



# Sharing unwanted sexual experiences online: A cross-platform analysis of disclosures before, during and after the #MeToo movement

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## ABSTRACT

Online disclosure of sexual violence victimisation is a relatively new phenomenon. While prior research has mainly relied on analysis of Twitter data from the #MeToo period, this study compares such disclosures across platforms over two years. Using machine learning, 2927 disclosures were identified for quantitative content analysis and multiple correspondence analysis. Online platforms differed in timing of the posts, information shared, information density, co-occurrence of information and the length of the disclosure message. Most disclosures were found on the platform Twitter, and during the #MeToo movement. These posts differ from disclosures on other platforms and outside the viral movement. Regarding the content, across all platforms and periods, clustering was found around offender-oriented information, making the offender an explicit part of the experience. This study shows that an exclusive focus on online disclosures on Twitter and during viral movements gives a biased and incomplete picture of what online disclosure of sexual victimisation entails. Our cross-platform analysis over time allows for more universal statements about the content and context of online disclosures of sexual victimisation.

## 1. Introduction

Online disclosure of sexual victimisation is a relatively new phenomenon. When in October 2017 the hashtag #MeToo was first used, it quickly caught on starting a movement in which people with unwanted sexual experiences revealed the magnitude of the problem by disclosing their stories. The hashtag #MeToo was used over 19 million times on Twitter in the year after the initial tweet by Alyssa Milano on 15 October 2017 (Anderson & Toor, 2018). The use of the hashtag was not limited to Twitter, with over 12 million posts on Facebook within the first 24 h after the tweet by Alyssa Milano (CBS News, 2017). Even though the #MeToo movement seemed to have put public online disclosure of unwanted sexual experiences on the map, several other viral online movements in fact preceded it (e.g., #BeenRapedNeverReported, October 2014; #NotOkay, October 2016) and followed (e.g., #WhyI-DidntReport, September 2018). In spite of the fact that it has been over six years since the first viral hashtag movement advocating disclosure of sexual victimisation emerged, research on this phenomenon is sparse.

Sexual violence is used as a general term to describe a broad spectrum of unwanted sexual experiences, physical (e.g., sexual abuse) or

without bodily contact (e.g., sexual harassment), attempted and completed acts taking place without the consent of the individual and/or by the use of force (Canan & Levand, 2019). Based on Liz Kelly's continuum model (Kelly, 1987), sexual violence can be defined as all behaviours that victims themselves experience as sexual violence, ranging from experiences that are often seen as 'minor' offences to behaviours that fall under legal definitions of sexual assault and rape. Sexual victimisation is a stigmatised experience, implying that social understanding remains that these experiences are private by social default (Ahrens, 2006; Dindia, 1998). Public online disclosure, as advocated in online campaigns like the #MeToo movement, is antithetical to this.

Research on *offline* disclosure of sexual victimisation is not new. There is an empirical basis for the factors that contribute to the offline sharing of unwanted sexual experiences and the barriers that victims experience when deciding on whether or not to disclose. The personal, social, as well as cultural context impact the labelling of a sexual victimisation experience and the choices regarding disclosing or concealing sexual victimisation (Petronio, 2002). The offline cultural values or (social) traditions creating barriers to disclose, such as shame and fear of repercussions, may be removed by the changed context and the

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characteristics of the internet.

Social media and online fora offer new opportunities to study the context and content of disclosure of sexual violence. Numerous public online platforms exist where victims of sexual violence can disclose and have disclosed their experiences, such as Twitter (e.g., Bogen, Bleiweiss, & Orchowski, 2018; Bogen et al., 2019; Fornari et al., 2018; Schneider & Carpenter, 2020), Reddit (e.g., Andalibi et al., 2016; Andalibi et al., 2018; O'Neill, 2018), Facebook (e.g., Lokot, 2018; Lowenstein-Barkai, 2020), blogs (Fawcett & Shrestha, 2016), YouTube (Harrington, 2019), Tumblr (Mendes et al., 2019), and forums like Yahoo! Answers and Somazone (e.g., Moors & Webber, 2012; Webber & Wilmot, 2012). However, the architecture, setup and practicalities of these platforms are different, which may affect the type of information they elicit and allow to post, and may also influence which people use these platforms. On social media such as Twitter and Facebook, unique and identifiable users and interaction with other users and content play a central role (Ellison & boyd, 2013). Conversely, platforms like Yahoo! Answers and Somazone are more focused on one-way communication and may in some ways be perceived as more private (i.e., separate from one's online social network) and directed. Yet, research on online disclosure has so far been limited to single platforms, mostly Twitter (Gorissen et al., 2021), and the content of disclosures on different platforms has seldom been studied let alone compared. This is striking, because the unique characteristics, goals, target groups and style of the platforms potentially bring about different disclosures, containing different information.

The study by Mendes et al. (2019) is one of the few examples where different platforms are compared, namely disclosures on Tumblr and Twitter, in which an attempt is made to gain insight into how 'platform vernaculars' (Gibbs et al., 2015) shape the ways in which posts are constructed. Mendes et al. (2019) state that disclosures of sexual violence differ across online platforms and are shaped by the specific platform architecture. Limitations of the study of Mendes et al. (2019) are, however, the relatively small sample size and the focus on specific viral hashtags. In addition, Mendes et al. (2019) merely compared disclosures on two platforms, while we know that more platforms exist where victims can disclose and have disclosed their victimisation and that affordances of these platforms may influence the content of the disclosures.

The literature on online disclosure of sexual victimisation is thus limited in a number of ways. First, due to the small and non-representative samples of many studies, and the focus on short periods of time, research has only scratched the surface of the subject. Second, a large part of the studies focus on specific hashtags or highly visible digital movements like #MeToo, often driven by activist principles. 'Ordinary' disclosures of sexual victimisation outside these movements or without specific hashtags are largely ignored. This focus may distort the understanding of what is disclosed and where and when disclosure takes place. Furthermore, previous studies were mainly focused on English disclosure messages. English is the most spoken language in the world, with around 1.35 billion speakers across the globe (Statista, 2021). This covers a large and diverse language area with vast heterogeneity in (social and cultural) contexts that potentially influence the degree and manner of disclosure. The way society and individuals perceive and deal with sexual behaviour and sexual violence is heavily influenced by culture (Kalra & Bhugra, 2013).

