

Whose Cancer? Visualizing the Distribution of Mentions to Cancer Sites on Instagram

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ABSTRACT: This article presents a quantitative analysis of mentions to cancer on Instagram. Using thousands of images with cancer-related hashtags, we build several visualizations to capture their distribution. Source images are clustered by their visual traits and by the incidence, prevalence, and mortality of the cancer site they refer to. Our goal is three-fold: to provide a quantitative basis for future research on the representation of cancer online; to offer an interpretation of the sources of the imbalanced representation of the different cancer sites; and to motivate a debate on how that representation may affect patients and families.

Keywords: *health communication; public understanding of science and technology; visual communication; social media and cancer*

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Introduction: why cancer, why social media, and why cancer on Instagram?

The internet is now the second main source of information for cancer patients in the US, only following the information provided directly by doctors (Blanch-Hartigan & Viswanath, 2015). For patients, social media can serve as the gate to a community of support and information, and as a tool for self-expression (Braun et al., 2019; Chou et al.,

27 2011; Crannell et al., 2016; Noar et al., 2018). In particular, images have been found to
28 be an important vehicle for a patient-owned discourse of illness (Pardo, 2019).

29 Visual social media are today amongst the fastest-growing and most-used globally,
30 especially for younger audiences (Pew Research Center, 2019). While online
31 photographs and other images are increasingly used by cancer patients to share and
32 obtain information (Struck et al., 2018), existing research has mainly focused on text and
33 speech analysis.

34 This paper aims to visualize the distribution of images on Instagram that make
35 explicit reference to cancer on Instagram, one of the leading visual social media. It is
36 framed within a broader project on “The Shape of Illness”, which seeks to analyze the
37 representation of cancer in visual social media, how it shapes social narratives, and the
38 emotional impact it has on patients and their social circles.

39 This first stage addresses the following two questions:

- 40 1. What is the distribution of mentions to each cancer site on Instagram images?
- 41 2. How is the number of images mentioning a cancer site on Instagram related to its
42 incidence, prevalence, and mortality rates?

43 The data visualizations and the correlations presented in the Method and Results
44 sections will allow us to respond to both questions.

45 *The function of social media for cancer patients and researchers*

46 A growing body of work highlights the functions that online communities and social
47 media can have for cancer patients. In general, these studies are based on the
48 understanding that patients have a strong desire and need for information after diagnostic
49 (Hawkins et al., 2008, p. 10). But networks like social media go beyond information-
50 sharing: they also provide a means to interact with other patients personally, build a
51 community around shared interests, and receive (and provide) emotional support
52 (Moorhead et al., 2013). This search for togetherness is an important function of online

53 networks (see Firth et al., 2019; Ridings & Gefen, 2004) that has positive results for many
54 patients (Attai et al., 2015).

55 On the other hand, the fast-paced nature of social media and the “attraction
56 mechanism” that determines their visibility and promotion through algorithms (Firth et al.,
57 2019, p. 120) leads some images to triumph over others. The “winners”—that is, the
58 images that capture our attention our achieve the highest number of “likes”—typically
59 show faces (Bakhshi et al., 2014), are aesthetically pleasing, look professional, and
60 inspire positive emotions (Tifentale & Manovich, 2018). As users and companies follow
61 the “rules” to achieve a likeable image on Instagram, a standardized visual discourse
62 begins to emerge. This process has been visible on mass media for several decades with
63 the widespread use of the survivorship discourse around breast cancer, which has also
64 been identified online. The use of such standardized narratives has been identified online
65 and found to affect the emotional well-being of patients negatively (Banerjee et al., 2018;
66 Pertl et al., 2014).

67 An early exploration of the nexus between social media and cancer is the work of
68 Chou et al. (2011). Theirs is an account of the cancer experience of young YouTube
69 users. Among their findings, they note that “the success of cancer communication efforts
70 depends largely on creating emotional engagement with message content” (Chou et al.,
71 2011, p. 7). Similarly, by Gibson et al. (2016) insist on the importance of storytelling to
72 understand the experience of younger patients and adapt informational and emotional
73 support. Their findings are consistent with general approaches to community-building in
74 social media: emotions and personal contact build lasting relationships.

75 The importance of social media for cancer patients is discussed also by Sugawara
76 et al. (2012), who highlight the potential of Twitter as a connector. The authors argue that
77 “Twitter could be a valuable medium for sharing information among cancer patients”
78 (2012, p. 5), particularly as users share daily messages about their treatment and life with
79 cancer more generally, helping normalize reactions to treatment and providing patients
80 with a safe space.

81 From a clinical perspective, the last ten years have seen a surge of research into
82 the functions of social media in cancer treatment. Zaid et.al. (2014) discuss how such
83 platforms can help identify patients and accelerate surveying processes; Attai et al. (2015)
84 remark that social media is “fertile territory” for cancer research and patient education
85 (2015, p. 3); Bottorff et al. (2014) explore the use of social media in tobacco prevention
86 campaigns; Bravo and Hoffman-Goetz (2016) assess mentions to prostate cancer in
87 social media, which Carneiro and Dizon (2019) expand on. Banerjee et al. (2018) put
88 emphasis on the online space as a source of support for patients of melanoma; Lee-won
89 et al. (2017) assess the impact of virality measures on screening intention, while Noar et
90 al. (2018) review how a single, viral photograph uploaded by a skin cancer patient resulted
91 in a peak of Google searches for this type of cancer. Taylor and Plagiari (2019) scanned
92 Facebook and Twitter for discussions touching on lung cancer. Like them, close to 100
93 academic papers were devoted to the topic by 2015 (Koskan et al., 2014; Moorhead et
94 al., 2013), focusing mostly on case studies, and speech and text analysis.

95 Despite the growing wealth of work, systematic reviews suggest that there is room
96 for improvement. Relying on top posts and small samples often means that studies focus
97 on the most visible cancer sites and neglect sites with comparable rates of incidence but
98 less visibility online (Crannell et al., 2016, p. 539; Döbrössy et al., 2020, p. 12; Han et al.,
99 2018; Moorhead et al., 2013, p. 5). In doing so, they are subject to the effect of the
100 attraction mechanism. A deeper review of the representation of each cancer site online
101 can help fill the gap and examine how online mentions are distributed and why.
102 Understanding the social roots of the representation of cancer in social media

103 Some of the papers reviewed for this work attempt a quantitative comparison of
104 the presence of different cancer sites on social media and note the overrepresentation of
105 breast cancer as compared to sites with similar incidence or mortality rates. Further,
106 Sugawara et al. “found it interesting that the cancer prevalence of [their] influential users
107 and the general population are so dissimilar” (2012, p. 5), signaling a distribution of cancer
108 sites online that does not match that of their epidemiology. Crannell et al. speak to this

109 imbalance, too, while specifying that the most tweeted cancers are breast, lung, prostate
110 and colorectal (Crannell et al., 2016, p. 538).¹

111 In a 2018 study on Instagram and Twitter traffic related to cancer, Vraga et al.
112 (2018) observe that the campaign for Movember outperforms breast cancer campaigns
113 only in the month of November while breast cancer dominates discussions the rest of the
114 year. They link this seeming seasonality to the decades-long development of breast
115 cancer awareness raising campaigns and their inclusive nature, which help give them
116 visibility during the year, while the male-focused, physical and actionable nature of
117 Movember gathers a great degree of attention during the month of November, especially
118 in visual networks like Instagram.² Importantly, Vraga et al. concede that “[w]hile the
119 Movember campaign generates traffic in November, Movember is not encouraging
120 communication about prostate cancer” (Vraga et al., 2018, p. 8), similarly to findings by
121 Bravo & Hoffman-Goetz (2016).

122 Common explanations to the unequal visibility of different cancer sites are based
123 on epidemiology and social media demographics. Breast cancer has a lower average age
124 of incidence and is one of the most prevalent cancer sites globally, which helps its
125 presence online (Sugawara et al., 2012, p. 5). A similar interpretation can be seen in
126 Crannell et al., who note that “the fact that the breast cancer was the toptweeted cancer
127 was not surprising, considering breast cancer is one of the most prevalent cancer types”
128 (Crannell et al., 2016, p. 538). This argument stands when looking at the next top-tweeted
129 cancer sites in Crannell et al., with high prevalence rates in the United States, but does
130 not align with our findings. Through a correlation test, we will show that the volume of
131 content produced discussing other cancer sites with high prevalence, like lung or prostate,
132 is not significantly comparable to that of breast cancer.

1 Findings from our study for Instagram do not reveal the same distribution for Instagram mentions, as can be seen in the results section.

2 While it started as a movement to give visibility to prostate cancer, the Movember movement encourages men to grow a moustache or a beard as a show of support to issues related to men’s mental and physical health more generally. See www.movember.com for more information.

133 Another interpretation offered by Sugawara et al. and in Hartigan & Visnawath
134 (2015) is that social media activity is related to well-being and the length of treatment.
135 Breast cancer is typically accompanied by longer-term treatment and higher survival
136 rates, allowing patients the strength and the time to post their experiences on social media
137 (Sugawara et al., 2012, p. 6). Breast cancer also presents generally higher rates of
138 prevalence and lower rates of mortality than other types of cancer that evolve quickly and
139 fatally; consequently, the assumption is that breast cancer patients have more of an
140 opportunity to use social media during treatment. Were that the case, it should be possible
141 to observe a clear correlation between prevalence and online presence for a cancer site,
142 a conclusion that does not emerge from our results either.

143 We will argue that a statistically significant correlation between online presence
144 and incidence, prevalence or mortality cannot be concluded on Instagram from the data
145 obtained.

