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Development of Smartphone Apps for Skin Cancer Risk Assessment: Progress and Promise

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Abstract

Skin cancer is a growing public health problem. Early and accurate detection is important, since prognosis and cost of treatment are highly dependent on cancer stage at detection. However, access to specialized health care professionals is not always straightforward, and population screening programs are unlikely to become implemented. Furthermore, there is a wide margin for improving the efficiency of skin cancer diagnostics. Specifically, the diagnostic accuracy of general practitioners and family physicians in differentiating benign and malignant skin tumors is relatively low. Both access to care and diagnostic accuracy fuel interest in developing smartphone apps equipped with algorithms for image analyses of suspicious lesions to detect skin cancer. Based on a recent review, seven smartphone apps claim to perform image analysis for skin cancer detection, but as of October 2018, only three seemed to be active. These apps have been criticized in the past due to their lack of diagnostic accuracy. Here, we review the development of the SkinVision smartphone app, which has more than 900,000 users worldwide. The latest version of the SkinVision app (October 2018) has a 95% sensitivity (78% specificity) for detection of skin cancer. The current accuracy of the algorithm may warrant the use of this app as an aid by lay users or general practitioners. Nonetheless, for mobile health apps to become broadly accepted, further research is needed on their health impact on the health system and the user population. Ultimately, mobile health apps could become a powerful tool to reduce health care costs related to skin cancer management and minimize the morbidity of skin cancer in the population.

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KEYWORDS

skin cancer; early detection; mhealth; smartphone app; mobile phone

Rationale for Using Mobile Health Apps for Early Detection of Skin Cancer

There are three main types of skin cancers—malignant melanoma (MM), squamous cell carcinoma (SCC), and basal cell carcinoma (BCC)—with the latter two also known as keratinocyte carcinoma (KC). In the United States, it was estimated that about 91,000 people will be diagnosed with melanoma and 9300 will die due to MM in 2018 [1]; in addition, in 2012, more than 5 million people were diagnosed and 3 million received treatment for KC, which is more than the values for all other cancers combined [2]. Globally, in 2015, there were about 351,000 new incident melanoma cases and 60,000 melanoma-related deaths [3], with the highest burden of disease in Australasia, North America, and Europe. In the last 30 years, the incidence of MM, adjusted for changes in the age distribution of the population, more than doubled in the United States (among Caucasians) and the United Kingdom; nearly doubled in Norway, Sweden, and New Zealand; and increased by approximately 75% in Australia [4]. This is mostly due to changes in risk factors such as increased exposure to ultraviolet light and indoor tanning [4-6]. Since these risk factors are mostly preventable, comprehensive prevention programs aimed at better sun protection behavior have been implemented in several countries, such as SunSmart in Australia [7].

Although several organizations have issued recommendations on how often to check skin lesions for individuals at higher risk (eg, Fitzpatrick scale I-III, a family history of melanoma, a history of sun-damaged skin, and multiple atypical nevi), ranging from every 3 months to every year [8], most countries do not have an organized early detection program for skin cancer. The US Preventive Services Task Force has issued an I-recommendation for skin cancer screening [9], indicating that there is insufficient evidence to evaluate the harms and benefits of skin cancer screening. Currently, there are only two major skin screening programs: (1) In the United States, the American Academy of Dermatology, which started in 1985, includes screening and skin cancer awareness education [10] and (2) in Germany, a national screening program was started in 2008 [11]; the program in Germany does not seem to be effective in reducing skin cancer–related mortality and morbidity [12].

In practice, it is difficult to provide a high-quality skin checks, even for high-risk individuals. Waiting times and, in some areas, dermatologist shortages, out-of-pocket costs, and distance to the nearest dermatologist [13] may discourage people at risk from receiving dermatological care. For example, in the United States, a study found that availability of a dermatologist within the county is associated with a 35% decrease in melanoma mortality [14]. Another US estimate found that only a quarter of individuals at higher risk of skin cancer have ever received a total skin body examination [8].

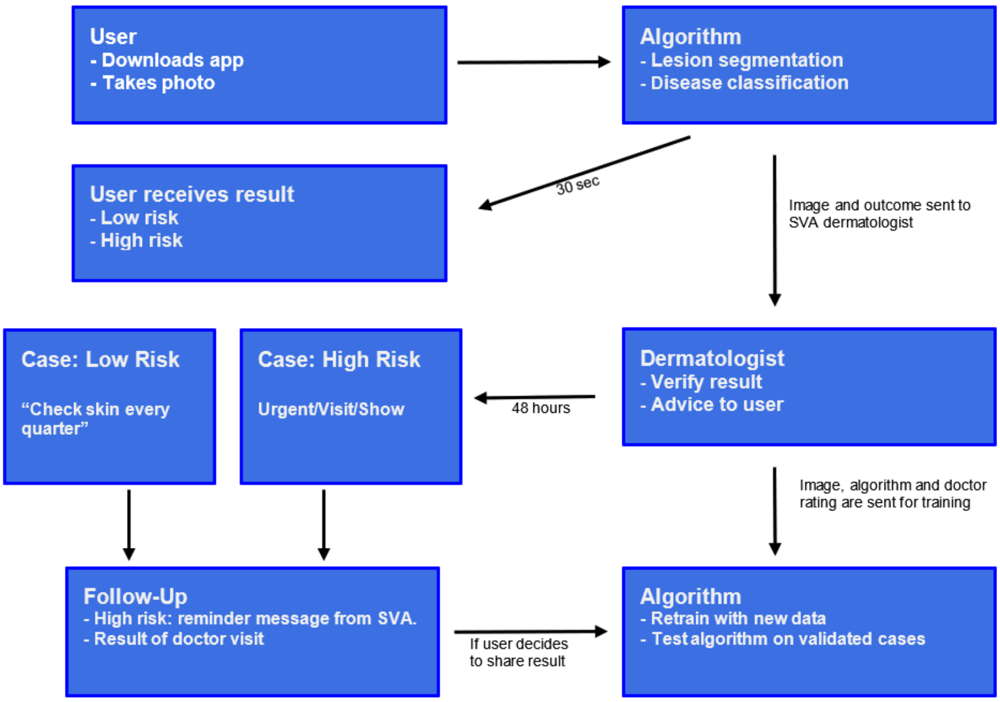
In several countries, namely, in the United Kingdom and the Netherlands, skin checks are first carried out by a general practitioner (GP, also sometimes referred to as primary care provider), who may then choose to refer a patient to a dermatologist if there is a suspicion of skin cancer. However, several studies suggest that the accuracy of GPs to detect skin cancer is relatively low [15-20]. The sensitivity of GPs without specific training to detect skin cancer was estimated to be below 60% in British and Dutch studies [15,16]. One US study found that only 35% of patients had a correct diagnosis [17]. Altogether, this may result in a delay in diagnosis or missing the cancer in its earlier stages when patient survival is more favorable and treatment is less costly. Furthermore, many GP consultations and subsequent referrals to a specialist to examine the skin for cancer result in a benign diagnosis. A Dutch study found that 69% of GP consultations related to suspicious skin lesions result in a benign diagnosis [19], and two separate studies in the Netherlands estimated that a large proportion (40%) of referral cases to the dermatologist due to suspicion of skin cancer turned out to be benign cases [19,20]. Two studies (in the United States and Germany) including more than 70 dermatologists found that dermatologists' disease classification decisions have a specificity of 60%-80% [21,22], which may result in unnecessary biopsies/excisions.

Early detection and surveillance of skin cancer could be more efficient with mobile health (mHealth) apps, which are easily accessible due to the ubiquity of smartphone usage. One example of a smartphone app for self-assessment of skin lesions for skin cancer is the SkinVision app (SVA), developed by SkinVision, BV, The Netherlands). In the next section, we review the development of SkinVision app over time.

Development of a Smartphone App for Skin Cancer Detection

SkinVision is a smartphone app built as a digital dermatology service for self-monitoring skin lesions. It was launched in 2011 and as of October 2018, it was on its fifth major version. The workflow of the app is given in Figure 1.

Figure 1. Workflow of the SkinVision app service. SVA: SkinVision app.



A user can self-assess the risk of a skin lesion for skin cancer by taking a photo with his/her smartphone, which is processed by an algorithm. The outcome of the procedure is a binary risk rating, which can be low or high. This smartphone app does not provide a diagnosis (eg, "you have melanoma"). For high-risk cases, the user receives advice from the costumer care team based on the image assessment of an in-house dermatologist.

Development of the SkinVision App Service

The history of the SkinVision app service is shown in Table 1. It went through several upgrades throughout its history, modifying the camera, the algorithm and its evaluation, type of lesions analyzed, and communication of the algorithm result to its user. One of the major initial challenges was related to image acquisition. In the beginning, there was no filter on the images sent for analyses, which meant that a significant proportion of the pictures taken by users was of insufficient quality to be analyzed by the disease classification algorithm or did not even contain a lesion to be analyzed. Since version 3 of the SkinVision app (2014), a special camera module [23] has been embedded, which only lets the camera take a photo after certain minimal quality conditions are met. Compared to unfiltered images taken with a standard smartphone camera, the camera module reduces the number of blurry photos by about 52% on an average (determined using 2018 data). Altogether, improvements in the camera module (namely, image quality checks) and the algorithm pipeline led to a reduction in the number of assessments that failed to produce a risk rating, from 26% in 2016 to 2% in 2018 on an average.

An overview of studies on the diagnostic accuracy of the SkinVision app is shown in Table 2. Diagnostic accuracy is evaluated based on two measures: sensitivity (proportion of lesions correctly classified as high risk) and specificity (the proportion of lesions correctly rated as benign). The first algorithm for skin lesion assessment was a rule-based fractal algorithm [24]. Initially, it was focused on pigmented skin lesions and only able to analyze whether MM was present in the lesion, and it was tested based on clinical review of images. The Munich University Hospital study was the first peer-reviewed publication where the SkinVision app algorithm was evaluated against histopathology [24], and thereafter, the algorithm achieved 73% sensitivity (83% specificity). During the Catharina Hospital Eindhoven study [25], the algorithm was recalibrated to analyze pigmented and nonpigmented lesions. Currently, it can detect several types of skin cancer (MM, SCC, and BCC) and skin conditions that can lead to skin cancer, namely, actinic keratosis and Bowen disease. It achieved 80% sensitivity (78% specificity) after inclusion of user clinical information. Although in the Eindhoven study, only 233 lesions were used for calibration, in 2018, the SkinVision app assembled a training dataset of more than 130,000 images that were risk classified by a dermatologist from the app's user database. This led to replacement of the rule-based classification algorithm by a machine learning approach (A Udrea et al, PhD, unpublished material, 2019).

Table 1. Development of the SkinVision smartphone app.

Version	Launch date	Algorithm	Camera	Type of skin lesion	Type of skin cancer detected	Testing
1	May 2011	Rule-based fractal algorithm version 1	Standard smartphone camera	Pigmented skin lesion only	Malignant melanoma	Preclinical testing using 600 images against the opinion of two dermatologists
2	December 2012	Rule-based fractal algorithm version 2	Standard smartphone camera, exclusion criteria introduced	Pigmented skin lesion only	Malignant melanoma	Preclinical testing using 600 images against the opinion of two dermatologists
3	September 2014	Rule-based fractal algorithm version 2	Camera module: exclusion criteria automated	Pigmented skin lesion only	Malignant melanoma	Clinical study, Munich University Hospital
4	July 2016	Rule-based fractal algorithm version 3, all outcomes checked by dermatologists (Sept 2016)	Camera module version 1	Pigmented and nonpigmented skin lesions	Malignant melanoma, squamous cell carcinoma, basal cell carcinoma, some premalignant lesions	Clinical study, Catharina Hospital Eindhoven (more types of skin cancer)
5	January 2018	Machine learning algorithm for image processing and classification	Camera module major version 2[a]	Pigmented and nonpigmented skin lesions	Malignant melanoma, squamous cell carcinoma, basal cell carcinoma, some premalignant lesions	Data from previous clinical studies and user database with new algorithm

[a]New features include a dynamic grey threshold to differentiate between normal skin and lesion and a feature that prevents taking pictures without uniform luminosity.

Table 2. Studies on the accuracy of the SkinVision app's risk assessment. All studies presented here were sponsored by the SkinVision app.

Study	Data	Algorithm	Test set	Sensitivity (%)	Specificity (%)	Remarks
Maier et al, 2014 [24]	University Hospital Munich	Rule-based fractal algorithm version 2	26 lesions with melanoma	73	83	Algorithm tested only on malignant melanoma
Thissen et al, 2017 [25]	Catharina Hospital Eindhoven	Rule-based fractal algorithm version 3	108 lesions including several types of skin cancer	80[a]	78[a]	Algorithm tested mostly on keratinocyte carcinoma (Munich data also used for testing)
Udrea et al, 2019[b]	Clinical studies and SkinVision app user database	Machine learning–based algorithm	285 lesions with skin cancer, from clinical studies and a user database with histopathology information	95	78	All types of skin cancer

[a]After incorporating answers into a questionnaire about the skin lesion.

[b]Manuscript under peer review (June 2019). For more details on these results, see Multimedia Appendix 1.

SkinVision App Service in 2018

Camera

Before downloading the app, the smartphone should be equipped with a camera capable of producing a video stream with sufficiently high resolution. Although the app uses a regular smartphone camera, the camera module embedded in the app automatically places some restrictions to ensure minimal quality requirements of the images are met: The image needs to be focused, the lesion should be present and contained in the image, and there should be no hair or shadows covering the lesion. The module also prevents the camera from taking images that cannot be assessed by the algorithm (eg, lesions under a nail or near clothing in a skin fold).

Algorithm for Lesion Assessment

There are several steps to analyze the lesion. The first task of the algorithm is to identify and separate the lesion from normal skin. This is done using a machine learning technique called conditional Generative Adversarial Neural Network [26] (A Udrea et al, PhD, unpublished material, 2019). After the lesion is segmented, all "noise" (eg, hair surrounding the lesion) is removed in the image by applying an inpainting procedure [27]. The third step is to extract the features from the lesion that are used in the disease classification algorithm. These features include 24 shape, color, and texture attributes that characterize the lesion. A Support Vector Machines (SVM) classifier is used to provide a risk rating, which can be high or low. The SVM model is obtained by maximizing sensitivity to detect cancer subject to a constraint of a minimal specificity value (eg, 80%). The optimization is performed using a Particle Swarm Optimization algorithm [28]. The classification algorithm is regularly updated and retrained with new data. This is necessary to maintain robustness to variation due to imaging, newer devices, and the user population adopting the app.

Training and Testing

For training of the algorithm, we used images obtained from the user database (more than 130,000 pictures from 30,000 users), which received either a low- or high-risk tag during quality control of the algorithm by a dermatologist affiliated with SkinVision. A selection of cases clinically validated as low risk were randomly selected from the user database, while all cases rated as high risk or with a histopathological report were used, since there were considerably fewer of them. For testing the sensitivity, we used 285 skin lesions derived from both previous clinical studies (Munich and Catharina Hospital, 195 skin lesions, containing most common forms of skin cancer) and the user database (90 cases of melanoma that received histopathological confirmation from users). Furthermore, to test the specificity, we used 6000 randomly selected cases from the user database (June to August 2018), which were tagged as benign by SkinVision-affiliated dermatologists and were not used in training. An overview of these datasets together with the participant flowcharts are shown in Multimedia Appendix 1.

Performance Evaluation

The gold standard (main comparator) to evaluate algorithm sensitivity is comparison against histopathologically validated cancers. The second comparator is the performance of the algorithm against the image assessment of the dermatologist (which is comparable to a teledermatology consult). In order to calculate the specificity, we use images of lesions that were classified by dermatologists as benign cases, since these are not usually biopsied, and therefore, there is no histopathology report. Sensitivity has improved from 73% in the first peer-reviewed study, where only MM was detectable, to 95% in the current version of the algorithm (78% specificity), where the SkinVision app can detect all forms of skin cancer (Table 2 and Multimedia Appendix 1).

Postassessment Follow-Up

Since 2016, images processed by the algorithm are reviewed by at least one affiliated dermatologist. To help users with the interpretation of high-risk cases, a senior dermatologist adds advice depending on the probable severity of the disease. The advice can contain the labels "Show," "Visit," or "Urgent." "Show" indicates that the lesion should be shown at the next planned doctor appointment, "Visit" indicates that the appointment should be made soon, and "Urgent" advises the user to show the lesion to a doctor as soon as possible. Users with a low-risk rating only receive a reminder to check their skin regularly.

Assessments with a high-risk rating given by the dermatologist are followed up by the customer support department of the SkinVision app. If the user does not respond, he/she may receive additional messages encouraging a visit to the doctor, depending on the perceived severity of the disease. Some users share their diagnosis of skin cancer with the SkinVision app (n=3806, Multimedia Appendix 1). Of these, a small proportion (338/3806, 8.8%) share the histopathology report. At the end of September 2018, about 338 users had shared histopathological reports, of which 58% (178/338) were of MM diagnosis. The histopathologically validated cases are used for training and testing the algorithm.

Smartphone App Users

In Table 3, we show self-reported demographic data on SkinVision app users. As of September 2018, the SkinVision app has performed more than 1.8 million assessments. Some of these users shared their demographic data with the SkinVision app: 56% (355,491/635,807) shared their age group and 28.5% (181,706/635,807) shared their gender. Although skin cancer is more prevalent in older age groups, only 7% of the people were older than 60 years of age (19,358/355,491) in the user database and about 31% (110,529/355,491) were younger than 30 years of age. More than 60% of the users were female (118,182/181,706). A majority of the users come from the following countries: The Netherlands (n=111,063, 17.4%), United Kingdom (n=109,178, 17.2%), Australia (n=109,126, 17.2%), New Zealand (n=70,244, 11%), and Belgium (n=21,328, 3.3%).

Table 3. Self-reported demographic characteristics of the SkinVision app users. The data are from the SkinVision app proprietary user database, accessed in September 2018. Numbers are based on users, who made a picture that was evaluated by the algorithm, and filled the online questionnaire.

