were considered (Table 3), both precision and F_1 score were lower.

Table 2: Initial Mapping Generated by Each Approach, Compared Against the Gold-Standard Mapping

Approach	Coverage	Missed Connections	Recall	Precision	F_1
Regular Expressions	71.4%	28/163	82.8%	52.1%	64.0%
Class List	41.7%	80/163	50.9%	83.0%	63.1%
Textwash	59.5%	43/163	73.6%	3.8%	7.2%
Regular Expressions + Class List	79.8%	19/163	88.3%	51.1%	64.7%
Textwash + Class List	65.5%	35/163	78.5%	4.0%	7.7%

Table 3: Initial Mapping Generated by Each Approach, Using Single-Word Names Only

Approach	Coverage	Missed Connections	Recall	Precision	F_1
Regular Expressions	82.1%	21/169	87.6%	56.7%	68.8%
Class List	41.7%	82/169	51.5%	87.9%	64.9%
Textwash	81.0%	24/169	85.8%	5.2%	9.7%
Regular Expressions + Class List	88.1%	16/169	90.5%	55.0%	68.5%
Textwash + Class List	84.5%	20/169	88.2%	5.3%	9.9%

5.2 Prevalence of Name Variants and Misspellings

To address **RQ2**, we quantified the prevalence of different types of personal names in the manually corrected data, where all personal names were consistently replaced by pseudonyms (2, 888 substitutions in total). We found that the registered names of the participants accounted for more than half of the connections and most of the substitutions, although full names were rare (Table 4). Nicknames and other shortened or stylised forms were common and accounted for 23.2% of substitutions. Misspellings tended not to be repeated, although the same name could generate several different misspellings. The distribution of participants' names across categories is shown in Figure 4.

5.3 Manual Edits to Remove Non-Names and Mistaken Connections

Some of the candidate names collected by the regular expressions were clearly not names at all: entries like *all* from "Hi all", *Cheers* from a sign-off, and *Again* from a message that began "Hi Again this is a question". These are easily removed, as discussed in Section 4.3. Mistaken connections between individuals and names are harder to resolve. In practice, the largest set of possible names suggested for an individual participant in our data set only contained 20 entries, so the task of filtering them manually to remove mismatches was acceptably fast – particularly as we had a class list to guide us. Frequency data is also informative: a name that is connected to one participant many times but only once to another participant may be the result of non-standard message nesting (Section 4.3).

We noticed a small number of cases where a personal name had clearly been run together with an adjacent word to form a glued word (*e.g.*, *thanksMary*). Our chosen remedy in this case was to edit the corpus data file directly to insert a space, and to remove the glued word from the list of candidate names. We also encountered several examples of people signing off with just an initial, picked up by the regular expressions as *Thanks X* or *Cheers X*. We removed those phrases from the list of candidate names and added the initial *X* instead. The most common unwanted substitution in our data was where a participant signed off using just the initial *G*. In addition to being used as a middle initial in an author's name, the value *G* appeared in a formula in several messages.

Surprisingly, we saw similar problems with the names identified by the BERT-based model used in Textwash as with those collected by regular expressions. There were many examples of phrases like *Hi Bob* and *Thanks Mary* being wrongly identified as names, along with words like *Thanks* and *Great*. Some of the words identified as names were not personal names at all, but instead names of technologies. Additionally, since there was no way to inform Textwash to select only the names of the actual participants in the discussion, references to research papers also yielded the authors' names. The recall score for the names found by Textwash was lower than the recall for the regular expressions (Table 2) but higher than the recall of the class list alone. However, the very low precision of the Textwash results, below 6% even after the addition of the class list, indicates that it would not be a good solution in practice. The amount of manual effort required to remove the mistaken connections between candidate names and participants would be prohibitive.

5.4 Missed Connections and Missed Names

Using the mapping that was generated automatically from the regular expressions, 28 of 163 possible connections between names and discussion participants were missed (Table 2). The largest group of these (10 examples) were multi-word names, all of whose individual parts were present in the mapping – meaning that the substitution step would replace each name with multiple copies of the correct replacement token. Although this is not the desired output, the participants' identities would not be revealed. There were 5 additional names where the only missing part was present in the class list.