146 While results from previous studies shed light on specific groups and cancer sites,
147 the approach to social media and cancer would benefit from a general understanding of
148 the volume of mentions to cancer online, their visibility, and their distribution. Doing so
149 would help enable a better understanding of the impact that cancer-related
150 communications can have on patients, family, and friends, before defining possible
151 interventions. Indirect exposure to cancer-related content (through social media
152 campaigns, events, or popular culture) may create expectations in future patients and
153 relatives, which are important to account for in health education (Fishman et al., 2010).
154 While there is an opportunity to use existing online infrastructures to build communities
155 of patients and offer continuous care, it is paramount to analyze the distribution of cancer
156 online and question the perceptions that it may lead to.

157 **Materials and Method**

158 Attempting a study of “cancer” as a global keyword on Instagram would yield too
159 many results for analysis. Instead, this study mixes manual and automated data
160 extraction to obtain a sample of photographs that can help sketch a global image of
161 cancer in English and Spanish-speaking Instagram.

162 *Identification of profiles for keyword extraction*

163 A first step covers the identification of relevant profiles, used to reveal the hashtags
164 most used when posting images related to cancer. These first few profiles include both
165 organizational and individual accounts.

166 The geographic reach of this initial search is limited to Spain, where the Spanish
167 Society Against Cancer (AECC, *Asociación Española Contra el Cáncer*) leads civil
168 society efforts on cancer research and support to patients.³ The profile was observed for
169 a week in April 2019, giving Instagram's Explore enough time to suggest similar profiles
170 and images for the researchers to follow.

171 Posts suggested by the Explore page were mainly focused on breast cancer, a site
172 that has great presence online (Sugawara et al., 2012). To allow for other sites to be
173 included in the sample, additional accounts were introduced manually.

174 The final sample for observation is made of 49 different profiles, with accounts
175 posting in Spanish, English, and Portuguese (see table 1). The handles of individual
176 accounts were not registered to protect the privacy of their owners and appear as "N/A"
177 in Table 1. All accounts were reviewed manually for relevance and only public accounts
178 were followed.

179 **Table 1. Initial sample of 49 profiles from which cancer hashtags were obtained**

Instagram Handle	Topic	Type
acancerprostata	Prostate Cancer	Support
aeacap	Lung Cancer	Support
aecc_es	All	Support
agradecidaypoderosa	All	Patient
cancer_de_pancreas	Pancreatic Cancer	Support
cancermetanoia	Breast Cancer	Patient
cr_uk	All	Support
donatupelodonatupelo	All	Support
ejercicio_fisico_oncologico	All	Support

3 Spanish social media served as a starting point, expanding the search globally in subsequent phases.

fundacionaladina	All	Support
grupagata	Breast Cancer	Support
hayguerrerosparato	All	Patient
macmillancancer	All	Support
mugronets	Breast Cancer	Support
N/A	All	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Support
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Lymphoma	Patient
N/A	Lymphoma	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Lung Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Breast Cancer	Patient
N/A	Lymphoma	Patient
N/A	Breast Cancer	Patient
notetapesdotcom	Breast Cancer	Support
oncolliga	All	Support
oncowellness	All	Support
psicooncologia_para_todos	All	Support
quimioencolombia	All	Support
savethemama	Breast Cancer	Support
standup2canceruk	All	Support
tatuajesolidario	Breast Cancer	Support
thecure_forcancer	All	Support
unoentrecienmil	Leukemia	Support
venci_el_cancer	All	Patient
wecanbeheroeses	Breast Cancer	Support

181 *Identification of keywords*

182 Over the course of two weeks in April 2019, the sample profiles returned a series
183 of phrases commonly used when mentioning cancer in online posts. The list included
184 specific mentions to cancer sites as well as phrases or slogans (such as “fuck cancer”.
185 “cancer sucks” or “breast cancer awareness”). The resulting list includes 9 different sites
186 and 11 phrases:

187 A. Cancer Sites:

- 188 (1) *Lung* (#LungCancer)
- 189 (2) *Breast* (#BreastCancer)
- 190 (3) *Pancreas* (#PancreaticCancer)
- 191 (4) *Leukemia*⁴ (#Leukemia)
- 192 (5) *Prostate* (#ProstateCancer)
- 193 (6) *Colorectum* (#ColorectalCancer)
- 194 (7) *Colon* (#ColonCancer, merged with #ColorectalCancer in the analysis)
- 195 (8) *Stomach* (#StomachCancer)
- 196 (9) *Uterus* (cervix and corpus, commonly referred to online as #WombCancer)

197 B. Cancer Keywords:

- 198 (1) *Cancer Research* (#CancerResearch)
- 199 (2) *Contra El Cancer* (#ContraElCancer, “against cancer”, in Spanish)
- 200 (3) *Fuck Cancer* (#FuckCancer)
- 201 (4) *Cancer Survivor* (#CancerSurvivor)
- 202 (5) *Cancer Sucks* (#CancerSucks)
- 203 (6) *Movember* (#Movember)
- 204 (7) *Breast Cancer Awareness* (#BreastCancerAwareness)
- 205 (8) *Breast Cancer Survivor* (#BreastCancerSurvivor)
- 206 (9) *Lung Cancer Awareness* (#LungCancerAwareness)
- 207 (10) *Pancreatic Cancer Awareness* (#PancreaticCancerAwareness)
- 208 (11) *Cancer Free* (#CancerFree)

209 *Extraction of data for descriptive visualization*

210 Manual searches were conducted for each of the 20 hashtags in the list between 1

4 The American spelling for leukaemia was selected as it returned a higher number of hits. Some of these types of cancer returned virtually no results, but the list was based on metrics of prevalence and mortality for each type of cancer, to test whether high prevalence translated into high presence in social media.

211 and 20 December 2019, and images downloaded manually from the Explore page using
 212 screen scrapers available in the Google Chrome Store (see Varela-Rodríguez & Vicente-
 213 Mariño, 2021, 2020). For each search, only public images were collected, with a minimum
 214 of 300 images per cancer site and phrase (Table 2).

215 **Table 2. Total images collected in the sample per site and phrase.**

Hashtag	Number of Images Collected
Cancer Site	
Breast Cancer	1,484
Colon Cancer	909
Colorectal Cancer	1,004
Leukemia	1,042
Lung Cancer	585
Pancreatic Cancer	331
Prostate Cancer	1,128
Stomach Cancer	1,241
Womb Cancer	327
Cancer-related phrase	
BreastCancerAwareness	1,558
BreastCancerSurvivor	738
CancerFree	1,338
CancerResearch	1,036
CancerSucks	772
CancerSurvivor	1,037
ContraElCancer	581
FuckCancer	1,398
LungCancerAwareness	773
Movember	1,278
PancreaticCancerAwareness	904
TOTAL	19,464

216 In total, 19,464 images were collected, renamed, cleared of metadata, and stored
 217 in an offline hard drive. Only the images and their associated keywords were stored,
 218 removing any information about the user profile. At no point were the original images
 219 released to the public. No additional metadata (such as location) was collected, as it is
 220 not made available by Instagram.

221 *Content review and visualization*

222 This first dataset allows for a visual representation of results using polar graphs,
223 following visualization methodologies close to those developed by Lev Manovich and the
224 Software Studies Initiative (Manovich, 2011).

225 Our method differs significantly from Manovich's approach to computational
226 analysis in cultural studies. In *AI Aesthetics*, Manovich advocates for the need to "learn
227 to see cultures in more detail, without immediately looking for, and noticing, only types,
228 structures or patterns" (Manovich 2018, 384). Our study does make use of structures and
229 categories to narrow down the search for images and allow for descriptive analysis that
230 sheds light on the different types of cancer represented online. In future phases, however,
231 it is expected that categorizations will lose importance, especially as the research looks
232 at emotions and social discourse.

233 Once stored and labelled, all images were put through the image-processing
234 software developed by the Software Studies Initiative⁵ to extract quantitative information
235 about their hue, brightness, and saturation. These data help identify clusters of color that
236 can reveal a visual identity for certain hashtags or cancer sites.

237 The results are reported using descriptive tables, distribution plots, and a series of
238 polar graphs that collect all the images and arrange them according to different indicators.
239 Two types of polar graphs feature in the results to answer the two research questions:

240 1. *What is the distribution of mentions to each cancer site on social media?* A
241 polar graph visualizes all the images in the sample. Distance from the center
242 of the graph indicates the dominant hue of the image: mostly red images along
243 the inner edge, mostly blue and violet images around the middle of the radius,
244 and mostly pink images along the outer edge. Each radius corresponds to the
245 hashtag that returned the image, which is indicated in text. A second polar
246 graph shows the same images, but adjusted to the total number of images

5 Mainly ImageMeasure, bundled in the ImagePlot pack provided at <http://lab.softwarestudies.com/p/imageplot.html>

247 returned by each hashtag. Distance from the center in this second graph
248 indicates the total amount of hits returned by the search for each hashtag.

249 2. *How is the number of images mentioning a cancer site related to its incidence,*
250 *prevalence, and mortality rates?* Values for cancer sites on prevalence,
251 incidence and mortality are superposed on the previous graphs, allowing for an
252 instant visualization of the tags that are most prominent on Instagram and how
253 they compare to their rates. In addition, distribution plots show data relevant to
254 the correlation tests.

255 The original montages online can be zoomed-in to a point where the viewer can
256 ascertain the presence of individuals, animals, or hospital equipment, but where it is not
257 possible to identify the people in them. For print purposes, a zoomed-in extract is
258 provided.