Characteristic	Users
Number of registered users	931,789
Total number of users with an assessment	635,807[a]
Gender[b], n (%)	
Male	62,914 (9.9)
Female	118,182 (18.6)
Missing	454,731 (71.5)
Age group[b] (years), n (%)	
<30	110,529 (17.4)
30-39	98,327 (15.5)
40-49	74,928 (11.8)
50-59	46,840 (7.4)
60-69	19,358 (3.0)
>70	5509 (0.9)
Missing	280,316 (44.0)
Country, n (%)	
The Netherlands	111,063 (17.4)
Australia	109,178 (17.2)
United Kingdom	109,126 (17.2)
New Zealand	70,244 (11.0)
Belgium	21,128 (3.3)
Others	215,355 (33.9)

[a]Some users may be health care providers taking pictures of multiple patients, so this is likely an underestimate.

[b]For the gender and age categories, about 75% and 44%, respectively, did not fill any data.

State of the Field

Available Mobile Health Apps for Skin Cancer Detection

A recent review [29] found that there are 43 smartphone apps developed for skin cancer detection, monitoring, and education. Of these, nine smartphone apps use an algorithm for image analysis [29]. We verified the current status of these smartphone apps in December 2018 with Google search and PubMed and in app stores. The results are presented in Table 4. We confirm that seven apps claim to use an algorithm for image analysis. Of these, four do not seem to be active as of October 2018. Compared to a previous review conducted in July 2014 [30], there are now less apps available for risk assessment of skin lesions through image analysis (three instead of four).

Table 4. List of smartphone apps that claim to perform skin lesion image analyses to detect skin cancer, based on a systematic review [29].[a]

Commercial name	Algorithm[b]	Evidence on PubMed	Status	Source[c]
DermaCompare	Machine learning	Not found	Removed from app store, last update on January 2017	[31]
Lubax	Content-based image retrieval, k-nearest neighbor	Yes, one supported peer-reviewed publication[d]	Removed from app store, last update on February 2015	[32,33]
MSkinDoctor[e]	Grab cut algorithm (segmentation) and SVM[f] (classification)	Not found; there is a conference abstract only	Removed from app store, update on February 2016	[34]
MySkinMap	Machine learning	Not found	Removed from app store, last update on September 2016	[35]
SkinScan	Image processing techniques, ABCDE rule	Unclear[g]	Available	[36]
SkinVision	Conditional generative adversarial neural network (segmentation) and SVM (classification)	Yes, two supported peer-reviewed publications, evaluated in independent publications	Available	[23-25,37], A Udrea et al, PhD, unpublished material, 2019
SpotMole	Image processing techniques, ABCDE rule	Yes, evaluated in independent publications	Available[h]	[38]

[a]After verifying the websites of every app (if available), it seems that two of the apps mentioned in the Ngoo et al study [29] with commercial names—Myskinpal and Skin Prevention - Photo Body—do not claim to perform automated image analysis for risk assessment. They only store images of moles to track changes.

[b]If available, the information is retrieved from scientific publications; otherwise, it is collected from the company's own website or app store description.

[c]Accessed on Dec 12, 2018.

[d]Results obtained in this publication [32] only for melanomas and large lesions.

[e]There is another app available with the same name; however, that one does not perform image analyses.

[f]SVM: support vector machines.

[g]There is an associated reference to an app of the same name from 2011; however, this does not appear to be the same app.

[h]This smartphone app has a website (spotmole.com); however, it was offline at the last time of access (Dec 12, 2018). It is unclear if this project is still alive, given the fact that the last update was in March 2016 and that it seems this app is being developed by a single individual.

Comparison of the SkinVision App With Other Apps

Currently, there seem to be three apps available for detection of skin cancer, including SkinVision app, SpotMole, and skinScan. All three allow the user to take a picture with the smartphone camera. The SkinVision app algorithm is based on machine learning techniques, while SpotMole and skinScan use algorithms inspired by the ABCDE rule [39]. The SkinVision app involves quality control by a dermatologist; however, the other apps do not seem to offer any further follow-up or advice to users.

Tables 2 and 5 show the diagnostic accuracy results from recent publications. We found five peer-reviewed studies and one submitted study about two available mHealth apps and two mHealth apps that do not exist anymore. Of the three currently available apps, no diagnostic accuracy or other studies were found for skinScan. The other two smartphone apps were evaluated in at least one study [40], and only one app (ie, SkinVision app) [24,25] has published evidence to show whether their proprietary algorithm is accurate.

mHealth apps for skin cancer assessment (including SkinVision app) have been criticized in past studies [40,41], because their accuracy was found to be significantly lower than that of a dermatologist. In Tables 2 and 5, only three studies showed a diagnostic accuracy close to that of a dermatologist, and one of these studies [32] only showed a high accuracy for large melanoma lesions. Although some of these studies are recent, these findings are possibly already outdated, as this is a rapidly evolving field. These results could also be explained by the limited sample size, including too few skin cancer cases and selected samples, which may be inadequate to calculate sensitivity or specificity or, in the case of SkinVision app, nonutilization of the full service with the dermatologists' advice.

Overall, the amount of evidence on the diagnostic accuracy of smartphone apps is still scarce, as there are few mHealth apps providing this service. It is also difficult to make an accurate comparison between different apps, since the rate of service or algorithm change is faster than the process of peer-review publication. It could also be the case that some developers may choose to publish their results in sources that are not referenced in PubMed, namely, ArXiv. An illustrative example of these difficulties is a Cochrane review [42] published in December 2018 on the diagnostic accuracy of smartphone apps, which only found two studies but only included articles published before August 2016, making it possibly obsolete at the time of publication. For these reasons, one should be cautious when interpreting the available literature.

Table 5. Recent studies on the diagnostic accuracy of smartphone apps for risk assessment of skin lesions.

App, study, year	Location for data collection	Algorithm	Test Set	Sensitivity (95% CI)	Specificity (95% CI)	Remarks
SkinVision app, Ngoo et al, 2018 [40]	Princess Alexandra Hospital, Brisbane	Rule-based fractal algorithm version 2	1 malignant melanoma, 41 clinically suspicious lesions[a]	iOS: 57% (41-73), Android: 72% (58-87)[b]	iOS: 50% (22-78), Android: 27% (1-56)[b]	Only 1 malignant melanoma was found
SpotMole, Ngoo et al, 2018 [40]	Princess Alexandra Hospital, Brisbane	Algorithm based on the ABCDE rule	1 malignant melanoma, 41 clinically suspicious lesions[a]	43% (28-58)	80% (60-100)	Only 1 malignant melanoma was found
Dr Mole, Ngoo et al, 2018 [40]	Princess Alexandra Hospital, Brisbane	Algorithm based on the ABCDE rule	1 malignant melanoma, 41 clinically suspicious lesions[a]	21% (9-34)	100% (100-100)	Only 1 malignant melanoma was found
Lubax, Cheng et al, 2015 [32]	DermNetNZ, New Zealand, and Los Angeles[c]	Content-based image retrieval	208 lesions with melanoma[d]	90% (86-94)	92% (85-95)	Algorithm tested only on malignant melanoma (large lesions only)
Not reported, Dorairaj et al, 2017 [41][e]	Galway University Hospital	Not reported	9 malignant melanomas	80% (52-96)	9% (0-41)	Algorithm tested only on malignant melanoma

[a]All lesions had a benign final histopathology diagnosis with the exception of one melanoma in situ.

[b]Ngoo et al 2017 [40] reported the results per type of operating system: iOS/Android.

[c]DermNetZN is a publicly accessible skin lesion image database from New Zealand containing about 20,000 images. Images collected within the Los Angeles county were collected by the app company. No reference to a clinical site of the data collection was given in the publication.

[d]Algorithm was only tested on "large lesions" defined as melanomas with a diameter ≥10 mm.

[e]Despite the study being published in 2017, the study took place in 2012.

Improving the Diagnostic Accuracy of Mobile Health Apps

A promising avenue to improve the diagnostic accuracy of mHealth apps is to train machine learning algorithms on large databases of skin cancer images. Several algorithms for skin cancer classification were recently developed based on clinical or dermoscopic images, with algorithm accuracy routinely on par with a dermatologist [21,22,43]. For mHealth apps, the task of skin lesion classification is more difficult, as the images are taken by the users themselves, with variability in angle, luminosity, and smartphone model. The SkinVision app showed that skin lesion classification based on smartphone images can also achieve high accuracy (Table 2; A Udrea et al, PhD, unpublished material, 2019).

Alternatives to Mobile Health Apps

Early detection of skin cancer could be significantly improved by launching a population screening program, but this is unlikely to become common due to the high costs and lack of evidence on harms and benefits [9,44]. As the main risk factors for skin cancer like indoor tanning or ultraviolet exposure are, in large part, preventable [45], primary prevention and awareness campaigns (eg, Melanoma Monday and SunSmart in Australia) could have a better cost-benefit ratio than early detection [46]. These campaigns are a way for the general public to proactively adopt preventive behaviors and possibly learn how to recognize suspicious skin lesions [7]; they seemed to have resulted in better sun protection behavior [47]. On the other hand, this success can be reversed if these awareness efforts are not continuous [47] and they do not solve the shortages or difficulties in access to high-quality skin checks.

Training GPs or nurses with a special interest in recognizing skin cancer increases the capacity for early and accurate detection. However, compared to mHealth apps, it still requires face-to-face contact, and it is likely not enough to address all needs [13,48]. Store-and-forward teledermatology [49] allows users to take a photo and have it analyzed remotely by a dermatologist. This may solve some of the problems with access to care, but is solely based on a clinical assessment of a health care professional and is thus not automated. Smartphone apps with good performance are likely to be more efficient and could lead to larger cost savings for the health system compared to the above mentioned alternatives.

Usability Risks of Smartphone Apps

Smartphone apps pose some risks for the user, specifically, if the algorithm returns a negative result while the user has cancer, and detection and treatment of skin cancer are delayed. It is very challenging to study the rate of false-negatives due to a lack of histological verification. The user may also fail to assess all relevant skin lesions, in particular, if they are located in places that are hard to reach or that the user cannot see. Given that the specificity of SkinVision app is about 80%, there will be a few false-positive cases. This may cause unnecessary stress on users or unnecessary visits to the GP/dermatologist. Finally, the user may not follow the advice given in the smartphone app due to a lack of trust or unawareness.

Evaluating the Health Impact of Mobile Health Apps

Impact of Mobile Health Apps on Health Care Costs

A Dutch study based on national claims data observed an increase of about 67% in skin cancer–related costs between 2007 and 2017 (E. Noels, MD, unpublished data, 2019). This is due to higher costs of skin cancer treatments, for example, newly available expensive targeted immunotherapies for late-stage melanomas and, to a lesser extent, due to an increase in the skin cancer incidence. mHealth apps for self-assessment of skin lesions could limit this cost increase by (1) by detecting cancers early, which will reduce the average cost of treatment (ie, less advanced disease) and recovery and (2) reducing the need for doctor visits, since many primary care (GP)–related consultations either result in a benign diagnosis or in referrals to a specialist of cases that are later diagnosed as benign [19].

Impact of Mobile Health Apps on Public Health

Easy access to a high-quality assessment of skin lesions may lead to detection of skin cancers at an earlier stage, when their prognosis and treatment are more favorable. On the other hand, this could also cause overdiagnosis and overtreatment. Currently, evidence on the benefits and harms of skin cancer screening is insufficient [9,44]. To date, there are no randomized skin cancer screening trials, and it is unlikely that there will be new trials launched in the near future, since they would require a substantial number of patients and a long follow-up and it would be difficult and possibly unethical to guarantee that people in the control group would not access skin cancer detection methods. Consequently, it is difficult to determine whether early detection of skin cancer reduces skin cancer specific mortality. Another important target outcome could be the incidence of advanced melanoma. Therefore, indirect evidence on harms and benefits could be obtained by comparing the stage distribution of cancers detected early with a smartphone app from national registries.

Implementation of Mobile Health Apps in the Health System

The health impact of mHealth apps also depends on where it is implemented, that is, whether it is restricted to health care professionals such as GPs or dermatologists or accessible to the lay population. Offering apps directly to lay users could result in significantly greater efficiency gains for the health system; however, some regulatory bodies may prefer to restrict the usage to health care professionals to minimize usability risks. The regulatory framework is evolving quickly, with the National Institute for Health and Care Excellence in the United Kingdom suggesting a comprehensive approach to regulate mHealth technologies, taking into account not only the safety and efficacy of the app, which can be shown by carrying out a diagnostic accuracy study, but also whether it can plausibly improve current health care pathways, acceptability with users, and cost-effectiveness compared to usual care [50].

Barriers to Access of Mobile Health Apps

After implementation, the health impact of mHealth apps will also depend on the persistence of barriers to adoption among users (either lay persons or care providers). Zhao et al [51] described a technology acceptance model for mobile health [51]. For lay users, age can play a role in the rate of adoption [51]. Middle-aged and older users (the ones who are at a higher risk of skin cancer) may give more importance to the perceived amount of effort needed to learn how to use the smartphone app and the perceived personal risk for skin cancer. For clinicians, we believe the perceived ease of use also plays an important role, since clinicians have a limited amount of time. Other important factors may include perceived usefulness and efficacy of the smartphone apps, namely, whether clinicians believe in the quality of the app and whether they believe it provides the necessary information to make a clinical decision.

Postmarket Surveillance of Mobile Health Apps

A key point for mHealth apps for skin cancer detection consists of performing appropriate market surveillance activities in order to minimize usability risks, since data based on clinical studies in a controlled setting are likely not sufficient to control for differences in image-taking behavior or characteristics of the smartphone model. Algorithms used in mHealth apps should then be updated periodically, given the feedback from its users, whether they are lay users or clinicians. It is not easy to have complete follow-up from users, since due to privacy reasons, it is not straightforward for the smartphone apps to obtain access to the final clinical or histopathological diagnosis after the lesion is assessed by the algorithm.

Future Research

Research is still needed to establish the societal value of mHealth apps. First, there remains a need for more high-quality studies on their diagnostic accuracy in different populations. Second, given that these smartphone apps are accurate enough to be used by laypersons and GPs, its health and cost effects are yet to be evaluated.

The impact on the health system in terms of cost reduction due to less skin lesion–related visits still needs to be tested, ideally with a randomized control trial (RCT) accompanied by a cost-effectiveness analysis. However, performing an RCT may prove difficult. To design a trial capable of detecting a difference in the number of doctor visits, the sample size needed to carry out such a study is in the thousands, as shown by the Dutch data from 2010 [52] suggesting that about 93 consultations for every 1000 patients are related to skin cancer. The main problem is that this type of RCT has a high risk of contamination in the control group (no smartphone app), since access to smartphone apps and their usage is relatively simple. An alternative solution could be to follow a quasi-experimental approach for the design of the study [53].

In the absence of large RCTs and long-term follow-up data, modelling could be used to estimate the harms and benefits of early detection of skin cancer. There are a few studies in the literature that modelled the incidence and mortality of skin cancer [54-56]. The main drawback of these modelling studies is the difficulty in estimating tumor onset and progression. This could be addressed by forming a coalition of multiple modelling groups for skin cancer, like the Cancer Intervention and Surveillance Modelling Network (CISNET) group has done for other cancer sites [57].

Summary and Conclusions

Given the difficulties in access to high-quality care for early detection of skin cancer, there is considerable interest in developing algorithms and apps for skin cancer lesion assessment. Although mHealth apps have been criticized in the past due to their poor accuracy, the SkinVision app has a high accuracy to evaluate the risk of skin lesions for skin cancer. This was achieved due to improvements in the processing of images taken with the smartphone camera and a large risk-labeled image database from users, which was used to train a machine learning algorithm.

However, there are still many open questions regarding the usage of mHealth apps. National health authorities need to decide where to position these apps in the health care system (lay population, GPs, or dermatologists). Health effects of early and more accurate detection are difficult to estimate. There is currently no high-quality evidence on the health and cost benefits and harms of early detection of skin cancer, namely, on the trade-off between doctor visits and lives saved/advanced cases avoided. The reduction of the skin cancer burden on the health system and in the population could be substantial, as earlier detection of skin cancer could result in a lower average cost of treatment and a reduction in the number of doctor visits. However, further studies are needed to confirm this.

Conflicts of Interest

AU is affiliated with SkinVision, MW is an occasional advisor for SkinVision, and TN has received an unrestricted research grant from SkinVision.

Multimedia Appendix 1

Datasets used to train and test the SkinVision algorithm.