Table 4: Counts of Unique Names, Connections, and Substitutions, by Category of Name

Category of Name	Unique Names	Connections		Substitutions	
Registered Name of Participant	83	88	54.0%	2,169	75.1%
Nickname, Shortened, or Stylised Form	36	41	25.2%	669	23.2%
Misspelled Name	34	34	20.9%	50	1.7%
Full Registered Name of Participant	8	8	4.9%	10	0.3%
Subset of Full Name (*e.g.*, First, First Last)	75	80	49.1%	2,159	74.8%
Total	148	163	100.0%	2,888	100.0%

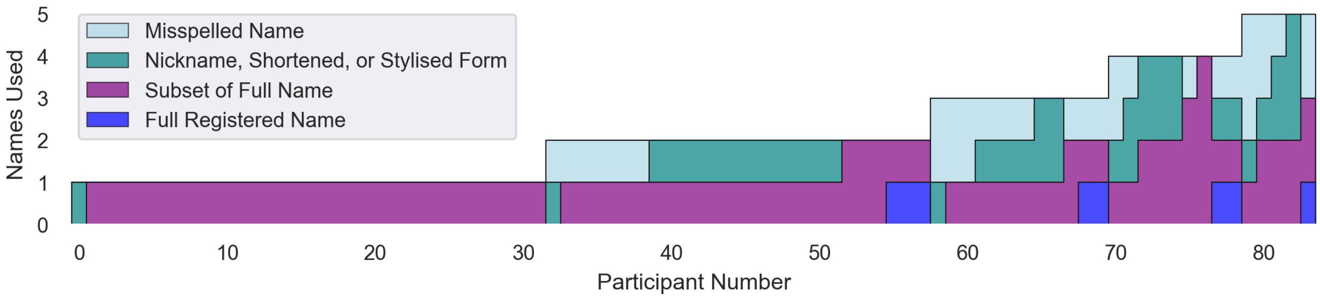

Figure 4: Distribution of Names Across Categories

There was also one example of an initial letter being used as a sign off; the mapping did not include the initial *X*, but it did contain the phrase *Thanks X*. The initial would be added to the mapping by the basic edits described in Section 5.3. Therefore, of the 28 missing connections, minimal manual intervention could be expected to restore 16 of them.

The remaining 12 missing connections all related to names that were not identified by the regular expressions and were not on the class list. This group of missed connections affected 11 individuals and accounted for 31 missed substitutions. Of these, 4 were nicknames, initials, or stylised forms of names. Another 6 missed names were one-off spelling errors, like *Arhtur*. In the final two cases, it appears that two participants were each addressed by the wrong name on one occasion, which we treated as a form of misspelling. For comparison, when the Textwash model was used to identify possible names, several of the misspelled names were again missed. Of the 34 misspelled names in the data set, the Textwash model found only 16.

5.5 Grouping Personal Names for Substitution

We found that substituting the names session-by-session worked best. There were 4 cases where duplicate names were found within a session; these were resolved manually. Taking each message thread separately risked missing mentions of the personal names of participants who did not post in that thread but were nevertheless known to the other participants. Replacing the names across the full data set at once generated 12 spurious duplicate name warnings.[6]

[6]For example, if two participants named *Robert* were enrolled on the course in different sessions, there could be no real ambiguity in any given message about which person was being addressed, so a warning about the duplicate name would be considered spurious.

Figure 5 shows the output from the full Textwash system when it was used directly to anonymise the example messages. The Textwash system assumes all instances of the same name are references to the same individual, such as when the name *Arthur* appeared twice in the first example message (Figure 1). In fact, the middle initial *C* was also connected to the same individual, due to its use in the name *Arthur C. Clarke*, and would be substituted with that individual's identifier even if it appeared alone in another message. Textwash has no concept of duplicate names and cannot generate warnings about them. There is also no way to indicate to Textwash that variants of a name refer to the same individual, such as *Mary Jane*, *Mary*, and *MJ*. Textwash has no mechanism to add missed names, such as *R o b e r t* in the final example message.