This study contributes to creating a broad empirical foundation to our understanding of this new phenomenon and to fill specific knowledge gaps. Not just by studying the information shared in a disclosure (content) on a single platform or with a specific hashtag, but by analysing most Dutch online disclosure messages of sexual victimisation from 2017 to 2018. Employing machine learning techniques allows for the analysis of not just a subsection of disclosures, as has been done mostly in previous research, but of virtually all Dutch disclosure posts in a two-year period. Manually sorting and analysing all the information shared in online messages is an arduous and prohibitively time-consuming task. By automating the process of filtering between texts

containing general discussions about sexual assault and personal stories of sexual assault experiences, the entire sample of online messages can be analysed.

In 2017, 97.1% of Dutch people aged 12 or older had access to internet facilities and 86.1% also used them almost daily. In doing so, it was found that 84.6% of individuals aged 12 years or older used the internet for communication through social media (Centraal Bureau voor de Statistiek, 2018). In that same year, the Netherlands had the highest percentage of households with internet access in Europe (Eurostat, 2021). This makes the Netherlands an eminently suitable country for studying online disclosure of sexual victimisation. Zooming in on the Dutch language area also enables us to broaden our knowledge base, while at the same time reduce the aforementioned heterogeneity and the inherent effects it causes. The research period from January 2017 to December 2018 allows for a study that compares the context (*when* and *where* disclosure takes place) and content of online disclosures before, during and after the viral #MeToo hashtag. This helps to gain a deeper understanding of online disclosure of sexual violence and the elements in online disclosures that are stable and generalisable over time and platform. At the same time, the effects of viral events such as the #MeToo movement and specific platforms can be identified.

### 1.1. The present study

The purpose of this study is to examine the context and content of Dutch public disclosure messages of sexual victimisation in the years 2017 and 2018 and make a cross-platform comparison. The study aims to identify *what* victims disclose (e.g., number of experiences, information about the perpetrator, location of the victimisation) and *when* (time and timing) and *where* (platform) sexual victimisation is disclosed. The type of information victims share regards information about the experience and the perpetrator that is generally known to most victims. Prior research has addressed the content of disclosure messages of sexual victimisation to a limited extent. The presence of information was qualitatively described, without paying attention to how much information is disclosed and what pieces of information generally co-occur. Bogen, Millman, et al. (2018), for example, described the content of disclosures in tweets with the hashtag #NotOkay. They reported what was disclosed about, for instance, the perpetrator (age, gender and relationship to the perpetrator), type of victimisation, age of the victim at the time of abuse and emotional impact. The average information density of disclosure messages (how much information was shared in the messages) or combinations of information were not considered. Along with describing which information about the experience known to most victims is shared in online disclosures, this study will also examine information density and co-occurrence of information. In other words, what information and how much information is disclosed and how do the various elements in disclosure messages interact? Do different online platforms or periods of time differ in this respect and if so, how do they compare or differ?

While previous studies have shown that victims of sexual violence use several platforms to disclose their experiences, it is also known that these different platforms have different affordances that can influence the users' decisions whether or not to share certain information or experiences. Twitter for example limits its users to the number of characters that can be used per post. A comparison between online platforms with regard to what information is shared in online disclosures of sexual violence is necessary due to the variation of affordances of different platforms. An additional question is whether disclosure of experiences of sexual violence online is something that takes place exclusively during viral hashtag movements or whether it is also happening outside of such events? Can it be considered a unique or distinctive occurrence, or is rather part of social media users' habitual posting behaviour? In other words, is disclosure part of one's routine activities on social media or does it fall outside the normal course of events? In case online disclosure of sexual violence also takes place outside of highly visible online

movements, previous research in which only those disclosures were studied may show a flawed or distorted perception of the phenomenon and thus does not do justice to the reality of how victims use social media to share about their experiences.

## 2. Method

### 2.1. Data collection

The data for this study were collected using a social media monitoring tool by the software company OBI4wan. This tool provides a historical archive of conversations on online public sources (such as forums, blogs, and social media) from the preceding three years. In addition to the online messages, OBI4wan provides metadata such as platform type, date and time of the post, URL, username of the poster and sentiment of the messages. A data file with conversations relevant to this research was compiled using keywords. Based on an exploratory study (Van den Berg and Gorissen, 2020), a corpus of words and sentences was developed to distinguish keywords that identify online disclosure messages of sexual victimisation. The keywords for this study consisted of combinations of general words and terms related to sexual victimisation and hashtags that are known to be associated with (online) disclosure of sexual victimisation, such as *#SGstorm*<sup>1</sup>, *#MeToo*, *#Breakthesilence* and *#abused*. Furthermore, keywords concern both the words and the words combined with a hashtag (the use of ‘#’ before a word or phrase).

Various inclusion and exclusion criteria were applied to the data collection. As stated in the introduction, this study focuses on Dutch messages. Other languages such as English, French and German were excluded from the search. Quotes and retweets were excluded as well since the study is focused on original content and this would incur a large number of duplicates. After a first exploration of the data, certain terms and tags were removed that appeared frequently but were not related to the subject of the study. An example of this is the tag ‘#generalnews’<sup>2</sup>. See supplementary material for an overview of the search terms.

The search period for this study was 1 January 2017 to 31 December 2018. The reason for this selection is twofold. The first rationale is technical—the data collection started in January 2019, which meant that the 2016 database was already partially inaccessible. The second reason to focus on this search period was the *#MeToo* movement, which took place in October 2017. By starting the data collection in January 2017, the period before the global movement could also be studied and compared. The dataset collected with the social monitoring tool consisted of 615,485 messages. All messages from the platforms ‘print’, ‘Blendle’<sup>3</sup> and ‘news’ were removed since the messages from these sources did not meet the inclusion criteria. The final sample consisted of 599,591 messages (see Table 1).