[PDF File (Adobe PDF File), 432KB - derma_v2i1e13376_app1.pdf]

References

1. Siegel R, Miller KD, Jemal A. Cancer statistics, 2018. CA Cancer J Clin 2018 Dec;68(1):7-30 [FREE Full text] [doi: 10.3322/caac.21442] [Medline: 29313949]
2. Rogers HW, Weinstock MA, Feldman SR, Coldiron BM. Incidence Estimate of Nonmelanoma Skin Cancer (Keratinocyte Carcinomas) in the U.S. Population, 2012. JAMA Dermatol 2015 Oct;151(10):1081-1086. [doi: 10.1001/jamadermatol.2015.1187] [Medline: 25928283]
3. Karimkhani C, Green AC, Nijsten T, Weinstock MA, Dellavalle RP, Naghavi M, et al. The global burden of melanoma: results from the Global Burden of Disease Study 2015. Br J Dermatol 2017 Jul 30;177(1):134-140 [FREE Full text] [doi: 10.1111/bjd.15510] [Medline: 28369739]
4. Whiteman DC, Green AC, Olsen CM. The Growing Burden of Invasive Melanoma: Projections of Incidence Rates and Numbers of New Cases in Six Susceptible Populations through 2031. J Invest Dermatol 2016 Jun;136(6):1161-1171 [FREE Full text] [doi: 10.1016/j.jid.2016.01.035] [Medline: 26902923]
5. Erdmann F, Lortet-Tieulent J, Schüz J, Zeeb H, Greinert R, Breitbart EW, et al. International trends in the incidence of malignant melanoma 1953-2008--are recent generations at higher or lower risk? Int J Cancer 2013 Jan 15;132(2):385-400 [FREE Full text] [doi: 10.1002/ijc.27616] [Medline: 22532371]
6. Apalla Z, Nashan D, Weller RB, Castellsagué X. Skin Cancer: Epidemiology, Disease Burden, Pathophysiology, Diagnosis, and Therapeutic Approaches. Dermatol Ther (Heidelb) 2017 Jan;7(Suppl 1):5-19 [FREE Full text] [doi: 10.1007/s13555-016-0165-y] [Medline: 28150105]
7. Iannacone MR, Green AC. Towards skin cancer prevention and early detection: evolution of skin cancer awareness campaigns in Australia. Melanoma Manag 2014 Aug;1(1):75-84 [FREE Full text] [doi: 10.2217/mmt.14.6] [Medline: 30190812]
8. Johnson MM, Leachman SA, Aspinwall LG, Cranmer LD, Curiel-Lewandrowski C, Sondak VK, et al. Skin cancer screening: recommendations for data-driven screening guidelines and a review of the US Preventive Services Task Force controversy. Melanoma Manag 2017 Mar;4(1):13-37 [FREE Full text] [doi: 10.2217/mmt-2016-0022] [Medline: 28758010]
9. US Preventive Services Task Force, Bibbins-Domingo K, Grossman DC, Curry SJ, Davidson KW, Ebell M, et al. Screening for Skin Cancer: US Preventive Services Task Force Recommendation Statement. JAMA 2016 Jul 26;316(4):429-435. [doi: 10.1001/jama.2016.8465] [Medline: 27458948]
10. Okhovat J, Beaulieu D, Tsao H, Halpern AC, Michaud DS, Shaykevich S, et al. The first 30 years of the American Academy of Dermatology skin cancer screening program: 1985-2014. J Am Acad Dermatol 2018 Nov;79(5):884-891.e3 [FREE Full text] [doi: 10.1016/j.jaad.2018.05.1242] [Medline: 30057360]
11. Geller AC, Greinert R, Sinclair C, Weinstock MA, Aitken J, Boniol M, et al. A nationwide population-based skin cancer screening in Germany: proceedings of the first meeting of the International Task Force on Skin Cancer Screening and

Prevention (September 24 and 25, 2009). Cancer Epidemiol 2010 Jun;34(3):355-358. [doi: 10.1016/j.canep.2010.03.006] [Medline: 20381443]
12. Trautmann F, Meier F, Seidler A, Schmitt J. Effects of the German skin cancer screening programme on melanoma incidence and indicators of disease severity. Br J Dermatol 2016 Nov;175(5):912-919. [doi: 10.1111/bjd.14758] [Medline: 27203791]
13. Kimball AB, Resneck JS. The US dermatology workforce: a specialty remains in shortage. J Am Acad Dermatol 2008 Nov;59(5):741-745. [doi: 10.1016/j.jaad.2008.06.037] [Medline: 18723242]
14. Aneja S, Aneja S, Bordeaux JS. Association of increased dermatologist density with lower melanoma mortality. Arch Dermatol 2012 Feb;148(2):174-178. [doi: 10.1001/archdermatol.2011.345] [Medline: 22351816]
15. Goulding JMR, Levine S, Blizard RA, Deroide F, Swale VJ. Dermatological surgery: a comparison of activity and outcomes in primary and secondary care. Br J Dermatol 2009 Jul;161(1):110-114. [doi: 10.1111/j.1365-2133.2009.09228.x] [Medline: 19438854]
16. Koelink CJL, Vermeulen KM, Kollen BJ, de Bock GH, Dekker JH, Jonkman MF, et al. Diagnostic accuracy and cost-effectiveness of dermoscopy in primary care: a cluster randomized clinical trial. J Eur Acad Dermatol Venereol 2014 Nov;28(11):1442-1449. [Medline: 25493316]
17. Swetter SM, Chang J, Shaub AR, Weinstock MA, Lewis ET, Asch SM. Primary Care-Based Skin Cancer Screening in a Veterans Affairs Health Care System. JAMA Dermatol 2017 Dec 01;153(8):797-801 [FREE Full text] [doi: 10.1001/jamadermatol.2017.1324] [Medline: 28593242]
18. Beecher SM, Keogh C, Healy C. Dedicated general practitioner education sessions can improve diagnostic capabilities and may have a positive effect on referral patterns for common skin lesions. Ir J Med Sci 2018 Nov;187(4):959-963. [doi: 10.1007/s11845-018-1788-z] [Medline: 29541934]
19. Ahmadi K, Prickaerts E, Smeets JGE, Joosten VHMJ, Kelleners-Smeets NWJ, Dinant GJ. Current approach of skin lesions suspected of malignancy in general practice in the Netherlands: a quantitative overview. J Eur Acad Dermatol Venereol 2018 Feb;32(2):236-241. [doi: 10.1111/jdv.14484] [Medline: 28750138]
20. van Rijsingen MCJ, Hanssen SCA, Groenewoud JMM, van der Wilt GJ, Gerritsen MP. Referrals by general practitioners for suspicious skin lesions: the urgency of training. Acta Derm Venereol 2014 Mar;94(2):138-141 [FREE Full text] [doi: 10.2340/00015555-1752] [Medline: 24352366]
21. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017 Dec 02;542(7639):115-118. [doi: 10.1038/nature21056] [Medline: 28117445]
22. Haenssle HA, Fink C, Schneiderbauer R, Toberer F, Buhl T, Blum A, Reader study level-Ilevel-II Groups. Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Ann Oncol 2018 Aug 01;29(8):1836-1842. [doi: 10.1093/annonc/mdy166] [Medline: 29846502]
23. Udrea A, Lupu C. Real-time acquisition of quality verified non-standardized color images for skin lesions risk assessment? A preliminary study, 18th International Conference on System Theory, Control and Computing (ICSTCC), 2014. 2014 Presented at: 18th International Conference on System Theory; 2014; Sinaia, Romania. [doi: 10.1109/ICSTCC.2014.6982415]
24. Maier T, Kulichova D, Schotten K, Astrid R, Ruzicka T, Berking C, et al. Accuracy of a smartphone application using fractal image analysis of pigmented moles compared to clinical diagnosis and histological result. J Eur Acad Dermatol Venereol 2015 Apr;29(4):663-667. [doi: 10.1111/jdv.12648] [Medline: 25087492]
25. Thissen M, Udrea A, Hacking M, von Braunmuehl T, Ruzicka T. mHealth App for Risk Assessment of Pigmented and Nonpigmented Skin Lesions-A Study on Sensitivity and Specificity in Detecting Malignancy. Telemed J E Health 2017 May 31. [doi: 10.1089/tmj.2016.0259] [Medline: 28562195]
26. Isola P, Zhou JY, Zhou T, Efros A. Image-to-Image Translation with Conditional Adversarial Networks. 2017 Presented at: IEEE Conference on Computer Vision and Pattern Recognition; 2017; Honolulu, Hawai, United States p. 3.
27. Telea A. An Image Inpainting Technique Based on the Fast Marching Method. Journal of Graphics Tools 2004;9(1):25-36. [doi: 10.1080/10867651.2004]
28. Li J, Li B. Parameters Selection for Support Vector Machine Based on Particle Swarm Optimization. Intelligent Computing Theory 2014;8588:41-47. [doi: 10.1007/978-3-319-09333-8_5]
29. Ngoo A, Finnane A, McMeniman E, Soyer H, Janda M. Fighting Melanoma with Smartphones: A Snapshot of Where We are a Decade after App Stores Opened Their Doors. Int J Med Inform 2018;118:99-112. [Medline: 30153928]
30. Kassianos AP, Emery JD, Murchie P, Walter FM. Smartphone applications for melanoma detection by community, patient and generalist clinician users: a review. Br J Dermatol 2015 Jun;172(6):1507-1518. [doi: 10.1111/bjd.13665] [Medline: 25600815]
31. AppAdvice. Derma Compare by Emerald Medical Applications URL: https://appadvice.com/app/derma-compare/982517772 [accessed 2019-07-02]
32. Chen R, Snorrason M, Enger S, Mostafa E, Ko J, Aoki V, et al. Validation of a Skin-Lesion Image-Matching Algorithm Based on Computer Vision Technology. Telemed J E Health 2016 Jan;22(1):45-50. [doi: 10.1089/tmj.2014.0249] [Medline: 26218353]
33. AppAdvice. Lubax - Skin lesion ID using image recognition by Lubax, Inc URL: https://appadvice.com/app/lubax-skin-lesion-id-using-image-recognition/956423382 [accessed 2019-07-02]

34. AppBrain. mSkin Doctor Mobile Application for Skin Cancer Detection by Aleem Technologies URL: https://www.appbrain.com/app/mskin-doctor/com.maleemtaufiq.mSkinDoctor [accessed 2019-07-02]
35. AppAdvice. MySkinMap by Xyrupt Technologies, LLC URL: https://appadvice.com/app/myskinmap/1151655127 [accessed 2019-07-02]
36. AppAdvice. SkinScan by TeleSkin ApS URL: https://appadvice.com/app/skinscan/1025190936 [accessed 2019-07-02]
37. SkinVision. URL: https://www.skinvision.com/ [accessed 2019-07-02]
38. Google Play. SpotMole URL: https://play.google.com/store/apps/details?id=com.spotmole&hl=nl [accessed 2019-07-02]
39. American Cancer Society. Signs and Symptoms of Melanoma Skin Cancer URL: https://www.cancer.org/cancer/melanoma-skin-cancer/detection-diagnosis-staging/signs-and-symptoms.html [accessed 2019-07-02]
40. Ngoo A, Finnane A, McMeniman E, Tan J, Janda M, Soyer HP. Efficacy of smartphone applications in high-risk pigmented lesions. Australas J Dermatol 2017 Feb 27. [doi: 10.1111/ajd.12599] [Medline: 28240347]
41. Dorairaj JJ, Healy GM, McInerney A, Hussey AJ. Validation of a Melanoma Risk Assessment Smartphone Application. Dermatol Surg 2017 Feb;43(2):299-302. [doi: 10.1097/DSS.0000000000000916] [Medline: 28165352]
42. Chuchu N, Takwoingi Y, Dinnes J, Matin R, Bassett O, Moreau J, Cochrane Skin Cancer Diagnostic Test Accuracy Group. Smartphone applications for triaging adults with skin lesions that are suspicious for melanoma. Cochrane Database Syst Rev 2018 Dec 04;12:CD013192. [doi: 10.1002/14651858.CD013192] [Medline: 30521685]
43. Brinker TJ, Hekler A, Utikal JS, Grabe N, Schadendorf D, Klode J, et al. Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review. J Med Internet Res 2018 Dec 17;20(10):e11936 [FREE Full text] [doi: 10.2196/11936] [Medline: 30333097]
44. Brunssen A, Waldmann A, Eisemann N, Katalinic A. Impact of skin cancer screening and secondary prevention campaigns on skin cancer incidence and mortality: A systematic review. J Am Acad Dermatol 2017;76(1):e10. [Medline: 27707591]
45. Linos E, Katz KA, Colditz G. Skin Cancer-The Importance of Prevention. JAMA Intern Med 2016;176(10):1435-1436. [Medline: 27459394]
46. Gordon L, Rowell D. Health system costs of skin cancer and cost-effectiveness of skin cancer prevention and screening: a systematic review. Eur J Cancer Prev 2015;24(2). [Medline: 25089375]
47. Makin JK, Warne CD, Dobbinson SJ, Wakefield MA, Hill DJ. Population and age-group trends in weekend sun protection and sunburn over two decades of the SunSmart programme in Melbourne, Australia. Br J Dermatol 2013 Jan;168(1):154-161. [doi: 10.1111/bjd.12082] [Medline: 23039760]
48. Porter M, Kimball A. Predictions, Surprises, and the Future of the Dermatology Workforce. JAMA Dermatol 2018;154(11):1253-1255. [Medline: 30193360]
49. Bashshur R, Shannon G, Tejasvi T, Kvedar J, Gates M. The Empirical Foundations of Teledermatology: A Review of the Research Evidence. Telemed J E Health 2015;21(12). [Medline: 26394022]
50. National Institute for Health and Care Excellence. 2019. Evidence Standards Framework for Digital Health Technologies, March 2019 URL: https://www.nice.org.uk/Media/Default/About/what-we-do/our-programmes/evidence-standards-framework/digital-evidence-standards-framework.pdf [accessed 2019-07-02]
51. Zhao Y, Ni Q, Zhou R. What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. International Journal of Information Management 2018 Dec;43:342-350. [doi: 10.1016/j.ijinfomgt.2017.08.006]
52. Koelink C, Kollen B, Groenhof F, van der Meer K, van der Heide W. Skin lesions suspected of malignancy: an increasing burden on general practice. BMC Fam Pract 2014;15. [Medline: 24517098]
53. Geldsetzer P, Fawzi W. Quasi-experimental study designs series-paper 2: complementary approaches to advancing global health knowledge. J Clin Epidemiol 2017;89:12-16. [Medline: 28365307]
54. Eisemann N, Waldmann A, Garbe C, Katalinic A. Development of a microsimulation of melanoma mortality for evaluating the effectiveness of population-based skin cancer screening. Med Decis Making 2015;35(2):243-254. [Medline: 25145574]
55. Pil L, Hoorens I, Vossaert K, Kruse V, Tromme I, Speybroeck N, et al. Cost-effectiveness and Budget Effect Analysis of a Population-Based Skin Cancer Screening. JAMA Dermatol 2017 Feb 01;153(2):147-153. [doi: 10.1001/jamadermatol.2016.4518] [Medline: 28002834]
56. Losina E, Walensky R, Geller A, Beddingfield F, Wolf L, Gilchrest B, et al. Visual screening for malignant melanoma: a cost-effectiveness analysis. Arch Dermatol 2007 Jan;143(1):21-28 [FREE Full text] [doi: 10.1001/archderm.143.1.21] [Medline: 17224538]
57. Lansdorp-Vogelaar I, Gulati R, Mariotto A, Schechter C, de Carvalho T, Knudsen A, et al. Personalizing age of cancer screening cessation based on comorbid conditions: model estimates of harms and benefits. Ann Intern Med 2014 Jul 15;161(2):104-112 [FREE Full text] [doi: 10.7326/M13-2867] [Medline: 25023249]

Abbreviations

BCC: basal cell carcinoma
CISNET: Cancer Intervention and Surveillance Modelling Network
GP: general practitioner
mHealth: mobile health

MM: malignant melanoma
RCT: randomized control trial
SCC: squamous cell carcinoma
SVM: support vector machine

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Original Paper

The Reach of the “Don’t Fry Day” Twitter Campaign: Content Analysis

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Abstract

Background: Skin cancer is the most common cancer in the United States, disproportionately affecting young women. Since many young adults use Twitter, it may be an effective channel to communicate skin cancer prevention information.

Objective: The study aimed to assess the reach of the National Council on Skin Cancer Prevention (NCSCP)’s 2018 *Don’t Fry Day* Twitter campaign, categorize the types of individuals or tweeters who engaged in the campaign, and identify themes of the tweets.

Methods: Descriptive statistics were used, and a content analysis of Twitter activity during the 2018 *Don’t Fry Day* campaign was conducted. The NCSCP tweeted about *Don’t Fry Day* and skin cancer prevention for 14 days in May 2018. Twitter contributors were categorized into groups. The number of impressions (potential views) and retweets were recorded. Content analysis was used to describe the text of the tweets.

Results: A total of 1881 Twitter accounts, largely health professionals, used the *Don’t Fry Day* hashtag, generating over 45 million impressions. These accounts were grouped into nine categories (eg, news or media and public figures). The qualitative content analysis revealed informative, minimally informative, and self-interest campaign promotion themes. Informative tweets involved individuals and organizations who would mention and give further context and information about the #DontFryDay campaign. Subthemes of the informative theme were sun safety, contextual, and epidemiologic information. Minimally informative tweets used the hashtag (#DontFryDay) and other types of hashtags but did not give any further context or original material in the tweets. Self-interest campaign promotion involved businesses, firms, and medical practices that would utilize and promote the campaign to boost their own ventures.

Conclusions: These analyses demonstrate the large potential reach of social media public health campaigns. However, limitations of such campaigns were also identified, for example, the relatively homogeneous groups actively engaged in the campaign. This study contributes to the understanding of the types of accounts and messages engaged in social media campaigns utilizing a hashtag, providing insight into the messages and participants that are effective and those that are not to achieve campaign goals. Further research on the potential impact of social media on health behaviors and outcomes is necessary to ensure wide-reaching implications.

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KEYWORDS

social media; skin neoplasms; health communication

Introduction

Background

Skin cancer is the most common form of cancer in the United States, with nearly 5 million people receiving treatment every year [1]. The average cost of treating skin cancer increased from US $3.6 billion dollars to US $8.1 billion dollars annually between 2002 and 2011 [2]. Melanoma is the deadliest form of skin cancer, resulting in approximately 9000 deaths annually, with rising incidence over the past 30 years. The link between a person's risk of skin cancer and either sunburn or indoor tanning has been well established [3-5].

Even though most skin cancers are preventable, ultraviolet (UV) exposure from both sun and indoor tanning remains common. About 37% of adults in the United States reported getting a sunburn in the past year, indicating inadequate sun protection behavior [6]. It is especially common for young adults to expose themselves to large amounts of natural and artificial UV rays, without proper skin protection (eg, wearing adequate sunscreen). For example, approximately 1 in 3 young, white women, aged 16 to 25 years, has engaged in indoor tanning, with rates as high as 40% among adolescent girls [1,7].