Message ID: 12   Parent ID: 10   User ID: U12
Hi `PERSON_FIRSTNAME_1` Interesting presentation. I have to disagree with `NUMERIC_1` of the statements you made though: [. . .] In fact, I was reminded of a science fiction novel by `PERSON_FIRSTNAME_3` `PERSON_FIRSTNAME_3`. `PERSON_LASTNAME_1`! What do you think? `PERSON_FIRSTNAME_3`

Message ID: 14   Parent ID: 12   User ID: U43
Hi `PERSON_LASTNAME_2` I am not sure if I understand what you mean. Can you explain a bit more? Thanks `PERSON_FIRSTNAME_5`

Message ID: 15   Parent ID: 14   User ID: U01
Hello `PERSON_FIRSTNAME_4` - I think I understand what our friend `PERSON_FIRSTNAME_6` was trying to say. [. . .] Hope that helps!
R o b e r t

Figure 5: Fictionalised Messages from Figure 1 After Pseudonymisation with Textwash

6 DISCUSSION

Our exploration of personal names used in a data set of discussion forum messages reinforced the importance of taking a data-driven approach to name discovery. If anonymisation or pseudonymisation relied on the class list alone, a large fraction of the personal names would be missed, potentially revealing the identity of the participants and compromising their privacy [7]. The most common category of alternative names in our data was that of nicknames and shortened forms, such as *Robbie* or *Bob* instead of *Robert*. In many cases, such names could be used to identify an individual just as easily as a full name. Sharing or publishing such data would be unethical [7], potentially illegal [23], and would certainly constitute a breach of trust with the participants [14].

Misspelled names accounted for a much smaller proportion of the names in the data set, but were also more difficult to identify. The regular expressions were successful in identifying 26 of 34 misspelled names, while the BERT-based model used in Textwash found only 16. Future work could adapt the set-theoretic approach of Bosch and colleagues [4] to find unknown words, and then compare the edit-distance[7] between each known name and the unknown words to identify misspellings like *Arhtur*.

The approach outlined in this work is widely applicable to other areas of educational research that make use of informal written messages exchanged between participants, although the details of the name identification step will vary with the data. The metadata we used is commonly available: an identifier for the person who posted each message, an identifier for the message itself, and an identifier for the parent message (if any). With this small amount of information, the candidate names found in each message can be tentatively connected with the participants, even in the absence of a class list [25]. In contrast, a general-purpose pseudonymisation tool like Textwash does not provide any mechanism for incorporating such domain knowledge.

We proposed two essential requirements for a pseudonymisation tool in the field of learning analytics:

- the ability to connect together multiple names for the same individual, and
- the ability to track and resolve duplicate names.

Both of these requirements are necessary in order to ensure that the resulting data is useful for researchers who want to track the flow of ideas between conversation participants, a use case that is not supported by simply masking all the names [4, 12, 23]. We found that the majority of participants in our data set were referred to by more than one name (Figure 4). By connecting those names together, we gained a fuller picture of each participant's input and interactions. Additionally, even a small data set may contain examples where more than one participant is referred to by the same name, leading to duplicate names in the data. These duplicates are often ignored [15, 19], but without the ability to identify and resolve such cases, the resulting pseudonymisation would be confusing and potentially misleading.

[7]The edit distance is calculated as the number of character insertions and deletions needed to transform one word into another.

6.1 Limitations

The specific regular expressions we used to collect candidate names were simple but proved to be effective. In another data set, the pattern of exchanges between participants will be different, and different regular expressions (or a different approach entirely) would be required at step 1 to gather an initial list of words and phrases that might be personal names. In step 2, there could be regional variations in the forms of names and nicknames that are considered valid, beyond what was seen in our data. It might also prove worthwhile to collect a list of names that should *not* be replaced at step 3 – for example, names of public figures from Wikipedia, or authors of reference books relevant to the domain.

6.2 Conclusion

The task of replacing personal names in a consistent way across a data set of informal messages is harder than it might appear at first sight. The need to identify the same participant across different variants of a name, and to distinguish between individuals using the same name – particularly where one is a public figure – presented some interesting challenges. The approach we have presented in this work was more successful on every measure than a general-purpose pseudonymisation tool, and suggests that the needs of the learning analytics community are not always best served by standard tools that cannot take account of domain knowledge.