#### 2.1.1. Ethical considerations

Authors of the online messages have not been asked for permission or consent. In social computing research, it is common practice to analyse publicly available data without the permission or knowledge of the authors (Andalibi et al., 2018). To ensure anonymity and limit the traceability of the messages, identifying data (e.g., usernames) were removed after data collection and before analysis. All messages were provided with an individual ID-code, composed of a meaningless combination of letters and numbers.

On 8 December 2020 advice was sought from the committee on ethics in law and criminological research of the Vrije Universiteit Amsterdam. The members of the committee advised positively on the execution of the study and identified no ethical concerns.

#### 2.1.2. Annotation online messages

Machine learning techniques were used to identify disclosure messages of sexual victimisation in the total sample of 599,591 online

**Table 1**

Messages complete dataset per platform (N = 599,591).

Platform	Number of messages OBI4wan (N) <sup>a</sup>	%
Facebook	150,086	25.0
Forum post	1843	0.3
Google+	2200	0.4
Instagram	10,264	1.7
LinkedIn	54	0.01
News response	2863	0.5
Pinterest	382	0.1
Review	37	0.01
Twitter	368,280	61.4
Weblog	51,554	8.6
Weblog response	11,647	1.9
YouTube	381	0.1

Note. The classification of the various platforms was based on the subdivision that was used by the social media monitoring tool. It is important to note that when looking at individual messages, overlap or exceptions are possible (e.g., a response to a news item on Twitter is classified as ‘Twitter’ and not as ‘News response’).

<sup>a</sup> The total number of messages per platform still contain duplicates.

messages. To do so, a subsample of the first 100,000 messages (in alphabetical order) was drawn from the complete dataset. These messages were selected as a training set for the machine learning classification.

The first author read all messages of the training set and manually classified posts by differentiating between those messages that did (coded as ‘1’) and that did not contain online disclosure of sexual victimisation (coded as ‘0’). This research focused only on disclosures from self-proclaimed victims of sexual violence about their personal experiences. Victims needed to have written their own story using their own words without editing by third parties. This means that reports from newspapers, magazines and television programs were coded as non-disclosures (‘0’). In addition, messages written by multiple authors, recollections of other people’s experiences, interviews, reposts from other websites and messages that did not clearly indicate whether they concerned sexual violence, for example messages about sexism or gender discrimination, posts with solely a hashtag (e.g., ‘*#MeToo*’) or messages that lacked any contextual information (e.g., ‘*#MeToo And who hasn’t actually?*’, VJ20071) were coded also with the label ‘0’.

On top of the annotation of the 100,000 messages, platforms with small samples (sample size below 400 messages, for example LinkedIn and Pinterest) were also annotated manually. Furthermore, a random sample of 5000 messages from the remaining set was selected using a random number generator. These messages were annotated manually to control for selection bias in the alphabetically sorted first 100,000 online messages. No biases concerning disclosure/non-disclosure ratio, dates, length of messages, and platform were observed. A second control for bias was done by randomly drawing 150 messages from the first subsample (N = 100,000) using a random number generator. This sample was oversampled on disclosure messages. A second annotator (CvdB), annotated these 150 messages independently, not being aware of the oversampling. After annotation, the results of the first and second annotator were compared and a solid overlap was found with a Cohen’s Kappa interrater reliability of  $\kappa = 0.878$ .

#### 2.1.3. Machine learning

The detection of online disclosure messages in the remaining messages using machine learning (ML) was formulated as a supervised binary classification problem. Before the machine learning took place, the following pre-processing measures were applied: lowercasing and removal of non-original content like quotes (from Tweets), URLs, special characters and interpunction (like @ and #), extra whitespaces between words, at the beginning and end of a sentence. After the pre-processing was completed some empty messages remained. This concerned messages that, for example, only consisted of quotes (non-original data),

URLs or special characters, which were removed in the pre-processing steps. On Twitter 2780 empty messages were found and 259 empty messages on the other platforms. A total of 3039 empty messages was thus removed from the database.

Two platform-specific models were created for supervised machine learning; one for the Twitter data and one for the remaining data. Twitter data differ from other text data like Facebook or blogpost. Twitter has a character limit of 280 characters<sup>4</sup>. Additionally, tweets often contain misspelled words, slang, acronyms and hashtags (Mahata et al., 2015). Therefore, Twitter data are significantly different from the other data in the complete dataset.

After annotation of the online messages, a random sample of 300 messages per model (Twitter and other platforms) that were classified as non-disclosures were checked for false negatives, of which none were found. See the flowchart for information on the classification process. Details about the machine learning process and developed models can be found in the supplementary material.

Flowchart disclosure messages (N).

## 2.2. Data analysis

Due to the low number of disclosures on various platforms, the following analysis will distinguish between Twitter, Facebook, weblog and other sources (forum post, Google+, Instagram, news response, Pinterest, review, weblog response and YouTube combined).

The disclosure messages (original content) were analysed using content analysis. Based on the exploratory study and annotation of the first 100,000 messages a coding scheme was developed. First, the coding scheme contained elements about the platform and date on which the disclosure was found and length of disclosure in the number of characters. The date disclosures were posted was coded accompanied by information about the timing of the disclosure in relation to the #MeToo movement. For the latter, the following dates were used: 1 January 2017 to 14 October 2017 was coded as 'Before #MeToo movement'; 15 October 2017 to 15 November 2017 was coded as 'During #MeToo movement'; 16 November 2017 to 31 December 2018 was coded as 'After #MeToo movement'. The date marking the period 'During #MeToo' was determined by the date of the initial use of the #MeToo by Alyssa Milano on 15 October 2017 (Milano, 2017). The cut-off point for during and after the movement was based on the viral activity of the hashtag #MeToo. The use of the hashtag had significantly decreased one month after the initial use. Although the hashtag has continued to be used occasionally in disclosure messages in the following period (and is still sometimes used today), it was no longer being used to the same extent as during the peak of the #MeToo movement.