The National Council on Skin Cancer Prevention (NCSCP) [8] is a group of over 45 organizations, agencies, and associations of researchers, clinicians, and advocates, with the goal of having a united voice to prevent skin cancer through education, advocacy, and awareness. Core members include the American Academy of Dermatology, American Cancer Society, Melanoma Research Foundation, and Skin Cancer Foundation. To address the rising rates of melanoma and publicize the dangers of UV exposure, the NCSCP created a public awareness campaign in 2009 called *Don't Fry Day* [9]. *Don't Fry Day*, the NCSCP's foremost activity, occurs annually the Friday before Memorial Day, to encourage sun safety awareness and proper sun protection behaviors, such as seeking shade, wearing and reapplying adequate sunscreen, and avoiding tanning. A committee of members runs the campaign, and all member organizations are asked to participate by promoting skin safety among their constituents, via traditional and social media and other means.

The *Don't Fry Day* campaign is not limited to one media channel, but because of the internet's accessibility and ease of use, the Web-based campaign that includes Twitter has been an increasing focus in recent years. As social media has become a major source of information and news for US adults, especially young adults, it is an ideal platform to reach the nearly 88% of this population who use social media and are also more likely to engage in unsafe UV exposure activities [10]. Nearly 45% of adults on the Web use Twitter, with close to 20% of adults using it on a daily basis [10,11], and Twitter has been shown to be amenable to public health surveillance, research, and intervention [12]. Previous research has examined the public health surveillance potential of Twitter, including tracking influenza rates [13,14], tobacco surveillance [15], and vaccination narratives following measles outbreaks [16]. Others have shown the potential of Twitter in sharing health information on antibiotics [17]. Although health organizations' use of Twitter for health promotion and public engagement has been explored more generally [18,19], few studies have explored the dissemination of health campaigns on Twitter [20,21]. A notable exception is the examination of e-cigarette public health campaigns and opposing campaigns in real time [22].

Objective

This study was conducted to assess the reach of the *Don't Fry Day* 2018 campaign on Twitter, categorize types of individuals or tweeters who are engaging in the campaign, and identify themes of the tweets.

Methods

Overview

Twitter is a social media platform that allows users to send and read "tweets" or messages that are limited to 280 characters in general and larger for quotes. Users view tweets in their Twitter timelines, and they can send, reply, or retweet tweets to individuals who are "following" them. Twitter users can use a "hashtag" (ie, #) to engage in trending topics and participate in ongoing conversations related to the topic. For this analysis, the hashtag *DontFryDay* was used to track the relevant conversation and identify and categorize participants. Non-English tweets were excluded.

A service was contracted to provide analytics across multiple social media platforms. A snapshot report provided the estimated reach, estimated exposure, level of activity, contributors, and tweets associated with a hashtag over a time period by utilizing the service's unique algorithm [23]. Estimated reach represents the potential size of the audience, by counting the number of unique Twitter accounts that received that particular tweet or hashtag. Estimated exposure, or impressions, aims to capture the total number of actual views, counting the total number of times the tweet was seen. The level of activity represents active engagement, such as replying to a tweet, quoting a tweet, and/or retweeting. We queried a snapshot report tracking *#DontFryDay* during a 14-day period around *Don't Fry Day*, from May 18 to June 1, 2018, to capture activity before the designated day and any activity shortly after Don't Fry Day, which occurred on May 28, 2018. The campaign comprised 83 tweets from the NCSCP during the month of May.

Contributor Categorization

Each Twitter user has a Twitter handle or username (eg, @JaneDoe). Each handle was categorized as one of the following: (1) government-affiliated account (federal); (2) government-affiliated account (state/local); (3) nongovernmental organization (eg, NCSCP; health); (4) cancer/health/medical center (eg, Mass General Hospital Center); (5) news/media organization; (6) public figure (verified account, ie, "an account of public interest that is authentic") [24]; (7) individual (nonverified account); (8) businesses (eg, dermatology clinic); (9) other/unknown. These categories were created on the basis of a review of a random sample of 100 accounts who tweeted with the hashtag, in addition to consultation with the study team and using previous analyses as a guideline. An interrater reliability analysis using the Kappa statistic was performed to determine consistency among raters. The interrater reliability for raters was found to be kappa = 0.92, which is almost perfect agreement between raters. Categorization was completed by 3 different coders, with one coder reviewing a random sample of 20% of the categorization. If a coder was unsure about who the tweeter was or how to classify the account, a qualitative consultant provided adjudication. The number of tweets, retweets, and potential impressions, including the hashtag, were also recorded. Potential impressions show how many individuals' timelines the tweet was delivered to, and this acts as a measure of views.

Content Analysis

Qualitative manual coding of tweets allowed for exploration of themes across the tweets. Tweets that were included in the sample included initial tweets, reply tweets, and quote tweets. These 3 subcategories all have content that could be thematically analyzed. Only the written content of the tweets was analyzed. Links and pictures attached to each tweet were excluded. A total of 2 researchers analyzed the remaining tweets, following standard guidelines for thematic analysis, which involves phases of familiarizing one's self with the data, to generating initial codes to searching, reviewing, and naming themes [25]. Utilizing NVivo 9 software (QSR International), the researchers moved from narrow units of analysis (eg, significant content) to broader units (eg, themes) that were evident across the tweets. Initial coding was often descriptive, with preliminary codes including "sun safe behaviors," "skin cancer," "date reminder," and "delayed consequences." Through the inductive, iterative process of recoding, condensing, and creating new codes, the main themes and associated subthemes were collectively agreed upon by the researchers. These themes are representative of the repeated patterns of meaning in the tweets. The researchers coded themes for each type of tweet independently; thereafter, they collectively resolved the codes across the tweet categories [26]. The researchers then collectively reached consensus on the main themes and associated subthemes. Tweets could be coded in more than one category.

Results

Categorization

A total of 1881 Twitter accounts used the hashtag during the 14-day period. Unverified accounts was the largest category, with 819 tweets generating 1,689,810 impressions, but their tweets only resulted in 78 retweets. A total of 255 business accounts tweeted the hashtag, with 935,462 impressions and 686 retweets. A total of 183 health organizations participated in the campaign, resulting in 13,645,339 impressions and 552 retweets. A total of 144 cancer, health, and medical centers used the hashtag, had 140 retweets, and had 2,336,928 impressions. A total of 88 state government entities used the hashtag, generating 70 retweets and 639,291 impressions. There were 70 news organizations, with 20,354,043 impressions and 113 retweets. A total of 33 federal government entities used the hashtag, resulting in 7,627,454 impressions and 308 retweets. Owing to lack of self-identification, changes in privacy settings, account suspensions, or account deletions during categorization, 259 profiles could not be categorized. Those accounts left 9,521,083 impressions and 106 retweets. Table 1 summarizes the results.

The qualitative thematic analysis resulted in three major themes across the tweets: informative campaign promotion, minimally informative campaign promotion, and self-interest promotion. A summary of each theme is provided in Textbox 1, highlighting a few representative tweets from public-facing accounts.

Table 1. Categorization of accounts.

Type of account	Contributors (N=1881), n (%)	Impressions (N=59,661,319), n (%)	Retweets (N=2071), n (%)
Unverified individuals	819 (43.54)	1,689,810 (2.83)	78 (3.76)
Businesses	255 (13.55)	935,462 (1.56)	686 (33.12)
Nongovernmental organizations (health)	183 (9.72)	13,645,339 (2287)	552 (26.65)
Cancer/health/medical centers	144 (7.65)	2,336,928 (3.91)	140 (6.76)
Government-affiliated (state/local)	88 (4.67)	639,291 (1.07)	70 (3.38)
News/media	70 (3.72)	20,354,043 (34.11)	113 (5.45)
Government-affiliated (federal)	33 (1.75)	7,627,454 (12.78)	308 (14.87)
Verified/person of interest	30 (1.59)	2,911,909 (4.88)	18 (0.86)
Other/unknown	259 (13.76)	9,521,083 (15.96)	106 (5.11)

Textbox 1. Paraphrases and excerpts of tweets of the three subthemes.

Informative campaign promotion

- "May 25 is #DontFryDay - Slip on a long-sleeved shirt…"
- "It's #DONTFRYDAY!...One in 5 Americans will get skin cancer before age 70..."
- "...Before you hit the beach or BBQ this weekend, remember to protect yourself. #DontFryDay"
- "…the rays of the sun get through even when it's overcast. Use sunscreen. #DontFryDay"
- "Sunburn as a kid could lead to skin cancer later in life...Today and everyday is #DontFryDay"

Minimally informative campaign promotion

- "Show us your #SunSafeSelfie #skincancer #dontfryday..."
- "WHAT'S HAPPENING THIS WEEK?...National Don't Fry Day..."
- "Today is #DontFryDay!"
- "May 25, 2018 is: #DontFryDay…"
- "#WackyHolidays:...Don't Fry Day

Self-interest promotion

- "…once again that [redacted] has been named to the Best...#Sunscreens… #DontFryDay..."
- "…are you wearing your #sunscreen today? #DontFryDay...contact your [redacted] provider for a skin scan!"
- "Make your own shade on #DontFryDay with one of our UPF 50+ sun protection umbrellas..."
- "...#DontFryDay is in TWO days! We're partnered up with [redacted] to bring you the coolest #GIVEAWAY ever! Enter on our FB post..."
- "...Our 3 piece travel set includes a drinking bottle, face spray and sun cream...#DontFryDay…"

Informative Campaign Promotion

The major theme from the sample was informative campaign promotion. These tweets involved individuals and organizations who would mention and give further context and information about the *#DontFryDay* campaign. Within this category, there were three distinct subthemes that the researchers identified. The first was a promotion of sun-safe behaviors. This included encouraging others to wear sunscreen and the correct level of Sun Protective Factor protection, as well as other behaviors, such as seeking shade, avoiding the sun in peak hours, and wearing eye protection. A second subtheme was the use of temporal, location, or activity-related contexts. This included reminding individuals of the designated day (the Friday before Memorial Day, May 25), suggesting staying out of the sun during peak UV hours, and mentioning specific outdoor activities, such as hiking or going to the beach. Other tweets also included local weather conditions for the region. There were also several tweets that highlighted and warned against the dangers of indoor tanning. The third subtheme involves the use of epidemiological information and facts as part of the campaign promotion. Examples include the rates of skin cancer among certain age groups, the correlation between sunburns and skin cancer later in life, and the high number of skin cancer diagnoses. Textbox 1 provides samples of this type of tweet.

Minimally Informative Campaign Promotion

The second main theme of the tweets comprised minimally informative campaign promotion. This includes tweets that used the hashtag, *#DontFryDay*, and other types of hashtags, but these did not give any further context or original material in the tweets. These tweets often had other hashtags that were related to the campaign, such as "#skincancer." Although these tweets increased the reach and traffic to the campaign, the content did not provide more substantial information about the campaign itself, such as the goals of the campaign or contextual information to support hashtag inclusion. Textbox 1 provides samples of this type of tweet. It is possible that these tweets included links, videos, and pictures, which would have made them be considered more informative.

Self-Interest Promotion

The third theme that emerged across the tweets was self-interest promotion. Businesses, firms, and medical practices would utilize and promote the campaign as a way to boost their own ventures. Businesses would promote products that could be part of sun-safe behaviors, such as sunscreen, beach umbrellas, and sunglasses. Other organizations used the campaign to publicize events, such as sporting events and zoo attendance, or more general offerings, such as hiking and camping opportunities. Some medical practices used the campaign to advertise for their services, such as skin cancer screenings. Textbox 1 provides samples of this type of tweet.

Discussion

Principal Findings

Comparable with last year's results [27], the largest category of participants were individuals from the general public (44%), but their tweets were not retweeted, and their reach was pale in comparison with the other categories. It is important to note that many of the individual accounts belonged to self-identified health professionals who are likely already aware of the dangers of excessive and unprotected UV exposure. Owing to the data collection and analysis limitations, it is unknown whether their followers are the target population that could benefit most from this campaign. News and media organizations accounted for most of the impact, with over 20 million impressions. A large media organization generated over 17 million impressions with one tweet because of the large number of followers (approximately 16.8 million). Interestingly, the account is CNN en Espanol, who tweeted the message in Spanish. However, large numbers of impressions did not necessarily translate into retweets. Retweeting information, specifically in the campaign in this study, is a way through which information is diffused through different social networks and organizations. Previous work, as explored, showcased the different motivations for retweeting, such as to show approval, to argue, to gain attention, or to entertain [28]. Retweeting can be a powerful tool for widespread diffusion of information, and retweeting can be a measure of viral research of information, as messages with many retweets are considered to be the most influential [29].

A thematic analysis of initial tweets, reply tweets, and quote tweets resulted in three main themes, with several subthemes. These themes were not mutually exclusive, as many quotes would combine two or more of the themes and subthemes. For example, some tweets encouraged the use of specific sunscreens or sun-safe products, which would fall into the informative campaign promotion and the self-interest promotion themes. This combination seemingly would improve on the visibility of the tweets and give more credibility to the tweet when paired with a legitimate public health campaign. Overall, the campaign had high levels of informative campaign promotion with individuals and organizations, especially as many of the tweets were from the list of suggested content from the Council [8]. Although the minimally informative campaign promotion did not provide context, it still generated traffic and attention for the campaign. Twitter has become a way to promote businesses and organizations by engaging in larger campaigns that can boost their own interests.

Strengths and Limitations

There are several limitations of this study. First, the analytic material was limited to standard text and user profiles, whereas, links, pictures, videos, and other hashtags were excluded from the analysis. Second, thematic analysis did not include the comprehensiveness of messages either in terms of length or content. For instance, some tweets comprised simple recommendations to use sunscreen when outside, whereas other tweets advocated for a multi-faceted behavioral approach beyond sunscreen (eg, wearing long-sleeved clothing, staying in the shade). Third, non-English tweets were omitted from the qualitative analysis, and we did not examine whether the messages had universal appeal or were limited to a particular population or culture. Thus, the extent of the campaign's reach for a diverse audience cannot be determined. Finally, the public health campaign examined here was time limited by the specific date around the holiday weekend and did not capture organic activity that could have occurred earlier, before the official "holiday" or around the summer holidays.

Further research is needed to better implement future public health Twitter campaigns. For example, it would be beneficial to include links, pictures, videos, and multiple hashtags in analyses. Assessing non-English tweets and the cultural context of tweets could be quite informative. Importantly, further research could explore the impact of the different types of tweets identified, that is, how they impacted the reach and engagement of the tweets. For example, examining the impact of single versus multiple calls to action would be useful. Future analyses may also include the valence of tweets. For instance, some of the tweets play on fear-based motivations, whereas others more positively encourage healthy behaviors.

The themes observed in this qualitative analysis demonstrate the large potential reach of social media public health campaigns. In today's viral media environment, research on the potential of social media on health behaviors and outcomes is an emerging field, with possibly wide-reaching implications. However, limitations of such campaigns were also identified, for example, the relatively homogeneous groups actively engaged in the campaign. This further supports the "echo chamber" effect, observed in other Twitter analyses [30-32]. A better understanding of how and why public health campaigns are shared on social media forums, such as Twitter, can lead to a more tailored message and approach, with the goals of having a far-reaching campaign that will be visible to the targeted communities.

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Conflicts of Interest

None declared.