259 *Statistical analysis*

260 While the profiles observed only returned nine cancer sites for image collection,
261 numerical data was collected also for 31 different sites listed in the Cancer Dictionary of
262 the Global Cancer Observatory (International Agency for Research on Cancer, 2021):

Bladder	Kidney	Mesothelioma	Pancreas	Uterus (Cervix or Corpus)
Brain	Larynx	Myeloma	Penis	Vagina
Breast	Leukemia	Nasopharynx	Prostate	Vulva
Colorectum	Lip-oral	Non-Hodgkin's Lymphoma	Sarcoma	
Esophagus	Liver	Nonmelanoma	Stomach	
Hodgkin's Lymphoma	Lung	Oropharynx	Testis	
Hypopharynx	Melanoma	Ovary	Thyroid	

263 Each of the 31 sites was manually searched for on Instagram on 22 January 2020,
264 collecting the number of results returned for each (variable Hits). In addition, data on

265 prevalence, incidence and mortality was collected from the Global Cancer Observatory
266 (World Health Organization, 2020). Since no further data was collected on the images, it
267 is not possible at this stage to categorize the images by location or other demographic
268 indicators.

269 A correlation test was performed for the variables Hits, Incidence, Prevalence and
270 Mortality on SPSS, returning their Pearson correlation coefficient as well as distribution
271 plots. Correlations were tested including all cancer sites at first and then excluding the
272 case of breast cancer, as it appeared to behave as an outlier in the data.

273 **Results**

274 *1. What is the distribution of mentions to each cancer site on social media?*

275 Visual traits

276 On their own, the images collected tell individual stories of recovery, hope and fear.
277 Collectively, they reveal patterns about the representation of cancer on social media
278 (Figure 1).

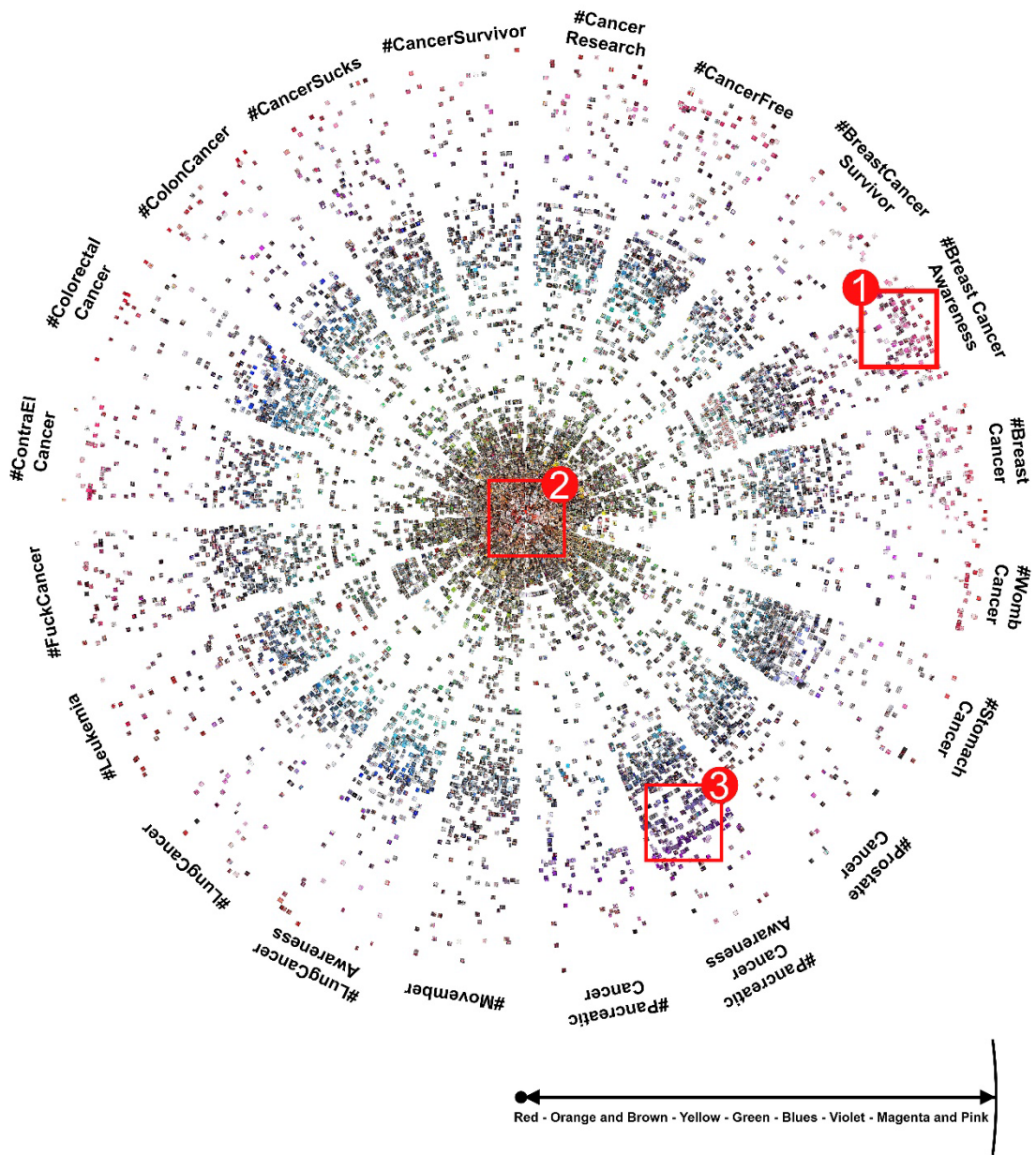
279 Most images in Figure 1 appear concentrated around the middle of the graph: these
280 are portraits, group photos and anatomical images that contain hues closer to orange and
281 brown emerging from the colors of the skins in the picture. Another cluster appears in the
282 “blues” section (half-radius): these are often photographs taken outdoors, with the blue
283 sky in frame. There is some concentration in the “greens”, too, from pictures taken
284 outdoors (around trees and on grass) and uploaded by the AECC (whose corporate color
285 is green).

286 Importantly, however, the graph reveals that posts associated with breast cancer
287 make more use of highly saturated magentas and pinks, through pink ribbons and
288 banners associated with breast cancer prevention and research campaigns. But it is not
289 the only hue strongly associated with a given cancer site in the dataset: violet hues appear
290 in photographs labelled as “pancreatic cancer”, a color that has been used to campaign
291 for more research, while dark blue is linked to campaigns to raise awareness on lung

292 cancer. Figure 1 shows that these two campaigns have a strong visual identity, like those
293 related to breast cancer.

294

Figure 1. Visual distribution of images in the sample per cancer site and phrase



297 Distribution per hashtag

298 While Figure 1 can reveal patterns about color, it does not account for total hits,
299 giving the impression that tags like “Pancreatic Cancer Awareness” have similar visibility
300 to “Breast Cancer Awareness”. To compensate this fact, Figure 2 is adjusted to show the
301 total number of images on the Explore page for each cancer site (Tables 3 and 4).

302 **Table 3. Results per cancer site on Instagram (search term: “[CancerSite]”)**

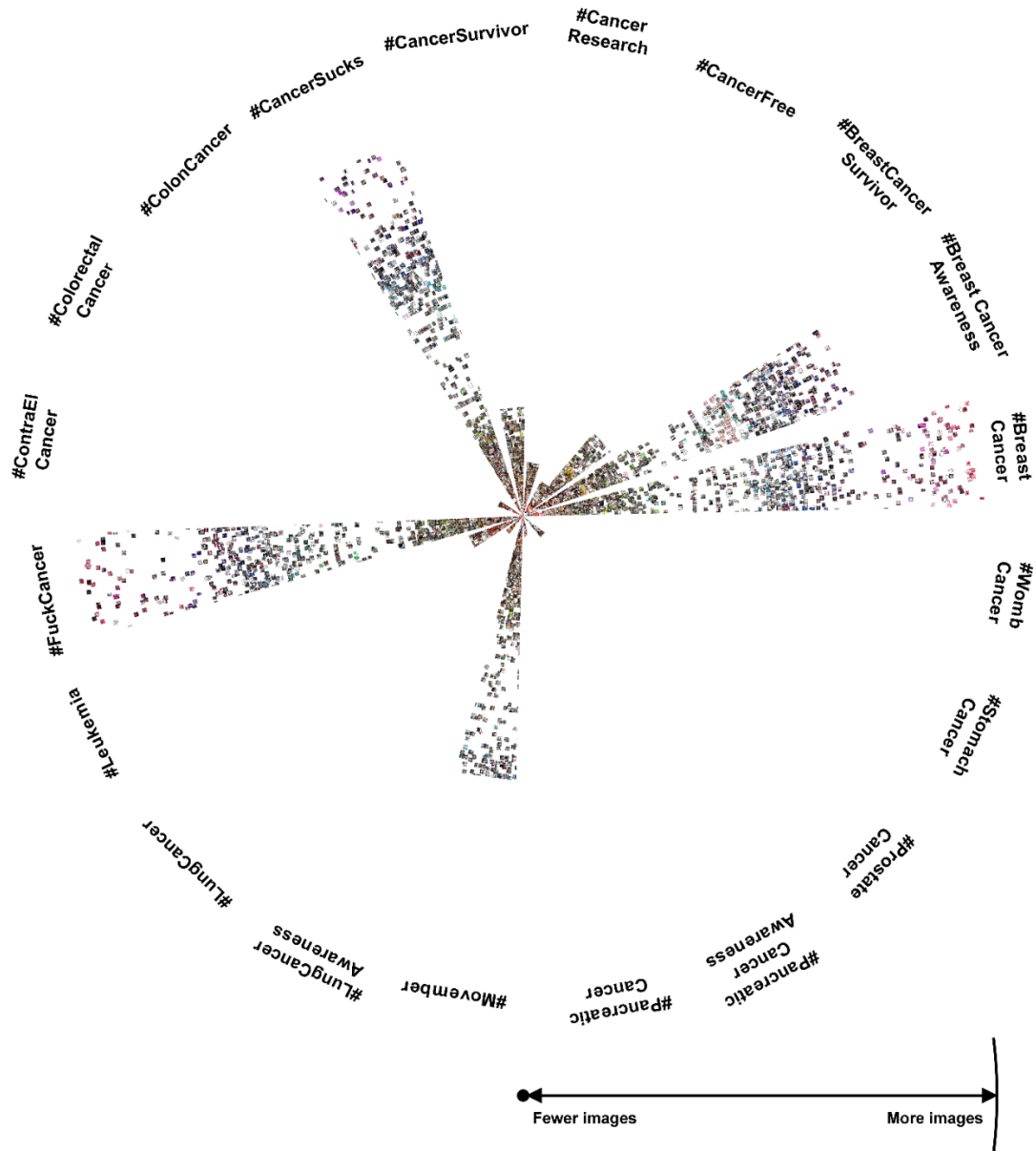
Site	Hits
Bladder	13,294
Brain	117,436
Breast	2,313,834
Uterus (Cervix or Corpus)	1,554
Colorectum	148,581
Esophagus	1,627
HodgkinsLymphoma	80,788
Hypopharynx	0
Kidney	19,562
Larynx	392
Leukemia	244,593
Lip-oral	20,028
Liver	22,112
Lung	112,823
Melanoma	176,836
Mesothelioma	12,664
Myeloma	18,378
Nasopharynx	7
Non-Hodgkins Lymphoma	24,016
Nonmelanoma	228
Oropharynx	22
Ovary	379
Pancreas	107,711
Penis	106
Prostate	146,097
Sarcoma	49,679
Stomach	12,361
Testis	49,558
Thyroid	108,169
Vagina	181
Vulva	1,053