Alongside information about where and when disclosures were posted, the presence or absence of information about the victimisation was noted. This included information that is generally known to victims, such as gender of the author; number of experiences; when victimisation occurred/duration; where victimised; number of perpetrators; relationship to perpetrator; identifying information perpetrator; gender perpetrator. It should be noted that the text provided by the social media monitoring tool was for some messages incomplete. For reasons unknown, the social media monitoring tool did not gather all text for all online conversations, causing some to be cut off. As a result, the presented presence of information may be an underestimation. Information on sexual orientation, ethnicity, age and other identifying information about the author often lacked and was therefore not coded. Coding individual disclosure messages enabled analysis both within a disclosure as well as across different platforms and time periods.

To assess the codebook and coding instructions, a second coder was provided with a random subsample of disclosures (N = 50). Based on this assessment, the coding instructions were further elaborated and specified.

Finally, in addition to coding the presence or absence of specific information (e.g., gender author), the information density of each

disclosure message was calculated. The information density was calculated by counting the number of times the aforementioned eight pieces of information were present in a disclosure. Information density thus ranged from zero to eight.

An analysis of variance (AN(C)OVA) was used to determine the statistical differences between the information density at different periods in time (before, during and after the #MeToo movement) and on different platforms. Multiple correspondence analysis (HOMALS) was performed to gain insight into combinations of pieces of information in disclosures. For the sake of interpretability, the results were clustered on two dimensions.

Apart from information about the content, the first author also placed some specific comments on several individual posts. A total of 130 disclosures were accompanied by a comment related to the credibility of the disclosure. These concerned messages which, based on the content of the messages, were suspected of not being serious disclosures of sexual victimisation or for instance when the tone of the messages was sarcastic. These disclosures were marked as atypical. Most atypical messages were found on Twitter (N = 106, 81.5%). An example of an atypical disclosure is the following:

*Tonight I was first assaulted and then raped by my neighbour when I was home alone ..... #MeToo I will not mention her name because then she will be in the pillory and I secretly hope she will come again tomorrow! (VJ548367).*

Removal of the atypical disclosures did not affect the conclusions substantially. Additionally, since the assessment of the credibility of disclosures could not be substantiated and validated, atypical messages were not removed from the analysis.

## 3. Results

After annotation and removal of duplicate disclosures, the final dataset consisted of 2927 unique disclosure messages of sexual victimisation. Online disclosure messages had an average length of 411.3 characters ( $SD = 1109.0$ ,  $Mdn = 166.0$ ; including spaces, punctuation, and URLs), with a mode of 255 characters and are thus relatively short. The shortest disclosure message was 18 characters, the longest 27,911 characters.

### 3.1. Where disclosure occurred

By far the most online disclosures of sexual victimisation were found on Twitter (80.4%,  $N = 2352$ ), followed by Facebook (12.8%,  $N = 375$ ), the platform weblog (3.8%,  $N = 112$ ) and other platforms (3.0%,  $N = 88$ ). Compared to the other platforms, Twitter also had the largest share of disclosures compared to non-disclosures within the complete dataset.

### 3.2. When disclosure occurred

Information about when disclosure occurred can be divided into the date, date in relation to the #MeToo movement (the largest viral hashtag movement during the researched period), time of the day and day of the week disclosures of sexual victimisation were posted online.

Analysis of the dates showed that sexual victimisation experiences were disclosed online before, during and after the #MeToo movement (Fig. 1). Although the lion's share of disclosures was placed during and after the #MeToo movement, online sharing of sexual victimisation is a phenomenon that certainly preceded the international viral campaign. As the periods are not of equal length (before is 286 days, during 31 days and after 410 days), it is important to calculate the average number of disclosures per day. The highest average was found during the #MeToo period (15 October 2017 to 15 November 2017) with an average of 36.5 disclosures per day. The same applied to the average number of disclosures per day when looking at the different platforms. On all platforms, the number of disclosures per day during the #MeToo movement



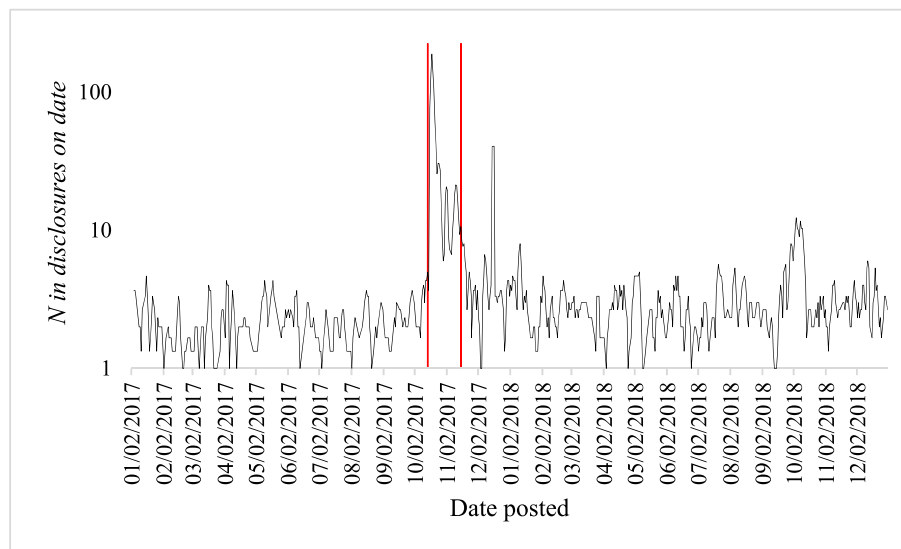


Fig. 1. Timeline disclosure messages 1 January 2017 to 31 December 2018.

was higher than before and after the viral campaign. On Twitter, the average number of disclosures per day during the #MeToo was 31.4. For all platforms except Facebook and weblog the average number of disclosures was higher *after* the #MeToo than *before*. On Facebook and weblog the average number of disclosures *before* (0.45; 0.14) was higher than *after* the #MeToo movement (0.37; 0.09).

*Note.* The first red line marks the first use of the hashtag #MeToo by Alyssa Milano on 15 October 2017. The second red line signifies the end of the viral activity of the #MeToo and thus indicates the start of the period after #MeToo.