References

1. The US Department of Health and Human Services. 2014. The Surgeon General's Call to Action To Prevent Skin Cancer URL: https://www.surgeongeneral.gov/library/calls/prevent-skin-cancer/call-to-action-prevent-skin-cancer.pdf [accessed 2019-03-25] [WebCite Cache ID 7793sQ5Rc]
2. Guy GP, Machlin SR, Ekwueme DU, Yabroff KR. Prevalence and costs of skin cancer treatment in the US, 2002-2006 and 2007-2011. Am J Prev Med 2015 Feb;48(2):183-187 [FREE Full text] [doi: 10.1016/j.amepre.2014.08.036] [Medline: 25442229]
3. Buller DB, Cokkinides V, Hall HI, Hartman AM, Saraiya M, Miller E, et al. Prevalence of sunburn, sun protection, and indoor tanning behaviors among Americans: review from national surveys and case studies of 3 states. J Am Acad Dermatol 2011 Nov;65(5 Suppl 1):S114-S123. [doi: 10.1016/j.jaad.2011.05.033] [Medline: 22018060]
4. Dennis LK, Vanbeek MJ, Beane Freeman LE, Smith BJ, Dawson DV, Coughlin JA. Sunburns and risk of cutaneous melanoma: does age matter? A comprehensive meta-analysis. Ann Epidemiol 2008 Aug;18(8):614-627 [FREE Full text] [doi: 10.1016/j.annepidem.2008.04.006] [Medline: 18652979]
5. Jemal A, Saraiya M, Patel P, Cherala SS, Barnholtz-Sloan J, Kim J, et al. Recent trends in cutaneous melanoma incidence and death rates in the United States, 1992-2006. J Am Acad Dermatol 2011 Nov;65(5 Suppl 1):S17-25.e1 [FREE Full text] [doi: 10.1016/j.jaad.2011.04.032] [Medline: 22018063]
6. Centers for Disease Control and Prevention. 2018. Sun Safety URL: https://www.cdc.gov/cancer/skin/basic_info/sun-safety.htm [accessed 2019-03-25] [WebCite Cache ID 7790VLf4s]
7. Mayer JA, Woodruff SI, Slymen DJ, Sallis JF, Forster JL, Clapp EJ, et al. Adolescents' use of indoor tanning: a large-scale evaluation of psychosocial, environmental, and policy-level correlates. Am J Public Health 2011 May;101(5):930-938 [FREE Full text] [doi: 10.2105/AJPH.2010.300079] [Medline: 21421947]
8. National Council on Skin Cancer Prevention. 2016. URL: https://www.skincancerprevention.org/ [accessed 2019-03-25] [WebCite Cache ID 7790yGSTd]
9. National Council on Skin Cancer Prevention. 2016. Don't Fry Day URL: https://www.skincancerprevention.org/programs/dont-fry-day [accessed 2019-03-25] [WebCite Cache ID 77916M0yw]
10. Pew Research Center. 2018. Social Media Use in 2018 URL: http://www.pewinternet.org/2018/03/01/social-media-use-in-2018/ [accessed 2019-01-04] [WebCite Cache ID 77920dLpk]
11. Wehner MR, Chren M, Shive ML, Resneck JS, Pagoto S, Seidenberg AB, et al. Twitter: an opportunity for public health campaigns. Lancet 2014 Jul 12;384(9938):131-132. [doi: 10.1016/S0140-6736(14)61161-2] [Medline: 25016994]
12. Seidenberg AB, Pagoto SL, Vickey TA, Linos E, Wehner MR, Costa RD, et al. Tanning bed burns reported on Twitter: over 15,000 in 2013. Transl Behav Med 2016 Jun;6(2):271-276 [FREE Full text] [doi: 10.1007/s13142-016-0388-6] [Medline: 27356997]
13. Lampos V, Cristianini N. Tracking the Flu Pandemic by Monitoring the Social Web. In: 2010 2nd International Workshop on Cognitive Information Processing. 2010 Presented at: CIP'10; June 14-16, 2010; Elba, Italy p. 411-416. [doi: 10.1109/cip.2010.5604088]
14. Signorini A, Segre AM, Polgreen PM. The use of Twitter to track levels of disease activity and public concern in the US during the influenza A H1N1 pandemic. PLoS One 2011 May 4;6(5):e19467 [FREE Full text] [doi: 10.1371/journal.pone.0019467] [Medline: 21573238]
15. Myslín M, Zhu S, Chapman W, Conway M. Using twitter to examine smoking behavior and perceptions of emerging tobacco products. J Med Internet Res 2013 Aug 29;15(8):e174 [FREE Full text] [doi: 10.2196/jmir.2534] [Medline: 23989137]
16. Radzikowski J, Stefanidis A, Jacobsen KH, Croitoru A, Crooks A, Delamater PL. The measles vaccination narrative in twitter: a quantitative analysis. JMIR Public Health Surveill 2016;2(1):e1 [FREE Full text] [doi: 10.2196/publichealth.5059] [Medline: 27227144]
17. Scanfeld D, Scanfeld V, Larson EL. Dissemination of health information through social networks: twitter and antibiotics. Am J Infect Control 2010 Apr;38(3):182-188 [FREE Full text] [doi: 10.1016/j.ajic.2009.11.004] [Medline: 20347636]
18. Park H, Reber BH, Chon M. Tweeting as health communication: health organizations' use of Twitter for health promotion and public engagement. J Health Commun 2016;21(2):188-198. [doi: 10.1080/10810730.2015.1058435] [Medline: 26716546]
19. Diddi P, Lundy LK. Organizational Twitter use: content analysis of tweets during breast cancer awareness month. J Health Commun 2017 Mar;22(3):243-253. [doi: 10.1080/10810730.2016.1266716] [Medline: 28248621]
20. Chung JE. A smoking cessation campaign on Twitter: understanding the use of twitter and identifying major players in a health campaign. J Health Commun 2016 May;21(5):517-526. [doi: 10.1080/10810730.2015.1103332] [Medline: 27115179]
21. Schlichthorst M, King K, Turnure J, Sukunesan S, Phelps A, Pirkis J. Influencing the Conversation About Masculinity and Suicidevaluation of the Man Up Multimedia Campaign Using Twitter Data. JMIR Ment Health Internet 2018 Feb :15.
22. Allem J, Escobedo P, Chu K, Soto DW, Cruz TB, Unger JB. Campaigns and counter campaigns: reactions on Twitter to e-cigarette education. Tob Control 2017 Mar;26(2):226-229 [FREE Full text] [doi: 10.1136/tobaccocontrol-2015-052757] [Medline: 26956467]
23. Union Metrics. 2017. Free Twitter snapshot report URL: https://unionmetrics.com/product/twitter-analytics/ [accessed 2019-03-25] [WebCite Cache ID 7793JQe5h]

24. Twitter. Request to Verify an Account URL: https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts [accessed 2019-03-25] [WebCite Cache ID 7793emVht]
25. Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol 2008;3(2):77-101. [doi: 10.1191/1478088706qp063oa]
26. Ozanne JL, Strauss A, Corbin J. Basics of qualitative research. J Mark Res 1992;29(3):382. [doi: 10.2307/3172751]
27. Nguyen JL, Heckman C, Perna F. Analysis of the Twitter 'Don't Fry Day' campaign. JAMA Dermatol 2018 Aug 1;154(8):961-962 [FREE Full text] [doi: 10.1001/jamadermatol.2018.1481] [Medline: 29926080]
28. Majmundar A, Allem J, Cruz TB, Unger JB. The why we retweet scale. PLoS One 2018;13(10):e0206076 [FREE Full text] [doi: 10.1371/journal.pone.0206076] [Medline: 30335827]
29. Alhabash S, McAlister AR. Redefining virality in less broad strokes: predicting viral behavioral intentions from motivations and uses of Facebook and Twitter. New Media Soc 2015;17(8):1317-1339. [doi: 10.1177/1461444814523726]
30. Colleoni E, Rozza A, Arvidsson A. Echo chamber or public sphere? Predicting political orientation and measuring political homophily in Twitter using big data. J Commun 2014;64(2):317-332. [doi: 10.1111/jcom.12084]
31. Barberá P. Birds of the same feather tweet together: Bayesian ideal point estimation using Twitter data. Polit Anal 2015;23(1):76-91. [doi: 10.1093/pan/mpu011]
32. Goldie D, Linick M, Jabbar H, Lubienski C. Using bibliometric and social media analyses to explore the 'echo chamber' hypothesis. Educ Policy 2014;28(2):281-305. [doi: 10.1177/0895904813515330]

Abbreviations

NCSCP: National Council on Skin Cancer Prevention

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Original Paper

Applying an Author-Weighted Scheme to Identify the Most Influential Countries in Research Achievements on Skin Cancer: Observational Study

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Abstract

Background: Skin cancers are caused by the development of abnormal cells that can invade or spread to other parts of the body. The countries whose authors contribute the most amount of articles on skin cancer to academia is still unknown.

Objective: The objectives of this study are to apply an author-weighted scheme (AWS) to quantify the credits for coauthors on an article byline and allocate the author weights to the country-level credits in articles.

Methods: On July 20, 2019, we obtained 16,804 abstracts published since 1938, based on a keyword search of "skin cancer" in PubMed. The author names, countries/areas, and journals were recorded. International author collaborations on skin cancer were analyzed based on country-level credits in articles. We aimed to do the following: (1) present country distribution for the first authors and the most popular journals, (2) show choropleth maps to highlight the most influential countries, and (3) draw scatter plots based on the Kano model to characterize the features of country-level research achievements. We programmed Excel Visual Basic for Applications (Microsoft Corp) routines to extract data from PubMed. Google Maps was used to display graphical representations.

Results: Our results suggest that researchers in the United States have published most frequently, accounting for 30.37% (5103), while Germany accounts for 7.34% (1234), followed by Australia (997, 5.93%). The top three continents for the proportion of published articles are North America, Europe, and Asia, accounting for 32.29%, 31.71%, and 10.41%, respectively.

Conclusions: This study offers an objective picture of the representativeness and evolution of international research on the topic of skin cancer. The research approaches used here have the potential to be applied to other areas besides skin cancer.

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KEYWORDS

choropleth map; author-weighted scheme; Google Maps; x-index; skin cancer; journal impact factor

Introduction

Skin cancers are tumors that arise mostly from the skin due to the development of abnormal cells that invade or spread to other parts of the body [1]. There are three main types of skin cancers: basal cell skin cancer, squamous cell skin cancer, and melanoma [2]. Skin cancers often appear as a painless raised area of skin with small blood vessels running over it but may present with an ulcer [2]; they may be caused by exposure to ultraviolet radiation from the sun [3].

Ultraviolet exposure has increased partly due to a thinner ozone layer [4,5]. Between 20% and 30% of melanomas develop from moles [6]. People with light skin are at higher risk as are people with reduced immune function [2,7] from taking immunosuppressant medications or through infection with HIV [8,9]. Skin cancer is the most common form of cancer, accounting for at least 40% of cases globally [8,10]. In 2012, melanoma occurred in 232,000 people worldwide and resulted in 55,000 deaths [6]. Australia and New Zealand have the highest rates of melanoma in the world [6]. Which countries have contributed the most to research on skin cancer based on author publications and quality of research is unknown.

We were motivated to investigate which countries contributed the most to research on skin cancer and how much authors from Australia and New Zealand have contributed to the current body of knowledge.

Given the multidisciplinary aspect of skin cancer research, it is necessary to gather specialists in medicine, pathology, and biomedical science to ensure collaboration through resource sharing, exchange of ideas, knowledge dissemination, and information acquisition. No researcher has investigated scientific collaborations on skin cancer, particularly using a fair author-weighted scheme (AWS) for quantifying coauthor contributions to their articles. As such, country-level research achievements are required to evaluate and compare whether AWS has been applied.

Some researchers have applied visualization approaches to interpreting their study results, notably in genetic research, which was identified as the primary collaborative field [11]. However, the pattern of data display was a static JPG format picture, unlike the dynamic dashboard on Google Maps. The dashboard allows readers to see more detail on research topics by using the zoom-in/zoom-out functionality [12-14]. Furthermore, all coauthors in an article sharing equal credits is problematic and unfair. Quantifying coauthor contributions has been proposed in the literature [15,16], but few published articles were applicable in the past. Similarly, country-level research achievements cannot be fairly obtained if the AWS has not been adopted.

It is also unknown whether the United States and Europe still dominate publication output in science [17,18] using the x-index [19] to measure, even though Australia and New Zealand have the highest rates of melanoma in the world [6]. The bibliometric x-index [19] (Figure 1), newly proposed in 2018, has a twofold implication. One is citation-oriented and another productivity-oriented. A graphical representation is required to complement the x-index and disclose the deeper insights and knowledge of the attribute toward the influential, the productive, or the neutral (or, say, one-dimensional performance in the Kano model) [19,20], which can be displayed by using the Kano model [21]. The five elements (ie, scatter plots based on the Kano model, x-index as the bubble, citations on the y-axis, publications on the x-axis, and the AWS) are worthy to carry out and demonstrate in this study.

The objectives of this study are to apply an AWS to quantify the credits for coauthors on an article byline and allocate the author weights to the country-level credits in articles. Three tasks will be achieved: (1) presenting country distribution for the first authors and the most popular journals, (2) showing choropleth maps to highlight the most influential countries, and (3) drawing scatter plots based on the Kano model to characterize the features of country-level research achievements.

Figure 1. Equation for the x-index.

$\sqrt{\max(i \times c_i)}$, where all c_i are sorted by article citations in descending order and i denotes the number of the individual author's publications

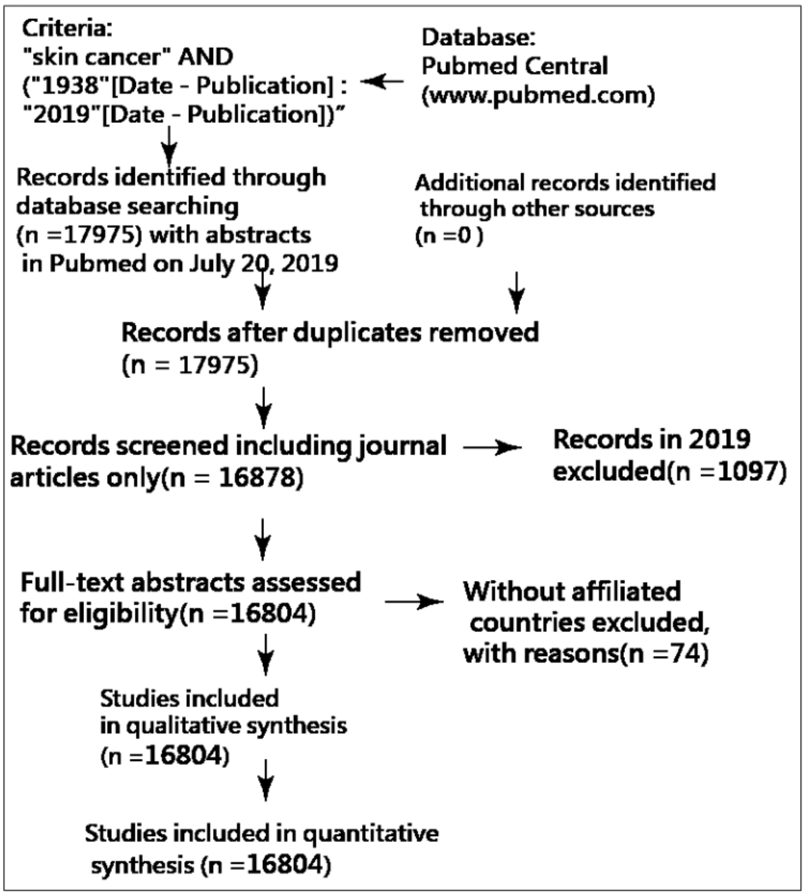
Methods

Data Source

We searched the PubMed database using the title keywords “skin cancer” on July 20, 2019. The search terms were the string “skin cancer” [Title/Abstract] AND (“1900” [Date-Publication]: “2018” [Date-Publication]); the process can be seen in a YouTube video [22]. A total of 17,975 articles published between 1945 and 2018 were extracted. Among these, 16,878 identified the nation/area of the first author (Figure 2).

We made an Excel Visual Basic for Applications (Microsoft Corp) module to handle the data. All downloaded abstracts met the requirement for the type of journal article. Others, like those marked with “Published Erratum,” “Editorial,” “conference abstracts,” “commentary,” or those that did not name the author’s nation, were excluded from this study. Ethical approval was not necessary for this study as no human subjects or personal data were involved.

Figure 2. Flow diagram of study selection.



Seven Elements Used for Displaying Study Results

The seven elements are as follows:

1. Scatter plots were based on the Kano model.
2. Bubbles were sized by the x-index and colored by the types of research achievements.
3. Citations used for computing the x-index for countries were replaced with the journal impact factors (JIFs) published by inCites Journal Citation Reports (Clarivate Analytics) 2018. The JIFs were shown on the y-axis on the scatter plot mentioned above.
4. The number of publications for countries/areas was located on the x-axis.
5. We applied the AWS [23,24] as below.
6. See Figure 3, where the powers (m) as the ordered author name (m) on the article from m–1 to 0, the author number is m–1, more importance is given to the first (=exp[m–1], primary) and the last (=exp[m–1]_ as the corresponding or supervisory authors. We assume that the others (the middle authors) have made smaller contributions to their articles. The sum of all authors in an article byline equals 1.0.
7. The trend of publications for countries/areas was computed by the correlation coefficients using the correl(A,B) function in Excel (Microsoft Corp), where A denotes the series from 2009 to 2018 and B represents the outputs across the 10 years.

Figure 3. Author-weighted scheme equation.

$$W_m = \frac{\exp\,(\gamma_m)}{\sum_{m=0}^{m-1}\exp\,(\gamma_m)} = \frac{(2.27)^{\gamma_m}}{\sum_{m=0}^{m-1}\exp\,(\gamma_m)}$$

Tasks to Reach the Study Goal

Country-Level and Journal-Based Publications on Skin Cancer in the Past

We applied two contingency tables to represent the country distribution for the first authors and the most popular journals.

Choropleth Maps to Highlight the Most Influential Countries

A choropleth map was used to highlight the most influential countries/areas where authors were affiliated. The country-level citations were replaced by the JIF as seen in Figure 4, where the author weight came from Figure 1 and the total weights on an article for a country (*h*) are determined by the country-level weights on the article (*i*). The x-index (Figure 1) [19] was used to denote the research achievements for a country by the steps:

(1) sorting the country-based C_{hi} in Figure 4 and (2) determining the number of publications at i and the responding c_i. The countries were dispersed with bubbles sized by x-index and colored by the types of research achievements using the Kano model to display.

Figure 4. The equation used for computing the country-level citations.

$$C_{hi} = \sum_{m=0}^{m-1}(W_{h\in m} \times c_i)$$

Scatter Plots to Characterize Types of Country Research Achievements

The scatter plot was based on the Kano model, which classified members on the plot into three types: the attribute toward the influential, the productive, or the neutral (or, say, one dimension along at the 45-degree line in the Kano model) [19,20].

Creating Dashboards on Google Maps

The x-index was yielded by author-made modules in Excel (Microsoft Corp). We created pages of HTML used for Google Maps. All relevant information on the entities (ie, countries or states in the United States) can be linked to dashboards on Google Maps.

Results

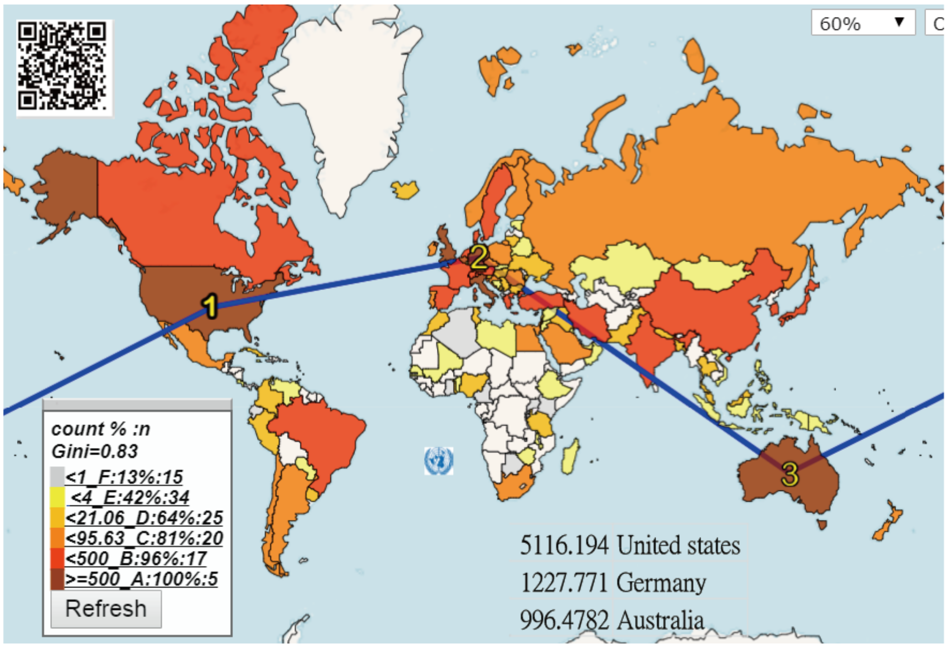
Distribution of Publications by Author-Affiliated Countries and Areas

Multimedia Appendix 1 presents 16,804 papers that included author-affiliated countries/areas. It is evident that researchers in the United States have published most frequently, accounting for 30.37% (5103), while German scholars account for 7.34% (1234), followed by Australia (997, 5.93%). The trend in the number of publications is presented at the bottom right (=1.0) of Multimedia Appendix 1, indicating a continuously increasing trend observed in this study. The three countries with the highest trends are Italy (0.98), China (0.97), and Germany (0.93).