303

Table 4. Results per phrase on Instagram (search term: “[Phrase]”)

Tag	Hits
BreastCancerAwareness	2,595,655
FuckCancer	3,405,325
CancerSucks	2,870,578
Movember	1,926,142
CancerSurvivor	796,272
CancerResearch	395,925
cancerfree	288,427
BreastCancerSurvivor	280,880
PancreaticCancerAwareness	35,257
ContraEICancer	26,837
LungCancerAwareness	26,385

Figure 2. Volume of images on Instagram per cancer site and phrase



306

307 If Figure 2 were to encapsulate the visibility of cancer on Instagram, only one
 308 cancer site would be distinctly identifiable: breast cancer. On Instagram, there are almost
 309 ten times more posts with the hashtag “#breastcancer” than posts with the hashtag
 310 “#leukemia”, which follows as second most mentioned, and 20 times more than highly
 311 prevalent and mortal sites such as lung cancer.

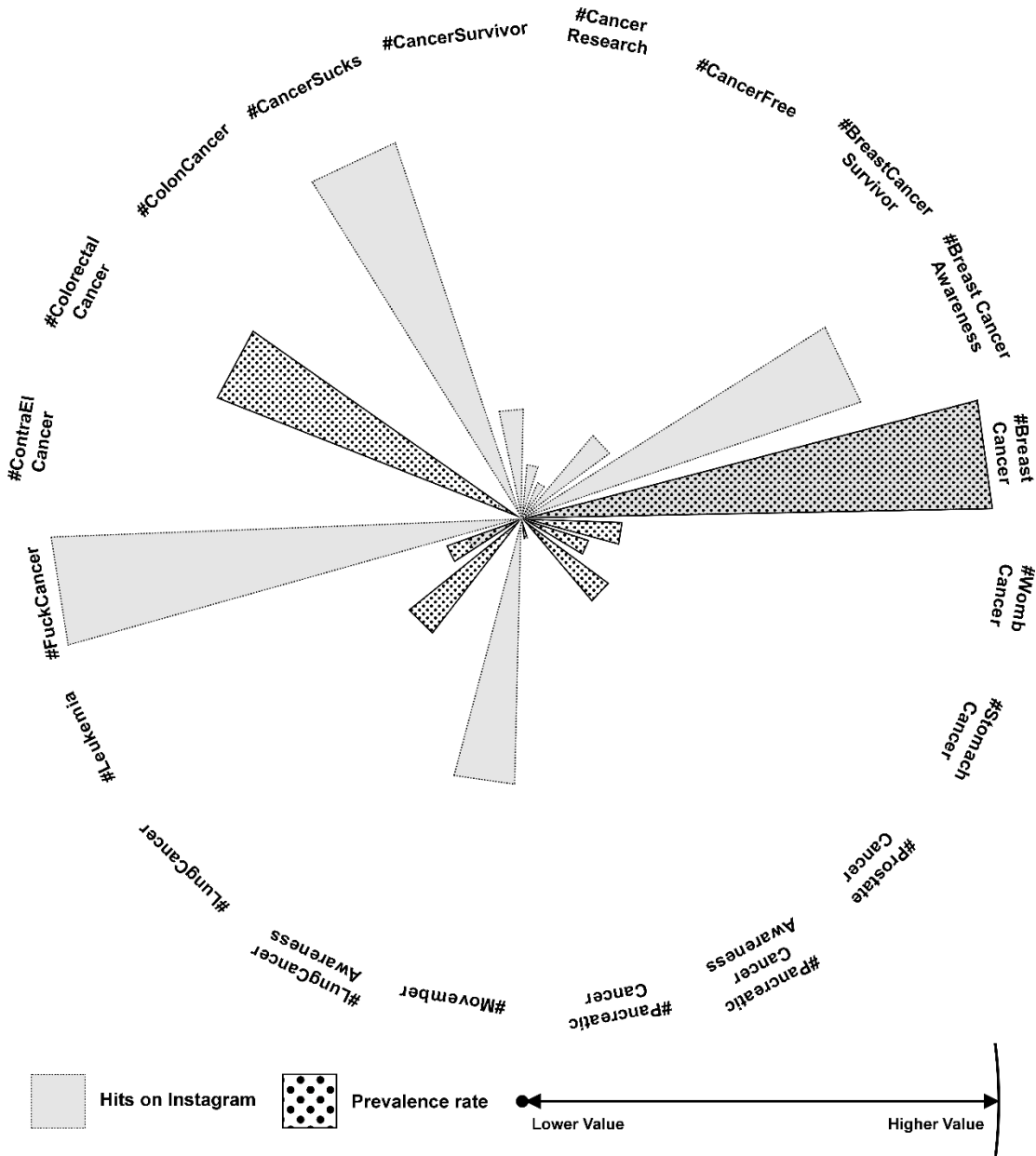
312 Meanwhile, the only other visible tags would be general phrases such as “cancer
313 sucks”, “fuck cancer”, “breast cancer awareness” and “movember”, with the latter being
314 the only one that does not show results linked to breast cancer.

315 *How is the number of images mentioning a cancer site related to its incidence,*
316 *prevalence, and mortality rates?*

317 Figure 3 overlays the prevalence of each cancer site (>5 years) in the sample with
318 the number of images returned on Instagram, to test the hypothesis that this
319 overrepresentation may be linked to the prevalence of breast cancer.

320
321

Figure 3. Volume of images on Instagram (Hits) and Prevalence rate (>5 years) for the cancer site represented



322

323 Indeed, with the highest prevalence rates of the cancer sites collected in the
324 sample, breast cancer also shows the highest number of images of all cancer sites
325 studies. Yet another cancer site with high prevalence rates, colorectal cancer, returned
326 virtually no results.

327 A Pearson correlation test using all 31 cancer sites rejects the null hypothesis of a
328 lack of correlation between Prevalence and number of images on Instagram (Hits),
329 seemingly indicating that the higher presence of breast cancer online is related to its
330 higher long-term prevalence rate:

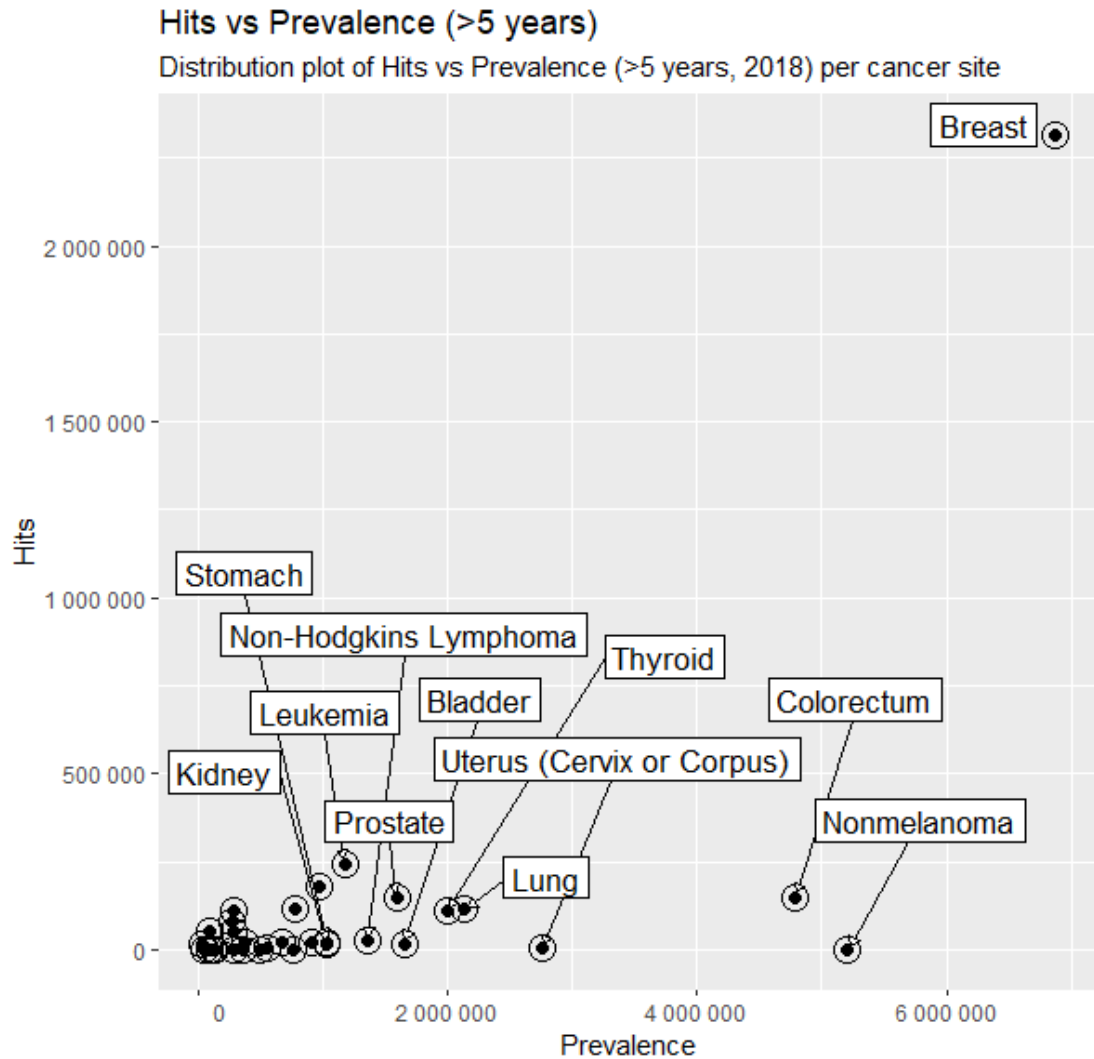
$$331 \qquad R(29) = .66, p < .01$$

332 However, without accounting for breast cancer, the results of the test change
333 dramatically, and the null hypothesis of a lack of correlation can no longer be rejected:

$$334 \qquad R(28) = .23, p < .221$$

335 Looking at both Figure 3 and the distribution plots below (Figures 4 and 5), it
336 appears that breast cancer behaves as an outlier, with an abnormal number of hits
337 returned. This behavior is relevant to understanding the imbalance in representation of
338 cancer online.

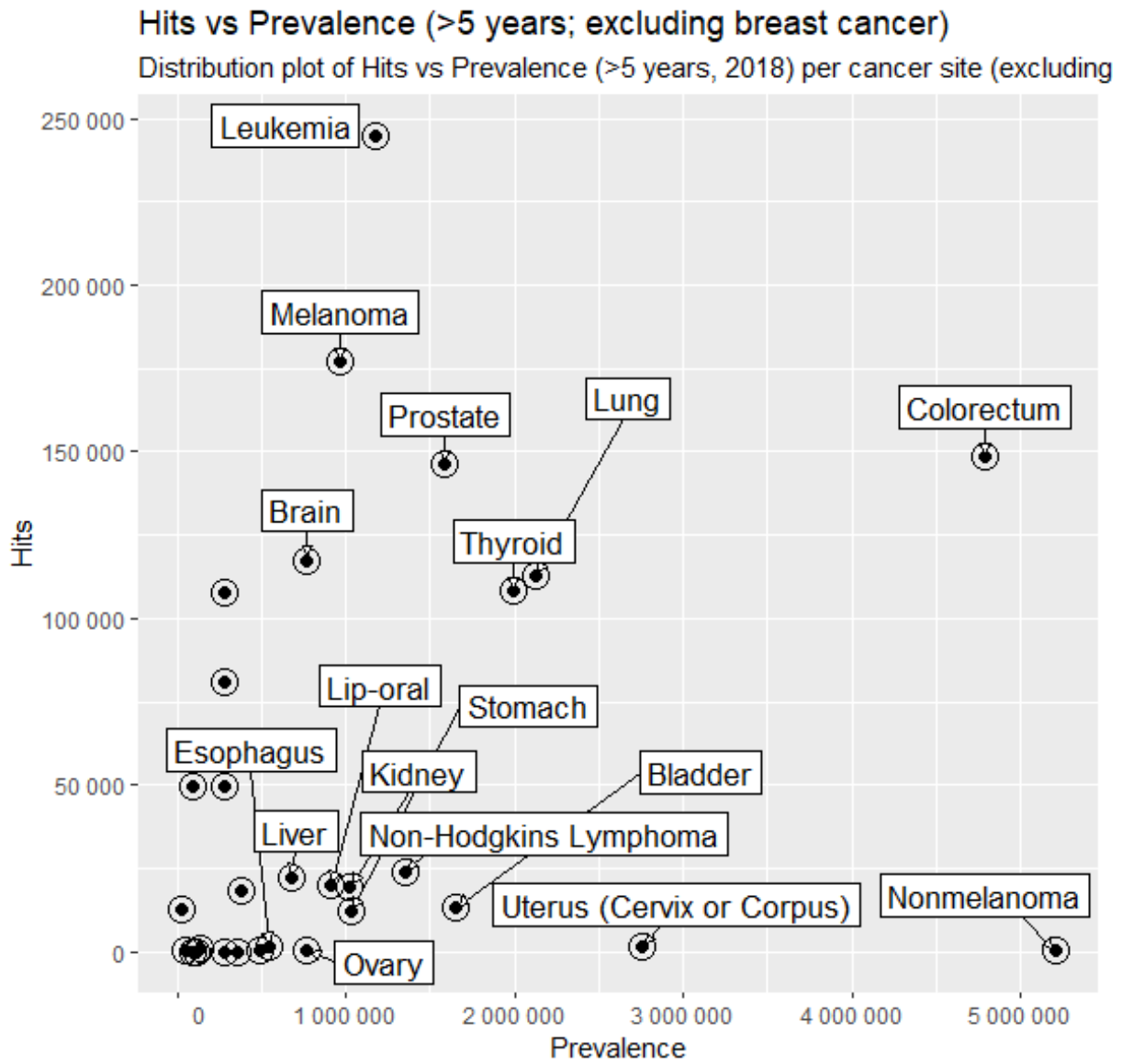
Figure 4. Distribution plot of Hits vs Prevalence (>5 years, 2018) per cancer site



Labels are provided for cancer sites with prevalence (>5 years, 2018) > 1 000 000

341
342

Figure 5. Distribution plot of Hits vs Prevalence (>5 years, 2018) per cancer site, excluding breast cancer



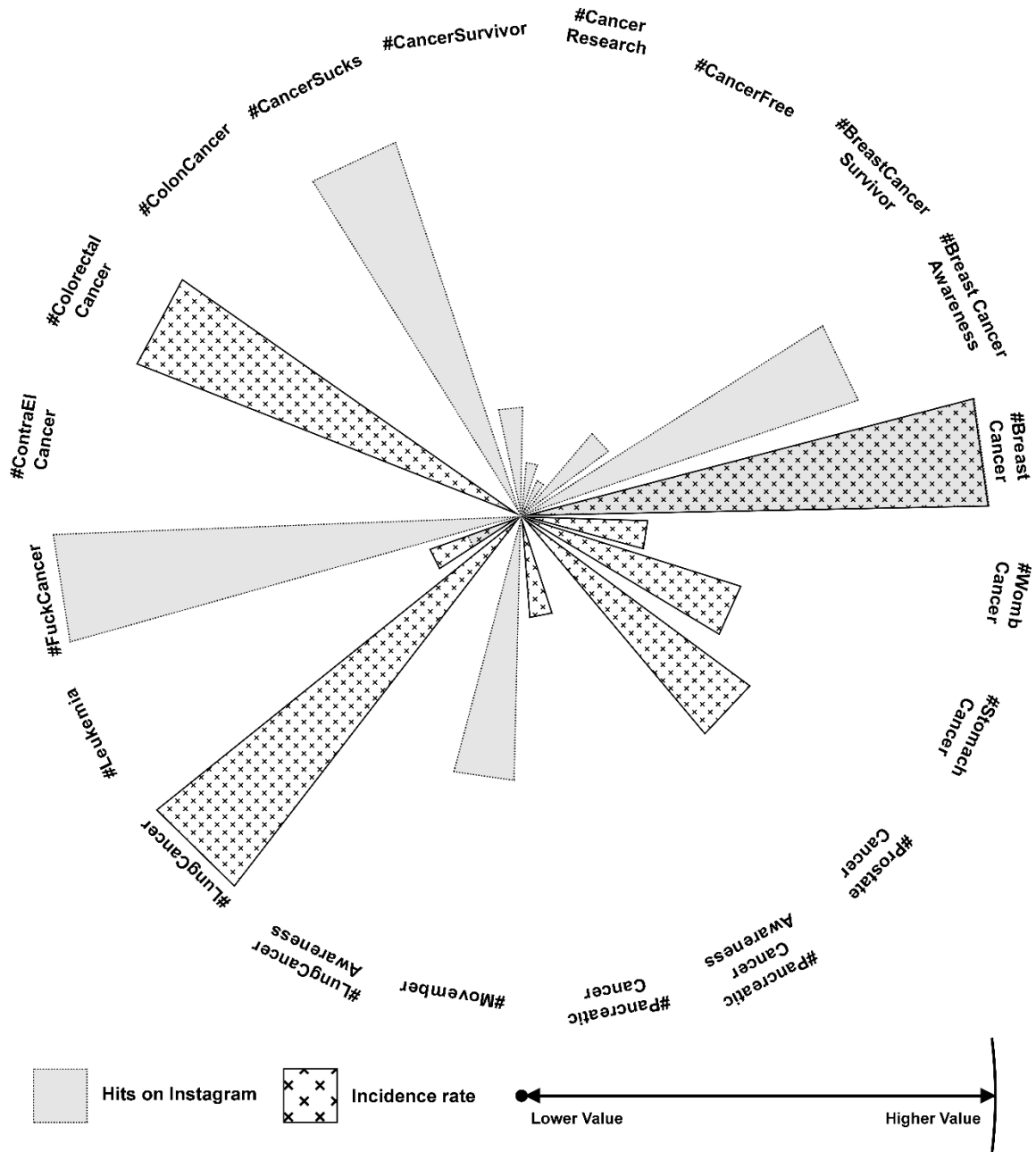
Labels are provided for cancer sites with a prevalence (>5 years, 2018) > 500 000