Regarding the day of the week on which disclosure of sexual victimisation occurs, the heatmap in Fig. 2 shows that as the week progresses fewer disclosures are found, with Friday being the exception. Most disclosures were found on Tuesday (17.7%,  $N = 518$ ), followed by Monday (17.4%,  $N = 509$ ), Wednesday (16.5%,  $N = 482$ ), Friday (15.8%,  $N = 46$ ), Thursday (13.3%,  $N = 390$ ) and Saturday (10.4%,  $N = 304$ ). On Sundays, the fewest disclosures were found (8.9%,  $N = 261$ ). This corresponds to the user peak of Dutch users of the platform Twitter. This platform has a user peak around 4 p.m., with activity concentrated on weekdays from Monday to Thursday (Slegers, n. d.). Posting disclosure messages of sexual victimisation therefore fits within normal timelines of posting behaviour of Twitter users.

The rows of the heatmap reveal that online disclosure of sexual victimisation took place throughout the day. Since all messages were written in Dutch, it can be assumed that the bulk would be written in the same time zone (CET)<sup>5</sup>. A day was divided into four equal segments, namely the morning, afternoon, evening and night. The results show that online disclosures were mainly found in the evening (38.3%,  $N =$

1121) and afternoon (33.5%,  $N = 982$ ). The fewest disclosures were found during the night (6.7%,  $N = 197$ )<sup>6</sup>.

Combining the findings of the columns (day of the week) and rows (part of the day), Fig. 2 shows that most disclosures were posted on Monday and Tuesday evenings.

### 3.3. What is disclosed

The information shared in most posts was the number of sexual victimisation experiences (44.9%,  $N = 1313$ ), when victimisation occurred or the duration of victimisation (38.9%,  $N = 1138$ ) and gender of the perpetrator (37.4%,  $N = 1095$ ). Online disclosures of sexual victimisation seldom contained information about the gender of the author (12.3%,  $N = 359$ ). See Table 2.

Table 2  
Frequency disclosed information.

Information	Number of disclosures with specific information (%)
Gender author	359 (12.3)
Number of experiences	1313 (44.9)
When victimised/duration	1138 (38.9)
Where victimised	604 (20.6)
Number of perpetrators	987 (33.7)
Relationship to perpetrator	754 (25.8)
Identifying information perpetrator	830 (28.4)
Gender perpetrator	1095 (37.4)

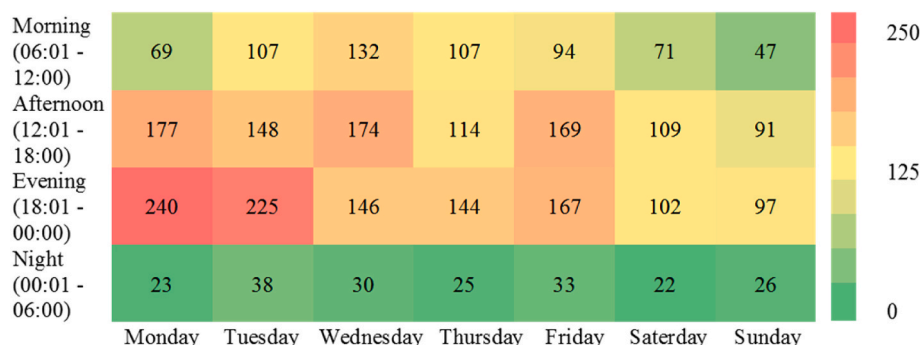


Fig. 2. Heatmap day and part of the day disclosures.

The average information density was 2.4 ( $SD = 2.0$ ). Fig. 3 shows that around one in five disclosures (20.0%,  $N = 585$ ) lacked information on all eight variables. The following message is an example: '@USER-NAME I was really assaulted ... Nothing happened to you, don't make a mountain out of a molehill' (VJ56188). In fact, most messages provided information on none (20.0%,  $N = 585$ ) or only one of the variables (20.0%,  $N = 584$ ) with just twelve messages (0.4%) containing information on all variables (Fig. 3). These messages had a relatively high average length of 5287.0 characters ( $SD = 5182.2$ ).

Multiple correspondence analysis (HOMALS) was used to analyse the relationship between the various nominal variables. From the plot in Fig. 4 there appears to be a cluster of categories related to the perpetrator. This concerns the variables 'number of perpetrators', 'relationship to perpetrator' and 'identifying information perpetrator'. This cluster indicates that disclosure messages in which information about the perpetrator is found often also contain other information about the perpetrator. This is not surprising, because when several perpetrators are mentioned, these perpetrators are often distinguished from each other by naming the different relationships to them. The following message is an example of this: 'I was raped three times when I was 10 by an uncle ... By 3 boys in my adolescence ... And by my brother-in-law ... Never believed' (VJ22095). An exception to the perpetrator cluster is information about the gender of the perpetrator.

A similar cluster seems to be present for information related to the experience, concerning the variables 'number of experiences', 'gender author' and 'when victimisation occurred/duration of victimisation'. For example: '#Metoo 2x when I was on IVs and tubes .... As an adolescent and young woman .... Later by 1 of my supervisor' (VJ18878).

### 3.3.1. Disclosed information per platform

Variation was found regarding the specific information that was shared on the various platforms (Twitter, Facebook, weblog and other). The highest mean information density was found on the platform weblog ( $M = 4.0$ ,  $SD = 2.5$ ), followed by Facebook ( $M = 2.8$ ,  $SD = 2.1$ ) and other ( $M = 2.7$ ,  $SD = 2.1$ ). ANOVA revealed significant differences in information density on platforms,  $F(3,2923) = 34.493$ ,  $p < .001$ . Information density differed significantly between weblog and Twitter ( $p = .000$ ), Facebook ( $p = .000$ ) and other ( $p = .001$ ). The volume of information found in disclosure messages thus differs depending on the platform on which the message was shared. On Twitter the lowest mean information density was found ( $M = 2.3$ ,  $SD = 1.9$ ; see Table 3). In accordance with the lowest mean information density, on Twitter the least information was shared on five of the eight variables namely, 'gender author', 'number of experiences', 'when victimised/duration', 'identifying information perpetrator' and 'gender perpetrator' (see Table 5). As expected, most information on all variables was disclosed on the platform weblog. This raises the question of whether the information density is related to the length of the disclosure message. Disclosures with the largest mean number of characters were found on the platform weblog, namely 4066.6 characters ( $SD = 3544.5$ ). On Twitter,