The top three continents for the proportion of published articles are North America, Europe, and Asia, accounting for 32.29%, 31.71%, and 10.41%, respectively. Australia and New Zealand in the Oceania continent account for a mere 6.46% (see Multimedia Appendix 1), far behind the three continents of North America, Europe, and Asia.

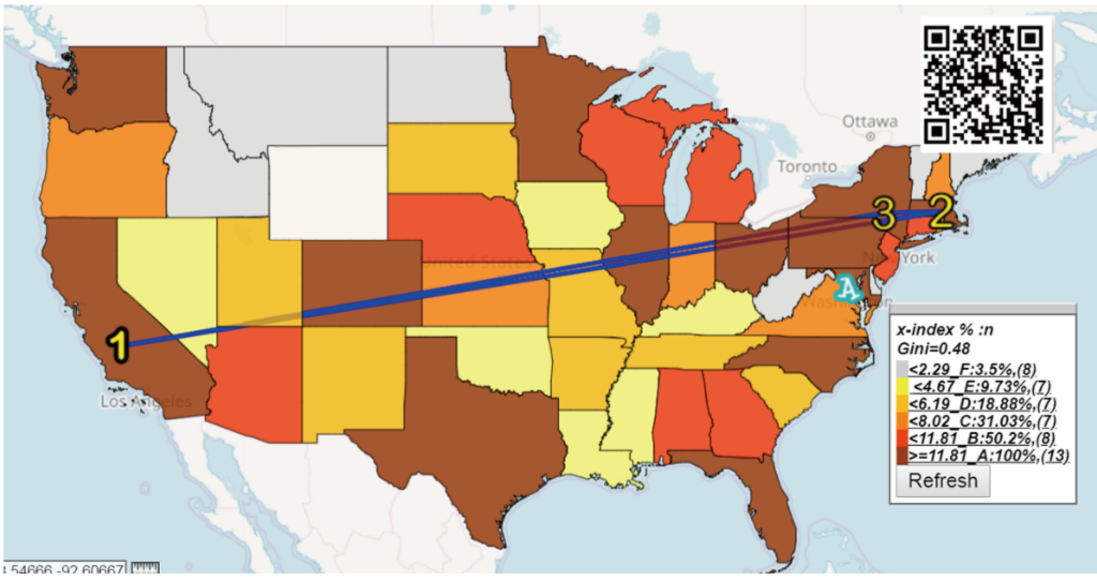
Figure 5 displays a choropleth map based on the publications and first authors. Overall, the most influential countries/areas are the United States and Germany in Europe. Further information is available on the Google map [25] by clicking on each bubble. Another choropleth map (Figure 6) is also based on the publications and first authors in the United States as shown on the Google map [26]. We see that the three states with the highest x-indexes are California, Massachusetts, and New York.

Figure 5. Choropleth map presenting the most productive countries and areas of articles on skin cancer since 1938 (n=16,804).



XSL•FO RenderX

Figure 6. Choropleth map presenting the most productive states in the United States for articles on skin cancer since 1938 (n=5103).



Published Papers in Journals

The top 20 journals with the highest numbers of publications on skin cancer are shown in Multimedia Appendix 2. The journals publishing the most articles on skin cancer are Journal of the American Academy of Dermatology, British Journal of Dermatology, and Journal of Investigative Dermatology. Journal of the European Academy of Dermatology and Venereology and JAMA Dermatology presented highly positive increases (>0.90 in trend) in the publication of papers on skin cancer (last column in Multimedia Appendix 2).

Scatter Plots to Characterize the Type of Country Research Achievements

Using the x-index [19] (Figure 1) makes it hard to discriminate the characteristics toward the influential, the productive, or the neutral. We applied the scatter plots based on the Kano model that can be easily used to identify the type for the country of interest.

We can see the United States is productivity-oriented and others are influence-oriented (Figure 7). As for states in the United States (Figure 8), both California and New York are productive. Massachusetts is neutral, and Minnesota is the influential type. Interested readers can scan the QR code in the figures for details about the name of the country (or state) on the dashboards.

Figure 7. Using the x-index to evaluate the achievements on skin cancer for different countries.

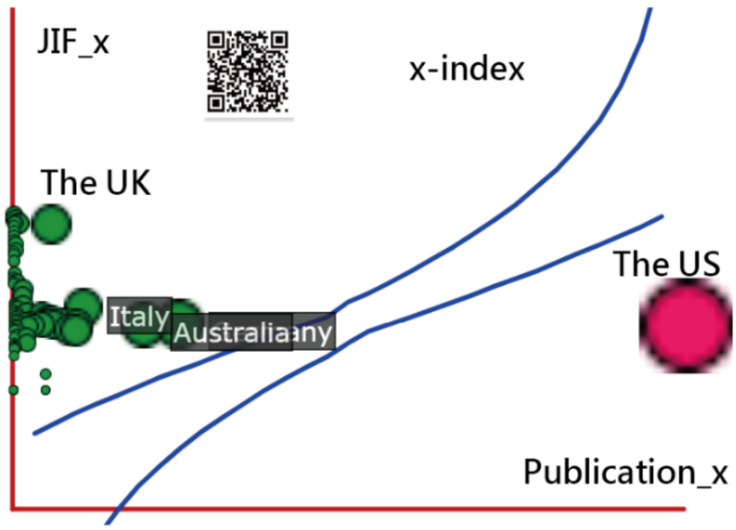
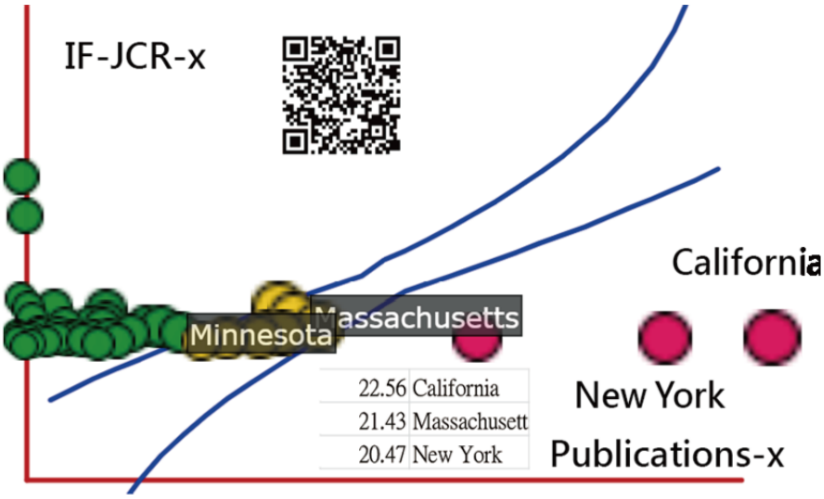


Figure 8. Using the x-index to evaluate the achievements on skin cancer for the United States.



Discussion

Principal Findings

The research question in this study was to disclose the country-level research achievements on the topic of skin cancer. The AWS was particularly applied to quantify the credits for coauthors on articles and allocate the weights to the countries/areas using the equations in Figure 1 and Figure 3. Three tasks were achieved and illustrated: (1) the top three most productive countries are the United States, Germany, and Australia based on the countries to which the first authors are affiliated, (2) the journal with the most frequent publications is Journal of the American Academy of Dermatology, and (3) the top three influential countries are similar to the productive results. The correlation coefficient is 0.86 between the two indices (ie, the x-indexes and the number of publications [Multimedia Appendix 1]) around the 116 countries/areas, and the three types of entities in Figure 7 and 8 are toward the productive, the influential, and the neutral, respectively, using the Kano model to classify.

Previous research has investigated coauthor collaboration using social network analysis [27-29]. Our research using AWS weights is similar to the computation of degree centralities based on the weights between two entities in social network analysis but markedly different as we employ unique visual representations displayed on Google Maps. The application of this visual allows us to compare countries through bubbles in color and size. If the entity bubble is clicked on, the country information will appear on the map. This animated dashboard has been used in applications in other scientific fields to demonstrate entity characteristics [12,23,24].

A total of 16,804 abstracts were identified when searching PubMed on the keywords “skin cancer” on July 20, 2019. No previous literature uses the seven elements mentioned in Methods to present relevant knowledge to readers or dynamically applies Google Maps as we did in this study. Scientific publication is one of the objective measurements to evaluate the achievements of a medical specialty or discipline as we did in Multimedia Appendix 1. Numerous scientometrics have been proposed to measure author-level research achievements, such as h, g, e [30-32], h′ [20], and R- and AR indexes [32]. The drawback is those indices ignoring the AWS for quantifying coauthors’ contributions in articles, not to mention the country-weighted scheme we applied in Figure 3. It is worth combining the seven elements and Google Maps to provide knowledge and information to the readership of journals in the future.

Strengths and Limitations

One strength of this study is the sophisticated use of Google Maps and in-text links for each topic [33-35]. Readers can manipulate the links independently to better understand author collaboration. The depiction of distribution by nation in figures is a useful feature to understand the research achievements on skin cancer. As it is said, a picture is worth a thousand words, so we hope future studies can report other types of information to readers using the Google application programing interface.

There are several limitations to this study. First, caution should be taken when interpreting and generalizing findings beyond this type of research, as data were extracted exclusively from PubMed.

Second, although the data were extracted from PubMed and carefully handled, the original download may have included errors, which may affect the resulting reports in this study.

Third, the formula (Figure 1) used in this study is also a special case of the general AWS model [23,24]. Any change in the parameters (eg, m in Figure 3) might present different weights for authors. Similarly, the assumption of corresponding (or supervisory) authors being the last authors might be challenged. Any parameters changed in our proposed formula would affect the computations of the metric.

Fourth, the data extracted from PubMed is different from other major citation databases such as the Scientific Citation Index (Clarivate Analytics) and Scopus (Elsevier). The results of the most influential countries/areas might be different if other databases were applied.

Fifth, the x-index [19] (Figure 1) is computed by both citations and publications. Replacing citations with the JIF to represent the quality of articles is another limitation. Although paper impact (ie, citations) and journal impact (ie, JIF) on researchers' performance are frequently related [36-39], applying citations to the x-index is recommended in future studies if citations for each article can be obtained.

Conclusion

In conclusion, this study offers an objective picture of the representativeness and evolution of international research on the topic of skin cancer by employing Google Maps to present results. We chose visualization technology to analyze country-level research achievements on skin cancer. As a result, researchers will be able to produce effective research diagrams on Google Maps, improve the efficiency of research work, and provide in-depth insight into the relationships among countries/areas and the types of their research achievements based on the Kano model. The results can provide readers with insight into the evolution of the skin cancer in publications across time and countries/areas.

Acknowledgments

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Authors' Contributions

TWC conceived and designed the study, HYW interpreted the data, and FJL monitored the process and the manuscript. TWC drafted the manuscript. All authors read the manuscript and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Number of papers distributed across nation/area and the published years.
[DOCX File , 18 KB - derma_v2i1e11015_app1.docx]

Multimedia Appendix 2
Journals on the topic of skin cancer distributed over the years.
[DOCX File , 17 KB - derma_v2i1e11015_app2.docx]

References

1. National Cancer Institute. Defining cancer URL: https://www.cancer.gov/about-cancer/understanding/what-is-cancer [accessed 2019-10-10]
2. National Cancer Institute. Skin cancer treatment URL: https://www.cancer.gov/types/skin/hp/skin-treatment-pdq#section/all [accessed 2019-10-10]
3. Gallagher RP, Lee TK, Bajdik CD, Borugian M. Ultraviolet radiation. Chronic Dis Can 2010;29 Suppl 1:51-68. [Medline: 21199599]
4. Maverakis E, Miyamura Y, Bowen MP, Correa G, Ono Y, Goodarzi H. Light, including ultraviolet. J Autoimmun 2010 May;34(3):J247-J257 [FREE Full text] [doi: 10.1016/j.jaut.2009.11.011] [Medline: 20018479]
5. Fabbrocini G, Triassi M, Mauriello MC, Torre G, Annunziata MC, De Vita V, et al. Epidemiology of skin cancer: role of some environmental factors. Cancers (Basel) 2010 Nov 24;2(4):1980-1989 [FREE Full text] [doi: 10.3390/cancers2041980] [Medline: 24281212]
6. McGuire S, World Health Organization, International Agency for Research on Cancer. World Cancer Report 2014. Adv Nutr 2016 Mar;7(2):418-419 [FREE Full text] [doi: 10.3945/an.116.012211] [Medline: 26980827]
7. Leiter U, Garbe C. Epidemiology of melanoma and nonmelanoma skin cancer—the role of sunlight. Adv Exp Med Biol 2008;624:89-103. [doi: 10.1007/978-0-387-77574-6_8] [Medline: 18348450]
8. Cakir B, Adamson P, Cingi C. Epidemiology and economic burden of nonmelanoma skin cancer. Facial Plast Surg Clin North Am 2012 Nov;20(4):419-422. [doi: 10.1016/j.fsc.2012.07.004] [Medline: 23084294]
9. Chiao EY, Krown SE. Update on non-acquired immunodeficiency syndrome-defining malignancies. Curr Opin Oncol 2003 Sep;15(5):389-397. [doi: 10.1097/00001622-200309000-00008] [Medline: 12960522]
10. Dubas LE, Ingraffea A. Nonmelanoma skin cancer. Facial Plast Surg Clin North Am 2013 Feb;21(1):43-53. [doi: 10.1016/j.fsc.2012.10.003] [Medline: 23369588]
11. Wu Y, Duan Z. Visualization analysis of author collaborations in schizophrenia research. BMC Psychiatry 2015 Feb 19;15:27 [FREE Full text] [doi: 10.1186/s12888-015-0407-z] [Medline: 25884451]
12. Chien T, Chang Y, Wang H. Understanding the productive author who published papers in medicine using National Health Insurance Database: a systematic review and meta-analysis. Medicine (Baltimore) 2018 Feb;97(8):e9967 [FREE Full text] [doi: 10.1097/MD.0000000000009967] [Medline: 29465594]

13. Dasgupta S, Vaughan AS, Kramer MR, Sanchez TH, Sullivan PS. Use of a Google Map tool embedded in an internet survey instrument: is it a valid and reliable alternative to geocoded address data? JMIR Res Protoc 2014;3(2):e24 [FREE Full text] [doi: 10.2196/resprot.2946] [Medline: 24726954]
14. Kobayashi S, Fujioka T, Tanaka Y, Inoue M, Niho Y, Miyoshi A. A geographical information system using the Google Map API for guidance to referral hospitals. J Med Syst 2010 Dec;34(6):1157-1160. [doi: 10.1007/s10916-009-9335-0] [Medline: 20703591]
15. Sekercioglu CH. Quantifying coauthor contributions. Science 2008 Oct 17;322(5900):371. [doi: 10.1126/science.322.5900.371a] [Medline: 18927373]
16. Vavryčuk V. Fair ranking of researchers and research teams. PLoS One 2018;13(4):e0195509 [FREE Full text] [doi: 10.1371/journal.pone.0195509] [Medline: 29621316]
17. Leydesdorff L, Wagner C, Park HW, Adams J. International collaboration in science: the global map and the network. 2013. URL: https://arxiv.org/pdf/1301.0801 [accessed 2019-10-10]
18. Glänzel W, Schlemmer B. National research profiles in a changing Europe (1983–2003): an exploratory study of sectoral characteristics in the Triple Helix. Scientometrics 2007 Feb;70(2):267-275. [doi: 10.1007/s11192-007-0203-8]
19. Fenner T, Harris M, Levene M, Bar-Ilan J. A novel bibliometric index with a simple geometric interpretation. PLoS One 2018;13(7):e0200098 [FREE Full text] [doi: 10.1371/journal.pone.0200098] [Medline: 29990357]
20. Zhang C. The h′-index, effectively improving the h-index based on the citation distribution. PLoS One 2013;8(4):e59912 [FREE Full text] [doi: 10.1371/journal.pone.0059912] [Medline: 23565174]
21. Kano N, Seraku N, Takahashi F, Tsuji S. Attractive quality and must-be quality. J Jap Soc Qual Cont 1984;14(2):39-48.
22. Kanomodel. URL: https://youtu.be/Ic9ixWxSfAc [accessed 2019-11-24]
23. Chien T, Chow JC, Chang Y, Chou W. Applying Gini coefficient to evaluate the author research domains associated with the ordering of author names: a bibliometric study. Medicine (Baltimore) 2018 Sep;97(39):e12418 [FREE Full text] [doi: 10.1097/MD.0000000000012418] [Medline: 30278518]
24. Chien T, Wang H, Chang Y, Kan W. Using Google Maps to display the pattern of coauthor collaborations on the topic of schizophrenia: a systematic review between 1937 and 2017. Schizophr Res 2019 Feb;204:206-213. [doi: 10.1016/j.schres.2018.09.015] [Medline: 30262255]
25. Chien T. Google Maps for author nationality on skin cancer. URL: http://www.healthup.org.tw/gps/dermatologycancer.htm [accessed 2019-10-10]
26. Chien T. Google Maps for author in the US on skin cancer. URL: http://www.healthup.org.tw/gps/dermatologycancerUS.htm [accessed 2019-10-10]
27. Sadoughi F, Valinejadi A, Shirazi MS, Khademi R. Social network analysis of Iranian researchers on medical parasitology: a 41 year co-authorship survey. Iran J Parasitol 2016;11(2):204-212 [FREE Full text] [Medline: 28096854]
28. Osareh F, Khademi R, Rostami MK, Shirazi MS. Co-authorship network structure analysis of Iranian researchers' scientific outputs from 1991 to 2013 based on the Social Science Citation Index (SSCI). Collnet J Scientometr Info Manag 2015 Feb 10;8(2):263-271. [doi: 10.1080/09737766.2014.1015301]
29. Liu X, Bollen J, Nelson ML, Van de Sompel H. Co-authorship networks in the digital library research community. Info Process Manag 2005 Dec;41(6):1462-1480. [doi: 10.1016/j.ipm.2005.03.012]
30. Hirsch JE. An index to quantify an individual's scientific research output. Proc Natl Acad Sci USA 2005 Nov 15;102(46):16569-16572 [FREE Full text] [doi: 10.1073/pnas.0507655102] [Medline: 16275915]
31. Egghe L, Rousseau R, Van Hooydonk G. Methods for accrediting publications to authors or countries: consequences for evaluation studies. J Am Soc Info Sci 2000;51(2):145-157. [doi: 10.1002/(sici)1097-4571(2000)51:2<145::aid-asi6>3.0.co;2-9]
32. Jin B, Liang L, Rousseau R, Egghe L. The R- and AR-indices: complementing the h-index. Chinese Sci Bull 2007 Mar;52(6):855-863. [doi: 10.1007/s11434-007-0145-9]
33. Zhang C. The e-index, complementing the h-index for excess citations. PLoS One 2009;4(5):e5429 [FREE Full text] [doi: 10.1371/journal.pone.0005429] [Medline: 19415119]
34. Gini C. [Concentration and dependency ratios]. English translation in Rivista di Politica Economica 1997;87:769-789.
35. Kendall MG, Smith BB. The problem of m rankings. Ann Math Statist 1939 Sep;10(3):275-287. [doi: 10.1214/aoms/1177732186]
36. Bornmann L, Haunschild R. Plots for visualizing paper impact and journal impact of single researchers in a single graph. Scientometrics 2018;115(1):385-394 [FREE Full text] [doi: 10.1007/s11192-018-2658-1] [Medline: 29527073]
37. Bornmann L, Daniel H. What do citation counts measure? A review of studies on citing behavior. J Documentat 2008 Jan 18;64(1):45-80. [doi: 10.1108/00220410810844150]
38. Onodera N, Yoshikane F. Factors affecting citation rates of research articles. J Assn Inf Sci Tec 2014 May 21;66(4):739-764. [doi: 10.1002/asi.23209]
39. Tahamtan I, Safipour Afshar A, Ahamdzadeh K. Factors affecting number of citations: a comprehensive review of the literature. Scientometrics 2016 Feb 15;107(3):1195-1225. [doi: 10.1007/s11192-016-1889-2]