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REFERENCES

[1] Allison Adams, Eric Aili, Daniel Aioanei, Rebecca Jonsson, Lina Mickelsson, Dagmar Mikmekova, Fred Roberts, Javier Fernandez Valencia, and Roger Wechsler. 2019. AnonyMate: A Toolkit for Anonymizing Unstructured Chat Data. In *Proceedings of the Workshop on NLP and Pseudonymisation*. Linköping Electronic Press, Turku, Finland, 1–7. https://aclanthology.org/W19-6501

[2] Hanna Berg, Aron Henriksson, and Hercules Dalianis. 2020. The Impact of De-identification on Downstream Named Entity Recognition in Clinical Text. In *Proceedings of the 11th International Workshop on Health Text Mining and Information Analysis*. Association for Computational Linguistics, Stroudsburg, PA, USA, 1–11. https://doi.org/10.18653/v1/2020.louhi-1.1

[3] BNC Consortium. 2007. British National Corpus, XML edition. http://hdl.handle.net/20.500.12024/2554 Oxford Text Archive.

[4] Nigel Bosch, R. Wes Crues, Najmuddin Shaik, and Luc Paquette. 2020. "Hello, [REDACTED]": Protecting student privacy in analyses of online discussion forums. In *Proceedings of the 13th International Conference on Educational Data Mining (EDM 2020)*, Anna N. Rafferty, Jacob Whitehill, Cristóbal Romero, and Violetta Cavalli-Sforza (Eds.). International Educational Data Mining Society, Massachusetts, USA, 39–49.

[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. http://arxiv.org/abs/1810.04805

[6] Elaine Farrow, Johanna Moore, and Dragan Gašević. 2022. Markers of Cognitive Quality in Student Contributions to Online Course Discussion Forums. *Journal of Learning Analytics* 9, 2 (Aug. 2022), 38–65. https://doi.org/10.18608/jla.2022.7250

[7] Rebecca Ferguson, Tore Hoel, Maren Scheffel, and Hendrik Drachsler. 2016. Guest Editorial: Ethics and Privacy in Learning Analytics. *Journal of Learning Analytics* 3, 1 (Apr. 2016), 5–15. https://doi.org/10.18608/jla.2016.31.2

[8] Brendan Flanagan and Hiroaki Ogata. 2017. Integration of Learning Analytics Research and Production Systems While Protecting Privacy. In *Workshop Proceedings of the 25th International Conference on Computers in Education (ICCE2017)*, Yusuke Hayashi, Moffat Mathews, Thepchai Supnithi, Wenli Chen, Jie-Chi Yang,

Ahmad Fauzi Mohd Ayub, Su Luan Wong, and Antonija Mitrovic (Eds.). Intelligent Computer Tutoring Group, University of Canterbury, Christchurch, New Zealand, 355–360.

[9] Josh Gardner, Christopher Brooks, Juan Miguel Andres, and Ryan Baker. 2018. Replicating MOOC predictive models at scale. In *Proceedings of the 5th Annual ACM Conference on Learning at Scale*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3231644.3231656

[10] Mehmet Emre Gursoy, Ali Inan, Mehmet Ercan Nergiz, and Yucel Saygin. 2017. Privacy-Preserving Learning Analytics: Challenges and Techniques. *IEEE Transactions on Learning Technologies* 10, 1 (2017), 68–81. https://doi.org/10.1109/TLT.2016.2607747

[11] Amy Isard. 2020. Approaches to the Anonymisation of Sign Language Corpora. In *Proceedings of the LREC2020 9th Workshop on the Representation and Processing of Sign Languages: Sign Language Resources in the Service of the Language Community, Technological Challenges and Application Perspectives*, Eleni Efthimiou, Stavroula-Evita Fotinea, Thomas Hanke, Julie A. Hochgesang, Jette Kristoffersen, and Johanna Mesch (Eds.). European Language Resources Association (ELRA), Marseille, France, 95–100. https://www.sign-lang.uni-hamburg.de/lrec/pub/20037.pdf