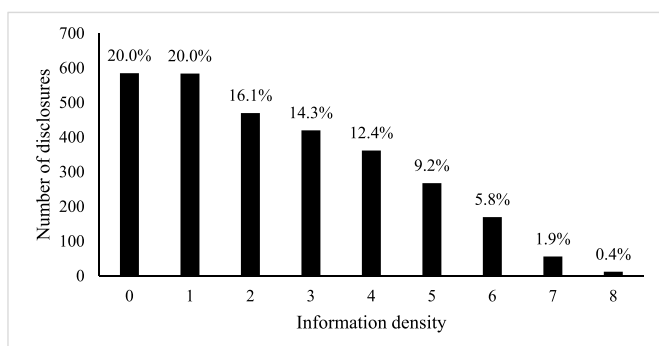


Fig. 3. Information density in online disclosures.

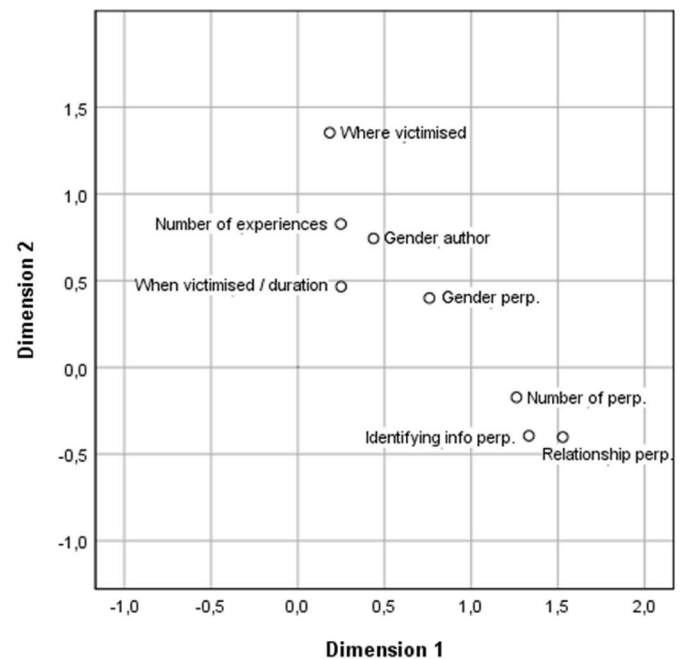


Fig. 4. Multiple correspondence analysis variables.

Table 3

Unadjusted and covariate adjusted descriptive statistics for information density.

Platform	N	Model 1 <sup>a</sup>		Model 2 <sup>b</sup>	
		M	SD	M	SD
Twitter	2352	2,27	1,87	2,32	,041
Facebook	375	2,83	2,06	2,79	,099
Weblog	112	3,96	2,46	3,15	0,24
Other	88	2,68	2,07	2,44	0,21

Note. M indicates Mean, SD indicates Standard Deviation.

<sup>a</sup> Model 1 is a one-way ANOVA without controlling for length of the disclosure message.  $R^2 = .034$ .

<sup>b</sup> Model 2 is the ANCOVA with the variable "length" as covariate.  $R^2 = .042$ . The effect size of length is  $\eta^2 = .008$ .

Table 4

Unadjusted and covariate adjusted descriptive statistics for information density.

Period	N	Model 3 <sup>a</sup>		Model 4 <sup>b</sup>	
		M	SD	M	SD
Before #MeToo	500	2,12	1,9	2,05	,084
During #MeToo	1133	2,98	1,88	3,02	,056
After #MeToo	1294	2,04	1,94	2,04	,052

Note. M indicates Mean, SD indicates Standard Deviation.

<sup>a</sup> Model 3 is the one-way ANOVA without controlling for length of the disclosure messages.  $R^2 = .052$ .

<sup>b</sup> Model 4 is the ANCOVA with the variable 'length' as covariate.  $R^2 = .092$ . The effect size of length is  $\eta^2 = .042$ .

the shortest disclosures were posted with a mean length of 168.9 ( $SD = 74.3$ ). After controlling for the length of the disclosure messages (ANCOVA), a significant effect remained for platform on information density,  $F(3,2922) = 8.362$ ,  $p = .009$  (Table 3). This implies that besides the length of the message, the platform also determines the volume of information that is shared. When the two models are compared (ANOVA and ANCOVA with correction for length of the messages) it becomes visible that the significant differences between weblog and Facebook

**Table 5**

Information per variable (%) by period and platform.

	Gender author	Number of experiences	When victimised/ duration	Where victimised	Number of perpetrators	Relationship to perpetrator	Identifying information perpetrator	Gender perpetrator
Before #MeToo	13.6	41.0	32.6	14.2	31.4	21.8	28.8	28.8
During #MeToo	12.6	57.9	47.5	30.7	39.8	32.0	30.9	46.7
After #MeToo	11.4	34.9	33.8	14.3	29.3	21.8	26.0	32.6
Twitter	8.8	41.9	36.0	19.7	32.3	25.4	27.8	35.3
Facebook	21.3	56.3	50.1	23.2	36.3	22.9	29.1	43.5
Weblog	42.9	62.5	58.0	35.7	57.1	45.5	37.5	56.3
Other	28.4	53.4	44.3	15.9	31.8	22.7	28.4	43.2

and weblog and other disappear. The covariate 'length', through an interaction effect between platform and length, causes this difference and explains the higher information density. The information density on the Twitter platform, where a character limit applies, is significantly different from the platforms weblog and Facebook. This means that these platforms invite a higher information density compared to the Twitter platform, whereby besides the available number of characters the information density of a disclosure is also determined by other platform characteristics. The covariate also greatly reduces the standard deviation.