Abbreviations

AWS: author-weighted scheme
JIF: journal impact factor

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Original Paper

Determinants of the Intention to Use Teledermatology: Evidence From Dermatologists and Primary Care Physicians

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Abstract

Background: Teledermatology (TD) is one of the applications of electronic health and telemedicine that involves the use of information and communication technologies (ICTs) for the care of skin diseases. Previous studies on TD indicate that it seems to be effective in diagnosing early malignant pathologies, such as melanoma, and in reducing waiting lists by prioritizing urgent cases of pathology. Despite these advantages, the implementation of TD is still low in many areas.

Objective: Most previous studies on TD have focused on analyzing the results of TD use. However, to completely understand TD, it is necessary to consider the determinants of its use. This study analyzes the factors that motivate medical professionals to use TD in their clinical practice.

Methods: A survey that targeted a total population of 743 medical professionals from health care institutions in Andalusia (Spain) was used. The study sample comprised 223 doctors (87 dermatologists and 136 primary care physicians).

Results: Using an extended Technology Acceptance Model and microdata for the 223 physicians, a cluster analysis (of the user's ICT profile) and binary logistic regression analysis were conducted. This analysis demonstrated the presence of 3 clusters in the sample with respect to the use of technology (cluster 1: advanced use of ICTs; cluster 2: moderate use of ICTs; and cluster 3: scarce use of ICTs). The analysis performed confirmed the model's goodness of fit, which allowed 69% of the variable's variance to be explained. The outcomes revealed that the factors that were most important when implementing a TD system were the user's ICT profile (P=.048), system efficiency (P<.001), and preference of the subjects involved (P=.008; P<.005). The quality of the assistance, the difficulties arising from the use of technology (information security and confidentiality), or interests of the administration were not decisive factors for the implementation of TD. Subsequently, we performed a logistic regression analysis, separating primary care doctors from dermatologists. For the former, the determining factors were the ICT profile and the efficiency of the system, whereas, among dermatologists, only the preference of each individual was considered to be a determining factor.

Conclusions: The use of TD should be accompanied by a comprehensive program of validation and evaluation. These results show that determinants of TD implementation differ depending on the subjects involved. Therefore, it is essential to perform studies before the implementation of a TD system to identify and influence the aforementioned predictive factors.

(JMIR Dermatol 2019;2(1):e14459) doi:10.2196/14459

KEYWORDS

telemedicine; dermatology; organizational innovation; health care surveys

Introduction

Background

Information and communication technologies (ICTs) constitute an opportunity for improvement in care quality, both in the effectiveness and efficiency of health services. Incorporating ICTs also contributes to the development of sustainable health systems, justifying its economic and political interest [1,2]. Telemedicine is defined as the use of ICT for the transfer of medical information for diagnostic, therapeutic, and educational purposes [3]. Telemedicine services include assistance applications that aid in the administration and management of patients, as well as provide information and distance training to users and professionals. When this service is used in dermatology, it is referred to as teledermatology (TD), which is probably the most used form of telemedicine.

Despite starting hesitantly, the development and cheapening of information technologies have led to an exponential expansion of TD since the beginning of the 21st century, for example, from having 21 centers that used TD in 2009 to 68 centers in 2014 in Spain [4]. In a recent systematic review, Trettel et al [5] showed that the application of TD increased over the years and is illustrated by the number of countries where digital patient communication is used. Currently, the most used TD model is that of asynchronous TD (one in which clinical data are stored and sent electronically to the dermatologist who responds to the primary care physician with the instructions to follow). This model was the predominant TD modality in 83% of hospitals in 2014 [6].

Previous studies on TD indicate that it seems to be effective when misleading benign or malignant dermatological tumors, improving consultation prioritization by discerning urgent or preferential pathology [5,7]. In addition, TD is also useful as a teaching instrument by facilitating training for primary care physicians and dermatology residents, termed as teletraining [8].

Although most studies have focused on analyzing the results of TD use, to completely understand TD, it is necessary to consider its determinants of use. Despite the advantages of TD and its rapid development, implementation of TD is still low. Only 1% of dermatology consultations are by TD [9], and it has been implemented only in 26% of the hospitals in their reference areas [6]. These data seem to be contradictory, given the good acceptance and the concept of utility regarding TD that both primary care physicians and dermatologists share [6].

Some previous studies have tried to analyze the determinants of TD implementation [10-12]. However, this issue remains unclear, and further research is needed to explain the determinants of TD adoption. In our immediate environment, a study was conducted to analyze the factors associated with the adoption of ICT and its barriers in Andalusia. However, TD itself was not an object of study in this research [13].

Objective

The objective of this work was to identify factors influencing intention to use TD by professionals of the Andalusian Health Service and the typology of the professional according to the use and expectations of the ICT. Subsequently, we proceeded to analyze what factors influence and to what extent these factors can enhance or inhibit the use of telemedicine in the organization where the professionals work.

Methods

Hypothesis and Model

The Technological Acceptance Model (TAM), proposed by Davis in 1989, is the most widely accepted model to assess the acceptance of an information technology within a given organization [11]. The model is based on the theory of reasoned action (TRA) [14]. Since its publication, it has been cited on numerous occasions, being one of the most widely used instruments to assess users' technology acceptance.

This model states that technology acceptance depends mainly on 2 variables: perceived utility (PU) and perceived ease of use (FUP). The PU refers to the belief that a technology system can improve the professional activity. This utility may refer to improving the quality of clinical practice or reducing economic costs, time, or resources. On the other hand, the FUP indicates the perception that the use of a particular system implies less effort to perform their tasks.

From this model, we obtained the following 2 hypotheses:

- H1. The PU of TD influences the professionals' intention to use.
  - H1.1. Improving the quality of care influences the intention to use TD.
  - H1.2. Reduction of costs and resources in the distance influences the intention to use TD.
- H2. The FUP of TD influences professionals' intention to use.

The TAM has been used to predict how the adoption of multiple technologies will behave, including the acceptance of telemedicine by health professionals [15]. It is a model shown to be suitable for both sex, different age groups, and most cultures [16].

Despite the aforementioned advantages, the TAM shows certain limitations. Some authors have pointed out the need to include additional variables to improve model predictions [17,18]. There are a number of variables including social, geographical, economic, and legal context that may influence users when accepting a new technology in our environment. These variables that are summarized in the social influence or *subjective norm* are included in the TRA and the theory of planned behavior. On the basis of these theories, the subjective norm can be included in our model. This rule corresponds to the directors of health care institutions, rest of the doctors, and the patients themselves.

In addition to the subjective norm, a patient's technological profile also determines how they will accept a new telemedicine tool. That profile may be defined according to the patient's use of electronic tools in their daily lives, both for recreational and work-related use. These tools include email, social networks, and the internet. The use of these tools by the subject determines its perception of usefulness and therefore can define a predisposition to accept or reject a new technology. For this reason, for an adequate study of intention to use TD, we consider it necessary to include the user's ICT profile in our variables. There are models, such as the theory of Grewal and Parasuraman on technological preparation [19], that allow variable incorporation relating the user profile of a professional with the intention of using ICTs in their work.

After including these variables (subjective norm and ICT profile) that we thought could influence the model, 2 more hypotheses were obtained:

- H3. The subjective norm (influence exerted by the administration, managers, doctors, and patients) influences the intention to use TD.
    - H3.1. The support of professionals and patients for TD influences the intention to use.
    - H3.2. The institution's support for TD influences its intention to use.
- H4. The ICT profile of a user influences the intention to use TD.

Figure 1 summarizes the TAM for TD, adding the hypotheses that have been discussed in this section.

Questionnaire and Validation

Data Collection

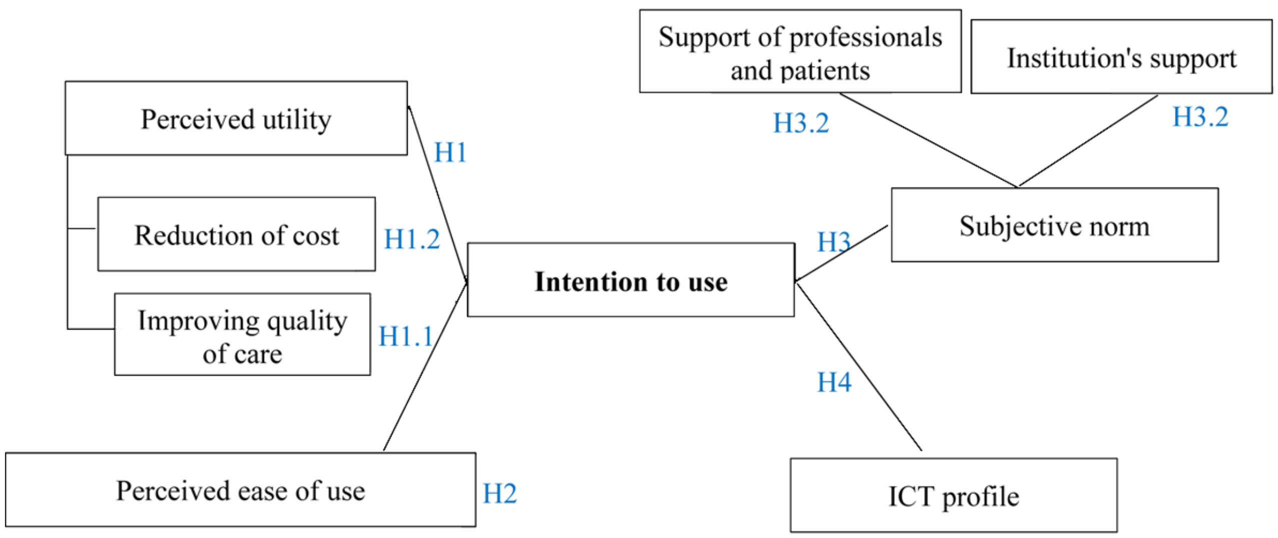
A specific questionnaire based on the TAM and its subsequent derivatives was designed by adapting a general questionnaire on telemedicine acceptance validated by the literature [11]. The final questionnaire is included in Multimedia Appendix 1. Different items that appear in the questionnaire have been formulated to measure variables that we expected to find in the model. In addition, we considered adding questions to these items to get participants' personal characterization (age, sex, professional category, experience, and type of center in which they are currently working). All these data would be used to build participants' technological profile, as described later.

Altogether, 18 questions, divided into 3 blocks, were included in the questionnaire: (1) demographic and professional characterization; (2) adoption of a TD system, and (3) Implementation of a TD system. Questions included in blocks 2 and 3 were based on a Likert scale of 10 points, from 1 (*nothing important* /*nothing agree*) to 10 (*very important* /*s* trongly agree).

An electronic version of the questionnaire was constructed and distributed through email using a corporate distribution list of the Andalusian Health System. This distribution list comprised all dermatologists and primary care physicians with a corporate mail in 5 centers with different complexity levels (from county hospitals to third-level centers) from Andalusia. We received answers from professionals (both dermatologists and general practitioners [GPs]) from all of the invited centers.

The questionnaire was addressed to both dermatologists and GPs, whether they were consultants or residents. A total of 574 general medicine physicians and 187 dermatologists were invited to participate (Textbox 1). Between May 25 and June 25, 2018, 2 reminders were sent to participants. Of 761 participants, 223 responses from professionals (29.4% of all invited) were obtained and included in the database leading to this study. Considering the amount of data, the profile of professionals who participated, and the centers involved, the final sample should be considered as representative of the Andalusian Health Service.

Figure 1. Model and hypotheses. H: hypothesis; ICT: information and communication technology.



Textbox 1. Study specifications.

Universe:

- 574 general medicine physicians; 187 dermatologists

Sample:

- 138 general medicine physicians; 85 dermatologists

Margin of error:

- 5.52% (p=q) 95% CI

Data collection method:

- Questionnaire

Sampling method:

- Random

Fieldwork:

- Between May 25, 2018, and June 25, 2018

Variables and Statistical Analysis

First, we wanted to analyze the user's ICT profile, owing to several items of the questionnaire measuring the intensity of internet use. A hierarchical cluster analysis was performed for this purpose. Cluster analysis is a multivariate technique that seeks to group objects to form object conglomerates or clusters, with a high degree of internal homogeneity and external heterogeneity. After obtaining 3 clusters in our sample to define 3 levels of the ICT profile, an analysis of variance (ANOVA) test was applied in the obtained clusters.

On the other hand, to test the hypotheses proposed in the model (see hypothesis and model), different contrast tests were used on the variables of the study. Through the questionnaire items, multiple variables could be obtained. First, these variables required an exploratory factorial analysis (EFA) to be defined and calculated. The EFA is a technique that allows to explore the set of latent variables or common factors explaining the answers to the items of a test. Therefore, it is one of the most frequently applied techniques in studies related to the development and validation of tests.

All the variables of the study (the ICT profile and those obtained after the EFA) are summarized in Table 1. All these variables could be framed in the hypotheses we had obtained from the TAM (see point 2.1 hypothesis and model) as is shown in Table 2.

Subsequently, an exploratory factor analysis was carried out, constructing as many metric variables as the EFA had revealed. All these, together with the dependent variable, constituted the final multivariate analysis. A logistic regression was performed to analyze the independent influence in the TD implementation of each factor showed in the EFA. Finally, we wanted to distinguish between factors that were more important for GPs to gain a better acceptance of this technology and those more important for dermatologists.

Table 1. Study variable.

Variable	Explanation
User's ICT[a] profile	Numerical variable obtained from the cluster analysis. This variable measures the use of the internet and social networks at a personal and professional level. The original variables included in the analysis were measured using a 5-point Likert scale
Quality of care	Numerical variable obtained from an exploratory factor analysis. It defines the quality of the medical act as an influencing factor for the implementation of TD[b]. This variable was obtained from questions 15.1-15.4 (see Multimedia Appendix 1) after EFA[c]. The original variables included in the analysis were measured on a 10-point Likert scale
System efficiency	Numerical variable obtained from an exploratory factor analysis. It defines the influence of efficiency (including workload and expenses) on the implementation of TD. This variable was obtained from questions 15.5-15.7 (see Multimedia Appendix 1) after an EFA. The original variables included in the analysis were measured on a 10-point Likert scale
Technological difficulties	Numerical variable obtained from an exploratory factor analysis. It refers to the complications related to technological systems (complexity of the devices, need for training, and security). This variable was obtained from questions 16.1-16.6 (see Multimedia Appendix 1) after an EFA. The original variables included in the analysis were measured on a 10-point Likert scale
Preference of the subjects directly involved	Numerical variable obtained from an exploratory factor analysis. It explains how preferences of professionals and patients influence the implementation of TD. This variable was obtained from questions 17.1-17.3 (see Multimedia Appendix 1) after an EFA. The original variables included in the analysis were measured on a 10-point Likert scale
Interest of the administration	Numerical variable obtained from an exploratory factor analysis. It defines the influence of administrations (including financing capacity or resources that they would have to devote to) on the implementation of TD systems. This variable was obtained from questions 17.4-17.7 (see Multimedia Appendix 1) after an EFA. The original variables included in the analysis were measured on a 10-point Likert scale

[a]ICT: information and communication technology.