[12] Mehmet Kayaalp, Allen C Browne, Fiona M Callaghan, Zeyno A Dodd, Guy Divita, Selcuk Ozturk, and Clement J McDonald. 2013. The pattern of name tokens in narrative clinical text and a comparison of five systems for redacting them. *Journal of the American Medical Informatics Association* 21, 3 (2013), 423–431. https://doi.org/10.1136/amiajnl-2013-001689

[13] Mohammad Khalil and Martin Ebner. 2016. De-Identification in Learning Analytics. *Journal of Learning Analytics* 3, 1 (Apr. 2016), 129–138. https://doi.org/10.18608/jla.2016.31.8

[14] Kirsty Kitto and Simon Knight. 2019. Practical ethics for building learning analytics. *British Journal of Educational Technology* 50, 6 (Nov. 2019), 2855–2870. https://doi.org/10.1111/bjet.12868

[15] Bennett Kleinberg, Toby Davies, and Maximilian Mozes. 2022. *Textwash – automated open-source text anonymisation*. arXiv. https://doi.org/10.48550/ARXIV.2208.13081

[16] Bryan Klimt and Yiming Yang. 2004. The Enron Corpus: A New Dataset for Email Classification Research. In *Machine Learning: ECML 2004*, Jean-François Boulicaut, Floriana Esposito, Fosca Giannotti, and Dino Pedreschi (Eds.). Vol. 3201/2004. Springer, Berlin, Heidelberg, 217–226. https://doi.org/10.1007/978-3-540-30115-8_22

[17] Jeonghyun Lee, Farahnaz Soleimani, India Irish, John Hosmer, IV, Meryem Yilmaz Soylu, Roy Finkelberg, and Saurabh Chatterjee. 2022. Predicting Cognitive Presence in At-Scale Online Learning: MOOC and For-Credit Online Course Environments. *Online Learning* 26, 1 (2022), 58–79. https://doi.org/10.24059/olj.v26i1.3060

[18] Michelle H. Lessly. 2016. *The de-identification of MOOC datatsets to demonstrate the potential FERPA compliance of MOOC providers.* Doctor of Law and Policy. Northeastern University. https://www.proquest.com/dissertations-theses/de-identification-mooc-datatsets-demonstrate/docview/1830782605/se-2

[19] Ben Medlock. 2006. An Introduction to NLP-based Textual Anonymisation. In *Proceedings of the Fifth International Conference on Language Resources and Evaluation (LREC'06)*. European Language Resources Association (ELRA), Genoa, Italy, 6 pages. http://www.lrec-conf.org/proceedings/lrec2006/pdf/200_pdf.pdf

[20] Vincent Ng. 2010. Supervised Noun Phrase Coreference Research: The First Fifteen Years. In *Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Uppsala, Sweden, 1396–1411. https://aclanthology.org/P10-1142

[21] Jennifer C. Richardson, Yukiko Maeda, Jing Lv, and Secil Caskurlu. 2017. Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior* 71 (2017), 402–417. https://doi.org/10.1016/j.chb.2017.02.001

[22] Vitor Rolim, Rafael Ferreira Leite de Mello, Vitomir Kovanovic, and Dragan Gaševic. 2019. Analysing Social Presence in Online Discussions Through Network and Text Analytics. In *2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT)*, Vol. 2161-377X. IEEE Computer Society, Los Alamitos, CA, USA, 163–167. https://doi.org/10.1109/ICALT.2019.00058

[23] Alex Rudniy. 2018. De-Identification of Laboratory Reports in STEM. *The Journal of Writing Analytics* 2, 1 (2018), 176–202. https://doi.org/10.37514/JWA-J.2018.2.1.07

[24] Na Sun, Xiying Wang, and Mary Beth Rosson. 2019. How Do Distance Learners Connect?. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300662

[25] Elad Yacobson, Orly Fuhrman, Sara Hershkovitz, and Giora Alexandron. 2021. De-identification is Insufficient to Protect Student Privacy, or – What Can a Field Trip Reveal? *Journal of Learning Analytics* 8, 2 (Sep. 2021), 83–92. https://doi.org/10.18608/jla.2021.7353