Multiple correspondence analysis was done to gain insight into the relationship between the different variables per platform. The clusters per platform largely resemble the presented HOMALS for all disclosure messages, in which clustering was visible around offender-oriented information. Minor differences were visible per platform. This is in line with the finding that there are differences on the various platforms not only in the amount of information shared but also in what information co-occurs more often. To conclude, both the information density and the type of information shared in disclosures of sexual victimisation differ per platform.

### 3.3.2. Disclosed information before, during and after #MeToo

Almost all variables showed a considerable increase of information shared in the period during the #MeToo movement compared to the periods before and after (Table 5). The largest increase was visible in where victimisation took place, the number of experiences and the gender of the perpetrator. Information about the gender of the author was more prevalent in disclosures before (13.6%) than during (12.6%) and after (11.4%) the #MeToo. This difference was not statistically significant ( $p = .41$ ).

Average information density differed significantly between the three periods in relation to the #MeToo movement ( $F(2,2924) = 80.610, p < .001$ ), namely between the period before #MeToo and the period during #MeToo ( $p < .001$ ) and the period during #MeToo and the period after #MeToo movement ( $p < .001$ ). The periods before and after the #MeToo movement did not differ significantly on average information density ( $p = 1.000$ ). The mean information density was the highest during the #MeToo movement ( $M = 3.0, SD = 1.9$ ) compared to the periods before ( $M = 2.1, SD = 1.9$ ) and after ( $M = 2.0, SD = 1.9$ ). In the period after the #MeToo, mean information density drops but remains higher than the mean information density before the international movement. This is surprising since the average length of disclosure messages is lowest during the #MeToo ( $M = 312.9, SD = 8680.0$ ). The highest average length of disclosures was found before the global campaign ( $M = 619.5, SD = 1677.6$ ), subsequently after ( $M = 417.0, SD = 1006.0$ ). After controlling for the length of the disclosure messages, a significant effect remained from the period of disclosure on information density,  $F(2,2923) = 94.092, p < .001$ . In other words, the volume of information found in disclosure messages differs depending on when the disclosure took place.

Comparing the two models (unadjusted and covariate-adjusted), the

highest mean information density is still found during the #MeToo movement. The average information density remains significantly different before and during the #MeToo ( $p < .001$ ) and during and after the #MeToo ( $p < .001$ ). The covariate 'length' does reduce the standard deviation (Table 4).

Similar results are found compared to the HOMALS in Fig. 4 regarding the co-occurrence of information in the different periods. A cluster of offender-oriented information is found before, during and after the #MeToo. The second cluster around more incident related information was found before and after the #MeToo. During the viral movement no other clusters of information were found (see supplementary material). This corresponds to the previous conclusion the period during #MeToo deviates from the periods before and after. Concluding, both the information density and the type of information shared in disclosures of sexual victimisation seem to differ before, during and after the global #MeToo movement.

## 4. Discussion

This study shows *where* victims disclose, *when* they share their experiences and *what* information about sexual victimisation is disclosed on the internet, transcending previous research and filling various knowledge gaps. The study focussed on Dutch disclosures of sexual violence in the research period from January 2017 to December 2018. Solely considering Dutch posts enabled us to reduce heterogeneity found in previous research and to build a deeper understanding of elements of online disclosures that are stable and generalisable over time and across different platforms. However, since all data collected were in Dutch, culture-specific factors may have factored into the results, particularly regarding what information is disclosed. Individuals' social interactions on social media are interwoven with their cultural values (Fung & Ma, 2002). However, it is not without problems to assume that all individuals in a country share the same culture (Myers & Tan, 2002), especially in multicultural societies such as the Netherlands.<sup>7</sup> Moreover, it has been suggested that increasing global digitization and the use of social media has led to cultural convergence (Jenkins, 2006). Individuals from different countries interact and participate in social and political movements, such as the #MeToo. It could be questioned to what extent one's culture can be based on the country of origin or the language one speaks.

Our results reveal that online disclosure of sexual victimisation also occurred before and outside viral hashtag movements such as the #MeToo, and does not just take place on large social media platforms like Facebook and Twitter. Even so, most disclosures were found on the platform Twitter and during and after the #MeToo movement. Posting disclosure messages of sexual victimisation seems to fit within normal timelines of posting behaviour of Twitter users. At first glance, the focus of previous research on disclosures on Twitter and disclosures during viral online movements thus seems less problematic than expected. Nevertheless, relevant differences between platforms were identified in the timing of the posts, the information shared and co-occurrence of

information, information density and length of disclosures.

On the platform Twitter, where users are restricted by a character limit, a lower information density was found compared to the other platforms. It seems that the space that victims have to share their experiences is (partly) indicative of the volume of information that is shared. However, after controlling for the length of the disclosures, a significant difference was found between the platforms and the information density. Other platform characteristics therefore also seem to play a role in what information is shared. Perhaps platform affordances such as the ability to share anonymously, block specific users or connect to a social media movement impact which information is disclosed and which is not.

Differences between disclosures were also observed when considering the period in which the disclosures were posted online. Although the highest number of disclosures per day was found during the #MeToo movement, the content of these disclosures is significantly different from those before and after the online campaign. In a nutshell, disclosure messages during the #MeToo movement were on average shorter with higher information density, in which more and different information was disclosed than before and after the movement. A possible explanation for this is a so-called #MeToo effect that resulted in more and different types of disclosures. Reading the stories of other victims, attention paid to the subject in newspapers and on TV and public debate about unwanted sexual experiences may have led to insights that past experiences were indeed experiences of sexual violence and victimisation (Palmer et al., 2021). In addition, seeing others, both celebrities and 'ordinary' people, disclosing details about their unwanted sexual experiences might have disinhibited victims in sharing information about their victimisation as well, as a result of (temporarily) reduced perceptions of stigma (Andalibi & Forte, 2018). Another explanation is that victims sought to participate in the social movement and shared their own experiences in solidarity with other victims. These justifications however do not explain the higher information density found during the viral movement. A limitation of this study is that—for practical reasons—disclosures were considered in isolation. However, online content is often part of a thread or discussion in which network effects might occur. The motives to disclose might have been different, potentially leading to different disclosures.