343

344 Similarly, the literature points to incidence as a possible reason for the higher
345 visibility of breast cancer. Yet contrasting the number of results per site with the incidence
346 of each cancer site does not appear to show a clear correlation (Figures 6, 7 and 8).

347
348

Figure 6. Volume of images on Instagram (Hits) and Incidence rate (2018) for the cancer site represented



349

350 In 2018, lung cancer had the highest incidence rate worldwide, followed by breast
351 cancer and colorectal cancer. Once again, breast cancer dwarves all other cancer sites
352 in terms of images on Instagram. A Pearson correlation test for Hits on Instagram and
353 Incidence (2018) cannot reject the null hypothesis of a lack of correlation between the

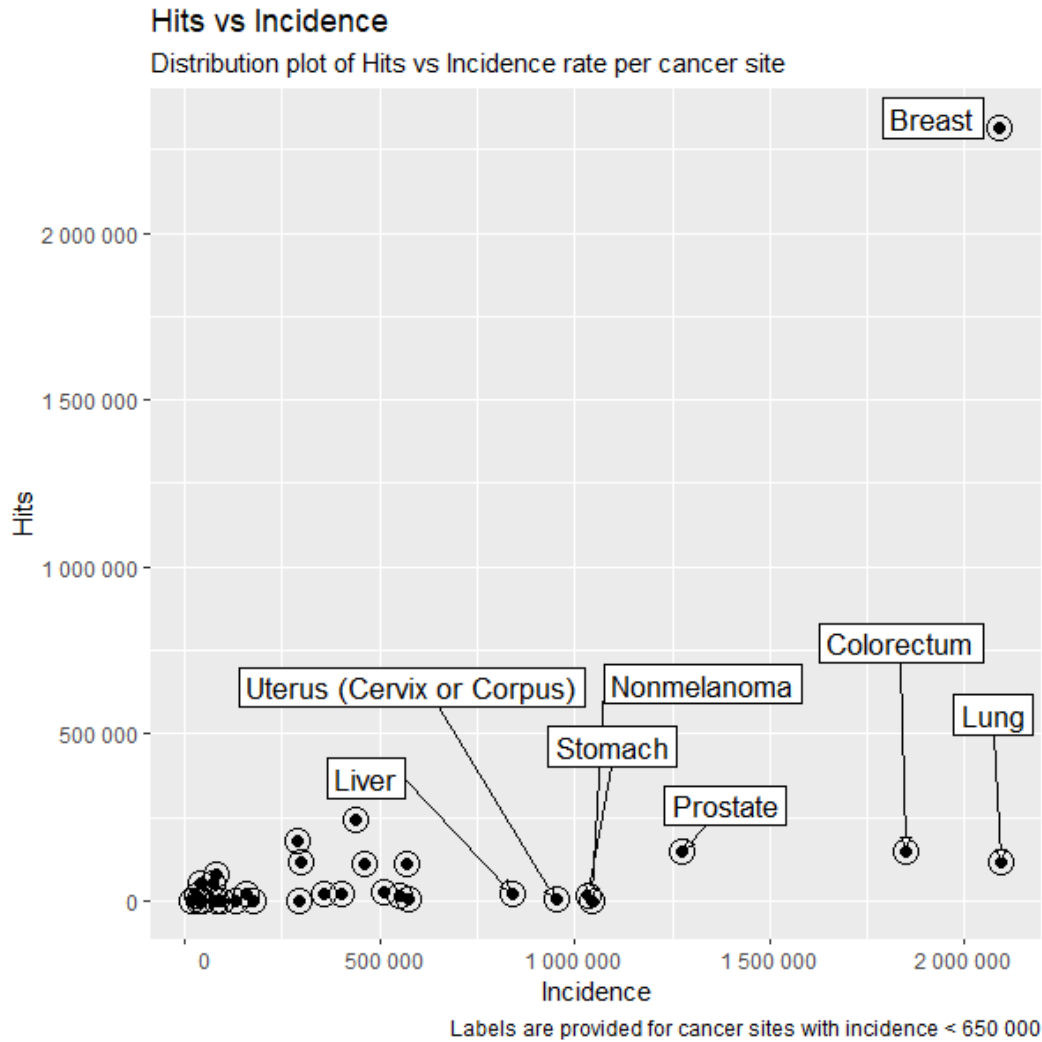
354 two, indicating a possible correlation where higher incidence rates lead to more visibility
355 online:

356
$$r(29) = .523, p < .01$$

357 As with prevalence, however, the significance of the test is lost (although by a small
358 margin) when breast cancer is removed from the equation:

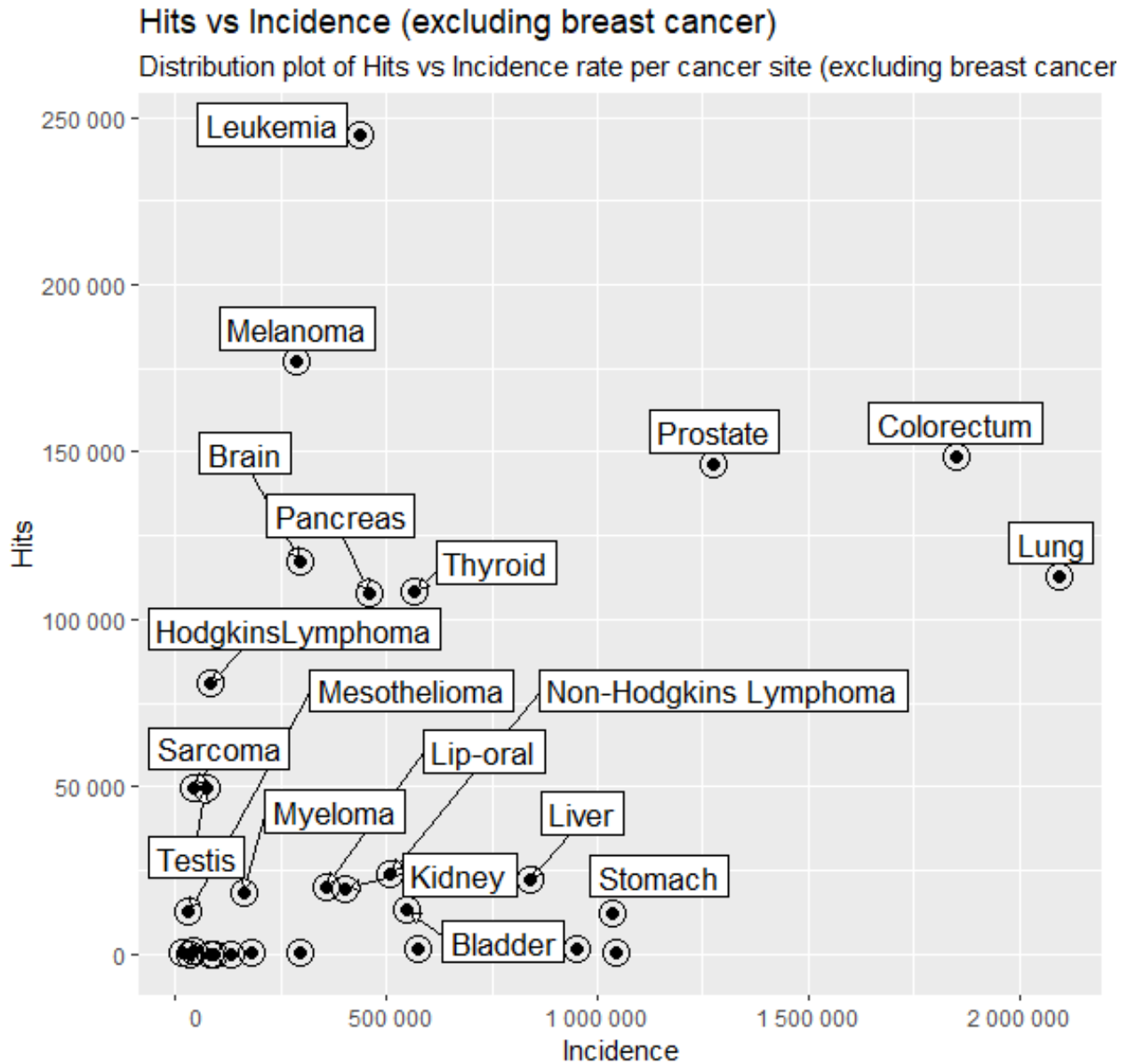
359
$$r(28) = .348, p = .06$$

360 **Figure 7. Distribution plot of Hits vs Incidence rate per cancer site**



361

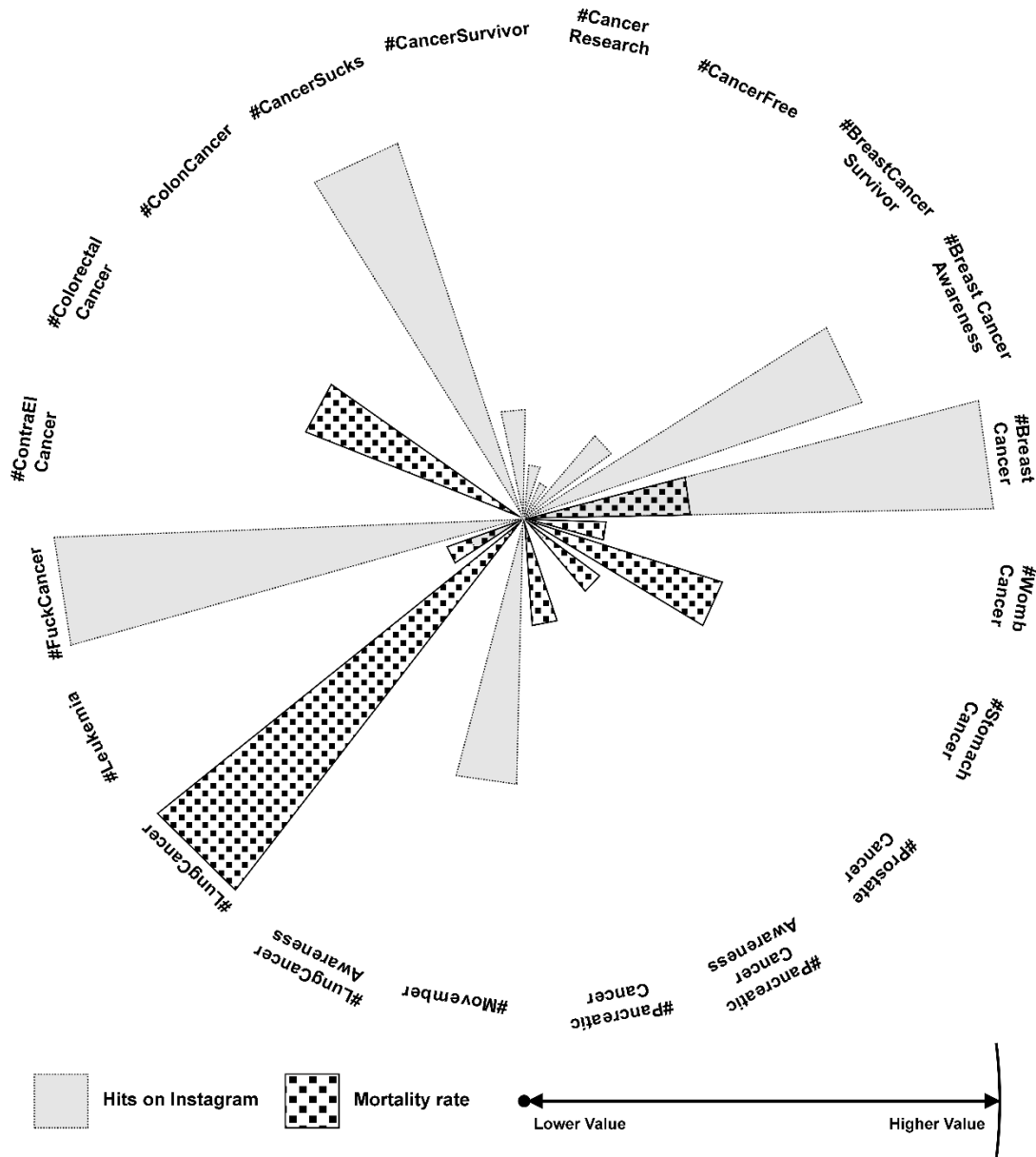
Figure 8. Distribution plot of Hits vs Incidence rate per cancer site, excluding breast cancer



Labels are provided for cancer sites that returned more than 5000 hits on Instagram

364 Finally, a visualization contrasting Mortality with Hits presents the most
365 contradictory image (Figure 9).

Figure 9. Volume of images on Instagram (Hits) and Mortality rates (2018) per cancer site



367

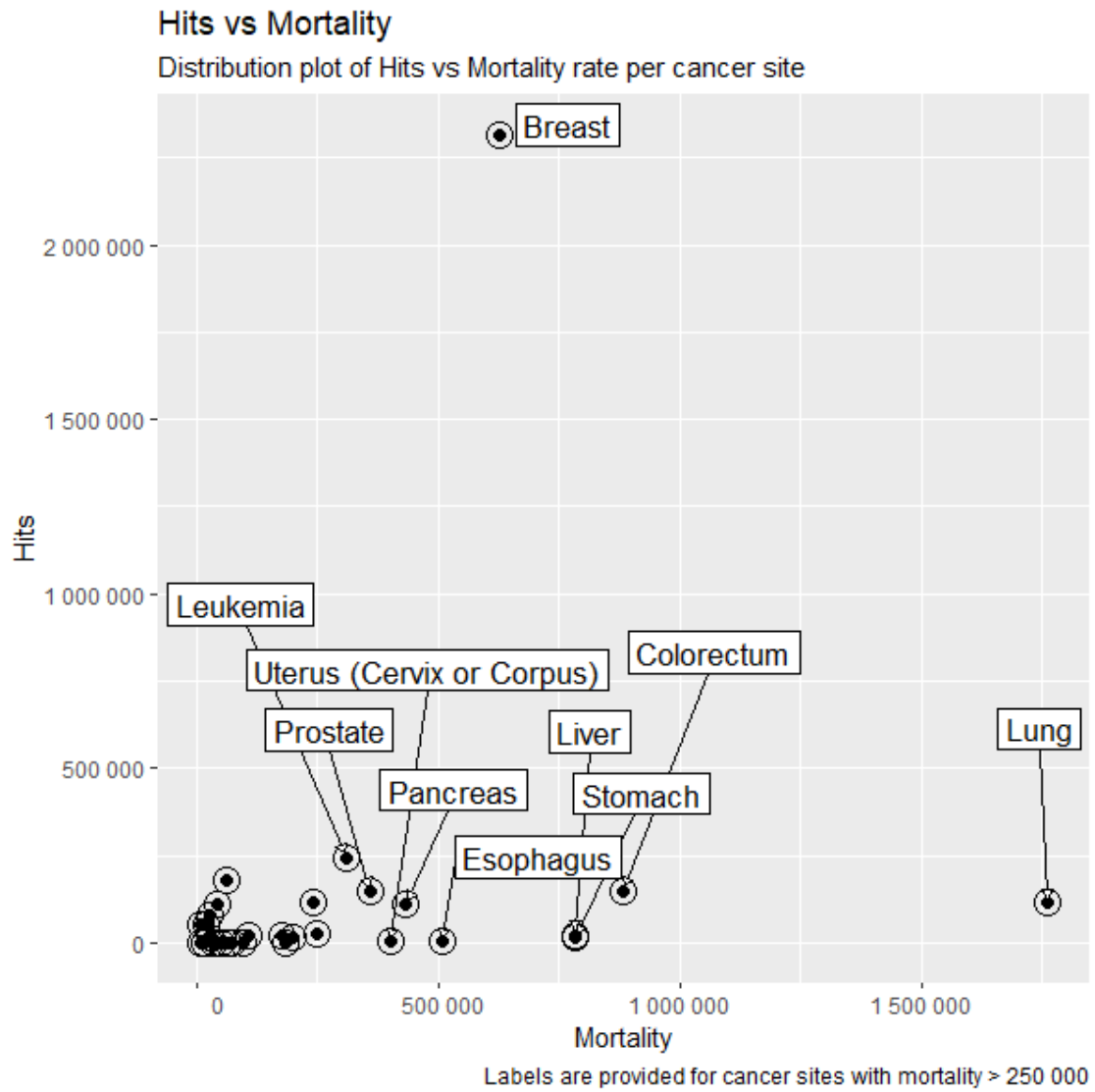
368 While lung cancer, stomach cancer and colorectal cancer have the highest
 369 mortality rates, they also have the lowest visibility online. This indicates that online
 370 visibility is not linked to the net human cost of the illness and may validate Sugawara's
 371 interpretation that online presence may be linked to survival rates. A Pearson correlation
 372 cannot reject the hypothesis of a lack of correlation between these two variables, be it
 373 maintaining breast cancer in the data:

374 $r(29) = .212, p = .251$

375 or removing it from the equation:

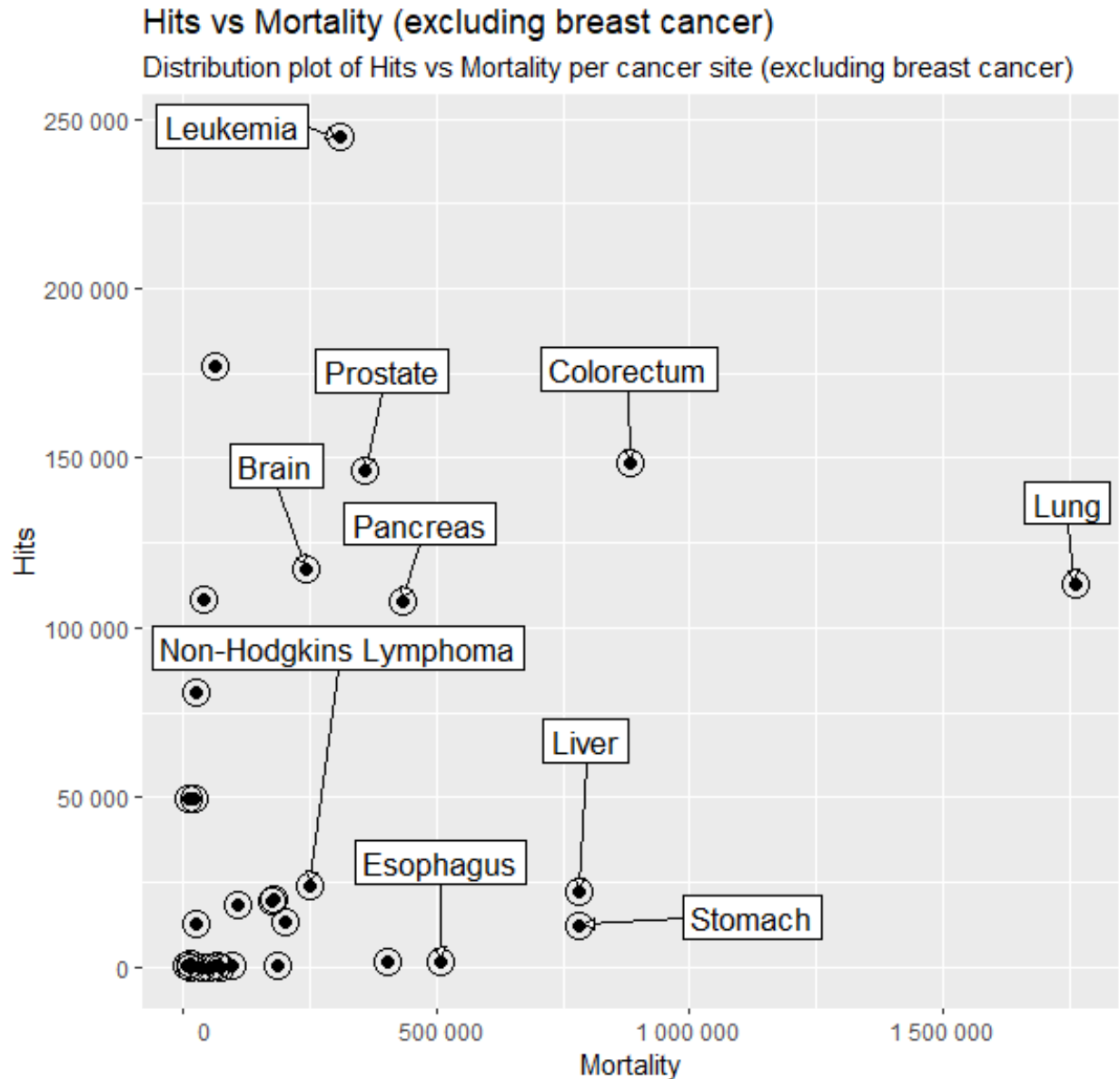
376 $r(28) = .276, p = .140$

377 **Figure 10. Distribution plot of Hits vs Mortality rate per cancer site**



378

Figure 11. Distribution plot of Hits vs Mortality rate per cancer site, excluding breast cancer



Labels are provided for cancer sites with mortality > 250 000

380

381 Consequently, it cannot be concluded that online visibility of a given cancer site is
382 related to its incidence, prevalence nor mortality rates.

383 Discussion

384 Previous research already indicated a dominance of breast cancer in online
385 discussions—findings in this paper help visualize such imbalance and give it visual entity.
386 That breast cancer appears to behave as an outlier in online representation is an

387 important finding. It is the most mentioned type of cancer on Instagram, outweighing the
388 next in line (leukemia) by a factor of almost ten. Meanwhile, sites with high incidence like
389 lung or prostate cancer appear to have little visibility on Instagram.

390 The explanation for this imbalance appears to be social rather than
391 epidemiological, supporting previous findings in the literature. Discussing Twitter posts,
392 Crannell et al. find that “only 1% of all breast cancer tweets were patient tweets” (Crannell
393 et al., 2016, p. 539). Their interpretation is that “nondiagnosed individuals are tweeting
394 about the disease for fundraising purposes or sharing feelings about a loved one”
395 (Crannell et al., 2016, p. 539), revealing the greater public awareness of breast cancer as
396 compared to other sites. This suggests that content discussing cancer sites with less
397 public awareness may be falling into an echo-chamber and not reaching the public
398 discourse, which may have implications for research funding and access to information
399 by patients.

400 While the literature points to social media and the internet as a key source of
401 information, community and support, the lack of representation of some cancer sites may
402 dissuade patients from sharing content. While breast cancer is prominent online, other
403 patients face the task of building a community and challenging common perceptions of
404 cancer that do not necessarily apply to their experience.

405 The implications are both individual (for patients) and social. Firstly, adding to the
406 burden of blame that patients of lung cancer and other sites carry with them, the lack of
407 support and visibility online for their illness can be demotivating and detrimental to their
408 emotional wellbeing.⁶ Secondly, the higher visibility of certain sites may impact research
409 funding, as individuals and organizations turn their attention to certain sites and neglect
410 others.⁷

6 For instance, Pertl, Quigley and Hevey (2014) reflect on this challenge when discussing cancer-related fatigue and how it contradicts social discourses related to survivorship.

7 Much work has been done on this issue with relation to breast cancer. See Sweeney & Killoran-McKibbin (2016) or King (King, 2008).

411 *Movember, a case of dissociation between campaign and illness*

412 While not the only campaign for awareness present in the sample, Movember is the
413 only hashtag that compares in results to breast cancer-related tags. The Movember
414 campaign, launched in the early 2000s, has been historically tied to raising awareness on
415 prostate cancer, but has since moved to other issues related to the mental and physical
416 health of males. Data from this study returns 105,214 results on Instagram carrying the
417 hashtag “#ProstateCancer”, while “#Movember” soars to close to two million mentions.
418 This result supports previous research that outlines the dissociation between the
419 aesthetics of awareness-raising campaigns and their intended impact (Bravo & Hoffman-
420 Goetz, 2016; Vraga et al., 2018), in a fashion not too dissimilar to the critique that
421 Ehrenreich (2001) would make of breast cancer awareness campaigns, which she found
422 to have moved from cancer awareness to a “cult of pink kitsch”.

423 *Limitations and opportunities for further research*

424 This research is limited by the volume of data available online. Its method relies
425 on mostly manual techniques, which may have led to important keywords being left out.
426 Importantly, the hashtag “cancer” could not be studied in isolation due to the vast number
427 of results and the use that is made of it to refer to other issues (such as the horoscope
428 sign). Similarly, cancer-related content that is not hashtagged requires a deeper dive into
429 the data.

430 Through observation, it is possible to detect the most used keywords when
431 referring to cancer by a small sample of users, but it is not possible to collect them all.
432 Similarly, Instagram does not allow for advanced searches, which impedes the use of
433 limited time ranges or location-specific searches. Future research should seek to
434 automate this process, enabling cross-references between hashtags and allowing for
435 more hashtags (including more common names for certain cancer sites, such as “throat
436 cancer”).

437 The demographics of social media need also be considered, with a higher number
438 of users being adolescents and young adults, while the incidence of certain cancer sites
439 (breast cancer included) is above the 50 years of age.

440 Further, social media access has been restricted in the last two years, which
441 impedes the use of automated data extraction, ordering of images, or the collection of
442 “likes” per image. These are all valuable research variables that should be sought in future
443 work, particularly to assess the impact of different images, hashtags, and cancer sites.
444 Researchers may explore a collaboration between Facebook/Instagram, data, social and
445 medical scientists. This may allow for further data, such as the average duration of
446 treatment, survival rates, and qualitative data on cancer discourse online.

447 **Conclusion**

448 This research indicates that the volume of mentions to a given cancer site on Instagram
449 does not correlate to its prevalence, incidence nor mortality rates, contradicting some of
450 the hypotheses in the literature. Instead, it demonstrates that breast cancer behaves as
451 an outlier in social media, with a large volume of posts that appear to be motivated by the
452 success of awareness raising campaigns.

453 Meanwhile, other cancer sites with high prevalence, incidence or mortality are
454 virtually absent from Instagram. Notable cases are those of lung, prostate, pancreas, and
455 stomach, some of the sites with highest mortality rates and lowest survival rates, and also
456 with some of the lowest visibility online. Patients of some of these types of cancer (mainly
457 lung cancer) are often burdened with social blame and find little support in the public
458 online space. While initiatives to provide informational and emotional support to such
459 patients using social media show positive results, it is important to bear this imbalance in
460 mind to understand the impact that social media may have on them.

461 While it is beyond the scope of this study, the high visibility of breast cancer online
462 merits further study on its causes, the shaping of social discourse on illness, and the
463 impact on patients’ well-being, in a similar vein to existing work done on Facebook (Chou
464 et al., 2020).

465 In an ocean of information like social media, volume matters. Regardless of their
466 features, campaigns to raise awareness will struggle to make themselves visible as they
467 row against millions of images and the attraction mechanism. When using social media

468 to connect patients, researchers must ask “whose cancer?” and anticipate the effects that
469 exposure to content related to other sites may have, and how that content shapes the
470 public discourse of cancer.

471 **Disclosure of interest**

472 The authors report no conflict of interest

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