#MeToo does not seem to have had any long-term effects on the content of online disclosure since the volume of information shared after the #MeToo peak is even lower than before the viral movement. This supports the overall conclusion that disclosures during viral hashtag movements, such as #MeToo, deviate from online disclosures outside such movements. Since disclosures on the platform Twitter and posts during the #MeToo movement differ, an exclusive focus on online disclosures on this platform and during viral movement gives a biased and incomplete picture of what online disclosure of sexual victimisation entails. Research as well as policy focused on online forms of disclosure of sexual victimisation thus do well to distinguish between the phenomenon on Twitter and other platforms, within and outside viral hashtag movements and pay attention to both manifestations.

Regarding the content of the disclosures, it is interesting to note that in a relatively large number of disclosure messages no information that is generally known to victims (such as when and where victimisation took place) was shared. Sharing information about factual characteristics of the experience therefore does not seem to be an essential part of disclosing. Information that was shared most often related to the number of experiences and when victimisation occurred/duration of victimisation and the gender of the perpetrator. The least information was shared in disclosures on Twitter. Twitter's 280 (previously 140) character limit subsequently seems to have influenced the content of disclosure messages. Posting within this constraint forces users to identify the most important information to disclose instead of providing a detailed description of the experience. Bogen, Millman, et al. (2018) explain that disclosers on Twitter may focus on sharing the parts of the victimisation they believe are of interest to a social media public. They

suggest victims might prioritise sharing more appealing parts of the experience on Twitter since they expect other users to respond more strongly to those aspects. The character limit is unique to Twitter, making results possibly distinctive to this platform.

When looking at the co-occurrence of the variables, clustering in the information about the offender is visible. This patterning in disclosures appears to be constant over time and across platforms. Victims seem to make the perpetrator an explicit actor of the event. The focus of disclosures appears to lie on the actions of the perpetrator and what was done to the victim in preference to the experiences of victims themselves. The victim is the object that was harmed and overpowered. Or as Spry puts it: "The power and agency of her [the victim's] body is denigrated or erased completely as we are linguistically asked to focus not on her, but rather on what was done to her by the male [the perpetrator] body" (Spry, 1995, p. 30). This is in stark contrast to the activist approach of international hashtag movements such as #MeToo, in which empowerment is an important motivation for disclosing sexual violence. Alternatively, making the perpetrator an explicit part of the story could also be a way of shaming and reclaiming (lost) power (Gorissen et al., 2021). Follow-up research is needed to provide insight into the relation between the motives to disclose and the information that is shared in these disclosures.

For technical reasons, context and possibly also an expansion of the disclosure offered by images, videos, music and the like could not be analysed in this study. Likewise, posts in which victims used visual material to disclose (e.g., in pictures, videos or text in an image) were not included because they were not recognized by the method of annotation based on textual analysis. In line with previous work by Mendes et al. (2019), future research should study visual indicators such as images and emojis accompanying online disclosures to gain insight into how victims construct online disclosures of sexual violence.

This study used a rich sample consisting of authentic disclosures of sexual victimisation over two years from the publicly available part of the internet. Through the use of machine learning techniques, shortcomings regarding sample and sample size of previous research on online disclosures of sexual victimisation were overcome. By analysing all online disclosure messages and not just looking at certain platforms (selection bias in users) or certain hashtags (bias in motives) more general statements can be made about the content and context of online disclosures of sexual victimisation both inside and outside viral movements and on various platforms. Based on the findings from this study we recommend that future research would gain from sharpening the definition of online disclosure of sexual victimisation and allowing a broad scrutiny of the phenomenon. A wide lens on a sharper defined phenomenon would benefit theory, science and policy as it will enable us to enrich our knowledge and analytical base of what constitutes online disclosure of sexual violence. Notwithstanding, several questions remain unanswered. Content of online disclosure posts was the starting point of this research, yet it remains unknown what leads people to disclose unwanted sexual experiences on the internet. What motives do victims have for sharing their experiences online and to what extent does this determine the content of disclosures? What considerations do victims make? This study analysed public disclosure messages, but do other factors play a role in the seclusion and anonymity of private and peer-support groups? These questions offer opportunities for qualitative follow-up research into the decision-making processes and platform choices by victims when disclosing their experiences of sexual violence online.

## Note

1. A Twitterstorm (sudden large increase in the number of tweets about a particular subject on Twitter; In Cambridge dictionary <https://dictionary.cambridge.org/dictionary/english/twitterstorm>) aimed at creating awareness of (the prevalence of) sexual violence.
2. In Dutch: #algemeennieuws



3. Blendle is a Dutch digital news kiosk where individual articles from various newspapers and magazines can be purchased.
4. Before November 2017 the character limit on Twitter was 140 characters (Tsukayama, 2017).
5. The Dutch language is also spoken in Aruba, Curacao, Saint Martin and Suriname which may skew the results about the posting time of disclosures slightly. Though worth bearing in mind, we believe this potential skew has not resulted in significantly different results because altogether less than a million people live here.
6. The time of 57 disclosures (1.9%) was 00:00:00. This may have been incorrect, possibly because of tools used to preschedule the placement of online messages, missing or incorrect data noted by the social media monitoring tool. No indicators were found that the time of the other disclosures was incorrect.
7. On January 1, 2022, individuals born outside the Netherlands, or with at least 1 parent born outside the Netherlands, make up over a quarter (26%) of the Dutch population (CBS, 2022).

### Credit author statement

**Marleen Gorissen:** Conceptualization, Methodology, Software, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing. **Chantal J.W. van den Berg:** Conceptualization, Methodology, Validation, Supervision, Writing- Reviewing and Editing. **Stijn Ruiter:** Conceptualization, Methodology, Supervision, Writing- Reviewing and Editing. **Catrien C.J.H. Bijleveld:** Conceptualization, Methodology, Supervision, Writing- Reviewing and Editing.

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### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.

### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chb.2023.107724>.

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