[b]TD: teledermatology.

[c]EFA: exploratory factorial analysis.

Table 2. Relationship between the hypotheses based on Davis' Technological Acceptance Model (TAM) and study variables (obtained after an exploratory factorial analysis [EFA] and a cluster analysis [information and communication technology (ICT) profile]).

Variables according to the modified TAM	Study hypothesis according to the modified TAM	Variables obtained after EFA and hierarchical cluster analysis
Perceived utility	H1. The perceived utility of TD[a] influences the professionals' intention to use; H1.1. Improving the quality of care influences the intention to use TD; H1.2. Reduction of costs and resources in the distance influences the intention to use TD	Quality of care (H1.1); System efficiency (H1.2)
Perceived ease of use	H2. The perceived ease of use of TD influences professionals' intention to use	Technological difficulties (H2)
Subjective norm	H3. The subjective norm (influence exerted by the administration, managers, doctors, and patients) influences the intention to use TD; H3.1. The support of professionals and patients for TD influences the intention to use; H3.2. The institution's support for TD influences its intention to use	Preference of the subjects directly involved (H3.1); Interest of the administration (H3.2)
User's ICT profile	H4. The ICT profile of a user influences the intention to use TD.	User's ICT profile (H4)

[a]TD: teledermatology.

Results

Demographic and Professional Characteristics

A total of 223 responses were obtained, including family doctors and dermatologists (29.3% rate of response). In addition, 135 (61%) were women. The professionals' average age was 43.7 years. In our sample, 38% comprised dermatologists (among them, 6% dermatology residents and the rest dermatology specialists). In addition, 61% corresponded to GPs, 14% of these being general medicine residents. The remaining 1.34% corresponded to other professional categories, such as occupational physicians or aesthetic doctors. Moreover, 54.71% of the participants were TD users (60.87% of GPs and 44.71% of dermatologists), and 40.36% of them had been TD users for more than 2 years. Demographic and social characteristics of the sample are summarized in Table 3.

Table 3. Demographic factors.

Variable	Value, n (%)
Age (years)	
25-34	80 (35.9)
35-44	39 (17.5)
45-54	48 (21.5)
>54	56 (25.1)
Sex	
Male	88 (39.5)
Female	135 (60.5)
Professional category	
Dermatology resident	14 (6.23)
Dermatologist (eventual or interim)	39 (17.5)
Dermatologist (owner)	31 (13.9)
General practitioner resident	32 (14)
General practitioner (temporary or interim)	35 (15.7)
General practitioner (owner)	69 (30.9)
Others	3 (1.3)
Working time in sanitary field (years)	
≤1	22 (9.9)
2-10	73 (32.7)
11-20	52 (23.3)
21-30	51 (11.2)
>30	25 (11.2)
Working time in the same center (years)	
≤1	54 (24.2)
2-10	106 (47.5)
11-20	47 (21.2)
21-30	14 (6.3)
>30	2 (0.9)

Information and Communication Technology Profile

To define the user's ICT profile, we used a hierarchical clustering analysis. This analysis showed the presence of 3 clusters in the sample with respect to the use of technology (cluster 1: advanced use of ICTs; cluster 2: moderate use of ICTs; and cluster 3: scarce use of ICTs). The result was compared with an ANOVA test that was statistically significant (P<.001). Advanced ICT users had a slightly lower average age (41.86 years) compared with intermediate users (45.65 years) and beginners (42.99 years). However, these findings were not statistically significant (P=.21). The number of components in each cluster was well balanced, as shown in Tables 4 and 5.

Table 4. Hierarchical clustering analysis (information and communication technology user's profile).

Cluster number	Distances between clusters		
	1	2	3
1	—[a]	3.419	3.306
2	3.419	—	4.777
3	3.306	4.777	—

[a]Data not aplicable.

Table 5. Number of cases in each cluster.

Cluster	Frequency (n)
Cluster 1 (high use)	98
Cluster 2 (moderate use)	52
Cluster 3 (scarce use)	73
Valid	223
Lost	0

Determinants of Teledermatology Use

After the EFA, 5 independent variables were obtained (see Table 1) to which a numerical value was assigned. The factors obtained were classified as quality of care, system efficiency, technological difficulties, preference of the subjects directly involved (which included patients and professionals), and interest of the administration. All variables of the correlation matrix showed high correlation, with a determinant value of .000005989. The value of Kaiser-Meyer-Olkin was 0.843 and that of Bartlett's spherical test was 2575.479 with a significance of <.001 This analysis explained 69.238% of the variance (see Table 6). The values of Cronbach alpha in the factors between 0.782 and 0.894 confirmed the reliability of the results obtained.

After extracting the factors involved in the implementation of TD through the EFA, a multivariate analysis was performed, specifically, a logistic regression to obtain variables showing an independent impact. The results of this analysis are shown in Table 7, which provided the following statistics: χ^2_6=25.1; *P*<.001; Hosmer-Lemeshow test=9.481; *P*=.30; R^2 of Nagelkerke=0.155.

The ICT profile of the users (*P*=.048), the efficiency of the system (*P*<.001), and the preferences were found to be influential factors when implementing a TD system (*P*=.008). The remaining factors obtained after the EFA (assistance quality, the possible technological difficulties, and the administration interest) did not show an independent influence in the multivariate analysis.

In this way, based on our results, we were able to accept hypotheses H1.2, H3.1, and H4, whereas H1.1, H2, and H3.2 could not be accepted.

Subsequently, the same analysis was carried out by separating the sample into 2 different groups: GPs (both residents and consultants) and dermatologists (both residents and consultants). A logistic regression was performed including only GPs (the results are shown in Table 8), which provided the following statistics: χ^2_6=4.8; *P*=.57; Hosmer-Lemeshow test=6.562; *P*=.59; R^2 of Nagelkerke=0.054.

In this subgroup, the ICT profile was influenced by the TD implementation implantation (*P*=.03) and system efficiency (*P*=.002). The same analysis was then carried out in the subgroup of dermatologists, finding that only the preference of the subjects directly involved was a significant variable (Table 9). It provided the following statistics: χ^2_6=16.2; *P*=.012; Hosmer-Lemeshow test=7.402; *P*=.39; R^2 of Nagelkerke=0.238.

Table 6. Exploratory factor analysis results.

Item	Quality of care	System efficiency	Technological difficulties	Preference of the subjects directly involved	Interest of the administration
How important are they in the implementation of teledermatology?					
15.1. Quality of care	0.864	—[a]	—	—	—
15.2. Patient health	0.877	—	—	—	—
15.3. Therapeutic compliance	0.844	—	—	—	—
15.4. Frequency of face-to-face consultation	0.712	—	—	—	—
15.5. The workload of professionals	—	0.742	—	—	—
15.6. Health expenditure	—	0.787	—	—	—
15.7. Paperwork/bureaucracy	—	0.790	—	—	—
How much do you worry about the following problems related to teledermatology?					
16.1. Security and confidentiality of patient data	—	—	0.674	—	—
16.2. Complexity of the devices to carry out teledermatology	—	—	0.803	—	—
16.3. Registration of professional's actions	—	—	0.745	—	—
16.4. The need for specific formation	—	—	0.703	—	—
16.5. Technical difficulties related to the use of ICT	—	—	0.783	—	—
16.6. The time required to perform a teledermatology consultation	—	—	0.714	—	—
How do you think the following factors affect the implementation of teledermatology in usual clinical practice?					
17.1. Patients' preference for face-to-face consultations	—	—	—	0.836	—
17.2. Professionals' preference for face-to-face consultations	—	—	—	0.759	—
17.3. Technological skills of patients	—	—	—	0.763	—
17.4. Technological skills of professionals	—	—	—	—	0.720
17.5. Time dedicated to each patient	—	—	—	—	0.692
17.6. Technological equipment suitable for the teledermatology project	—	—	—	—	0.855
17.7. Financing of the teledermatology program	—	—	—	—	0.723
Variance explained by each factor (%)	17.636	16.458	12.997	11.318	10.889
Cumulative variance (%)	17.636	34.094	47.091	58.409	69.298
Cronbach alpha	.801	.894	.801	.858	.782

[a]Values lower than 0.5 have been suppressed to facilitate reading.

Table 7. Results of the logistic regression (global sample).

Variable	B	Standard error	Wald	df	*P* value	Exp (B)
User's ICT[a] profile	0.430	0.234	3.926	1	*.048* [b]	1.589
Quality of care	0.021	0.194	0.012	1	.91	1.021
System efficiency	0.858	0.197	19.047	1	*<.001*	0.986
Technological difficulties	−0.14	0.199	0.005	1	.95	0.986
Preference of the subjects directly involved	−0.557	0.211	6.982	1	*.008*	0.573
Interest of the administration	0.148	0.195	0.579	1	.45	1.160
Constant	0.928	0.442	4.400	1	.04	2.529

[a]ICT: information and communication technology.

[b]Italicized values mean statistical significance.

Table 8. Results of the general practitioners' subgroup of the logistic regression.

Variable	B	Standard error	Wald	df	*P* value	Exp (B)
User's ICT[a] profile	1.160	0.535	4.708	1	*.03* [b]	3.191
Quality of care	−0.212	0.455	0.216	1	.64	0.809
System efficiency	1.356	0.447	9.202	1	*.002*	3.883
Technological difficulties	0.002	0.330	0.000	1	.995	1.002
Preference of the subjects directly involved	−0.394	0.387	1.038	1	.31	0.674
Interest of the administration	0.090	0.376	0.057	1	.81	1.094
Constant	283	0.804	0.124	1	.73	1.327

[a]ICT: information and communication technology.

[b]Italicized values mean statistical significance.

Table 9. Results of the dermatologists' subgroup of the logistic regression between the factors obtained after an exploratory factorial analysis.

Variable	B	Standard error	Wald	df	*P* value	Exp (B)
User's ICT[a] profile	0.350	0.282	1.324	1	.25	1.384
Quality of care	0.098	0.233	0.178	1	.67	1.103
System efficiency	0.202	0.277	0.531	1	.47	1.224
Technological difficulties	0.040	0.271	0.021	1	.88	1.041
Preference of the subjects directly involved	−0.807	0.353	5.226	1	*.02* [b]	0.446
Interest of the administration	0.167	0.257	0.421	1	.52	1.182
Constant	0.579	0.639	0.819	1	.37	1.784

[a]ICT: information and communication technology.

[b]Italicized values mean statistical significance.

Discussion

Principal Findings

The objective of this study was to identify factors influencing the intention to use TD in a group of GPs and dermatologists. The influence of the typology of the professional (based on the use and expectations of the use of ICT) was also analyzed. To this end, an expanded TAM containing 5 scales that were previously validated [11,12,20] was used. To our knowledge, there are few previous studies regarding the use of TD in a health institution. The study evaluating influencing factors in the intention to use telemedicine by a group of professionals of the Andalusian Health Service deserves special mention. In this study, Villalba-Mora et al [13] concluded that telemedicine was fully adopted. According to these authors, utility perceived by professionals was the main factor related to telemedicine adoption. However, they did not focus on TD implementation, but in all forms of telemedicine in this region, it was found that financial issues remain as a major barrier even with a strong policy commitment from the government. In 2018, Romero et al [6] published a study analyzing TD models in Spanish real practice, focusing on the organization, the technical aspects, and the perceived advantages/disadvantages of Spanish dermatologists but were not able to establish variables influencing their implementation. In their study, TD is being described as implanted in 26% of Spanish hospitals and their health areas. Dermatologists' overall satisfaction with TD is good, scoring a 6.9 on a scale up to 10 [6].

Furthermore, 3 variables of the study showed an influence on the intention to use TD in the global analysis with statistical significance: the user's ICT profile, system efficiency, and preferences of the subjects involved. Regarding the first, as expected, the personal and professional level of use of the internet and social networks of the user makes them prone to the use of telemedicine methods. This result is concordant with that of Pereyra et al [10], where the user's ICT profile was also considered to be a significant factor to established telemedicine use. In addition, another study [13] on the factors associated with the adoption of ICT in Andalusia concluded that the doctor's PU was related to telemedicine adoption. The preferences of the subjects involved have also been a determining variable so that the acceptance and support of professionals and patients is one of the factors that would most influence the implementation of the TD system.

In terms of efficiency, understood as cost reduction, the doctor's PU also showed significance as a determining variable for the implementation of TD. These results overlap those of the acceptance of telemedicine in Malaysia's public hospitals [21]. Cost-effectiveness of TD has been analyzed widely [7]. In 2018, Vidal-Alaball et al [22] carried out a cost-saving analysis comparing TD with dermatology face-to-face visits in Bages, Spain. They demonstrated how TD could save money from administrations, improving the efficiency of the system.

It is important to highlight the lack of significance in terms of the administrations' interest in TD system implementation. In most previous studies [11,21,23], this was a determining factor. Pereyra et al established the administrations' interest as the most related factor in the use of telemedicine through the studied institution [10].

Regarding the analysis by subgroups, it is highlighted that the only significant variable in the group of dermatologists was the preference of the subjects involved. Perhaps, the efficiency was not very decisive in this subgroup because it is not the dermatologist who makes the referral (the efficiency was significantly variable in the group of GPs). On the other hand, the ICT profile was only significant in the group of GPs probably because they perform most activities involved at this level, such as taking photographs, editing them, sending the teleconsultation, receiving the answer, and acting accordingly.

However, there are several limitations to consider in this study. First, the questionnaire distribution method consisted mainly of a Web-based tool that may have facilitated the response among users with greater familiarity in the use of ICTs, therefore implying a selection bias. Although paper questionnaires were also delivered, the answers through this format were scarce in number (32 vs 201). In addition, some user subgroups were underrepresented in our sample, such as dermatology residents (only 14 participants).

However, even considering the previously mentioned limitations, we could establish some recommendations to implement a TD system. Priority should be given to projects associating efficient, agile, and easy-to-use systems, resulting in a reduction of both economic and temporary costs in the medical practice. Projects that implement the ICT profile of users adapting to them to facilitate the implementation of the TD should also be encouraged.

Given the large differences expected in each population or health system (economic, social, cultural factors, and use of ICT), the determining variables to implement a TD or telemedicine system are likely to show great variability. It is therefore necessary to carry out more studies before the implementation of these systems. This will allow better adaptability to different target populations, thus multiplying acceptance and usefulness possibilities.

Conclusions

Despite its many advantages, the implementation of teledermatology (TD) is still low in some areas. To better understand this phenomenon, it is necessary for a comprehensive program of TD determinants of use. On the basis of an extended TAM, we obtained the following after an EFA of 3 determinants of TD use: user's information and communication technology profile, system efficiency, and preference of the subjects involved. According to our results, the quality of assistance, the difficulties because of the use of technology, and the interest of the administration were not decisive factors for the implementation of TD. Given the large differences expected in each population or health system, the determining variables to implement a TD show great variability. As a consequence, further studies are needed to better adapt TD to target populations.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Final questionnaire.

[DOCX File, 21KB - derma_v2i1e14459_app1.docx]

References

1. Chaudhry B, Wang J, Wu S, Maglione M, Mojica W, Roth E, et al. Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. Ann Intern Med 2006 May 16;144(10):742-752. [Medline: 16702590]
2. Schwamm LH, Holloway RG, Amarenco P, Audebert HJ, Bakas T, Chumbler NR, American Heart Association Stroke Council, Interdisciplinary Council on Peripheral Vascular Disease. A review of the evidence for the use of telemedicine within stroke systems of care: a scientific statement from the American Heart Association/American Stroke Association. Stroke 2009 Jul;40(7):2616-2634. [doi: 10.1161/STROKEAHA.109.192360] [Medline: 19423852]
3. Norris AC. Essentials of telemedicine and telecare. Chichester: J Wiley; 2001.
4. Moreno-Ramírez D, Romero-Aguilera G. Teledermatology: From the Tempest of Debate to Calmer Waters. Actas Dermosifiliogr 2016 Jun;107(5):366-368. [doi: 10.1016/j.ad.2016.01.006] [Medline: 26956401]
5. Trettel A, Eissing L, Augustin M. Telemedicine in dermatology: findings and experiences worldwide - a systematic literature review. J Eur Acad Dermatol Venereol 2018 Feb;32(2):215-224. [doi: 10.1111/jdv.14341] [Medline: 28516492]
6. Romero G, de Argila D, Ferrandiz L, Sánchez MP, Vañó S, Taberner R, et al. Practice models in teledermatology in Spain: longitudinal study, 2009-2014. Actas Dermosifiliogr 2018 Sep;109(7):624-630. [doi: 10.1016/j.ad.2018.03.015] [Medline: 29807618]
7. Snoswell C, Finnane A, Janda M, Soyer HP, Whitty JA. Cost-effectiveness of store-and-forward teledermatology: a systematic review. JAMA Dermatol 2016 Jun 01;152(6):702-708. [doi: 10.1001/jamadermatol.2016.0525] [Medline: 27074289]
8. Gimeno Carpio E. Teledermatology: a useful tool for physicians, patients, and administrators? Actas Dermosifiliogr 2018 Sep;109(7):577-578. [doi: 10.1016/j.ad.2018.07.001] [Medline: 30031487]
9. Buendía-Eisman A, Arias-Santiago S, Molina-Leyva A, Gilaberte Y, Fernández-Crehuet P, Husein-ElAhmed H, et al. Outpatient dermatological diagnoses in Spain: results from the national DIADERM random sampling project. Actas Dermosifiliogr 2018 Jun;109(5):416-423. [doi: 10.1016/j.ad.2018.02.003] [Medline: 29571521]
10. Pereyra-Rodriguez JJ, Jiménez-Zarco AI, Saigí-Rubió F. [Factors that determine the intention to use telemedicine in a healthcare organisation]. J Healthc Qual Res 2018;33(6):319-328. [doi: 10.1016/j.jhqr.2018.08.004] [Medline: 30482649]
11. Saigi-Rubió F, Jiménez-Zarco A, Torrent-Sellens J. Determinants of the intention to use telemedicine: evidence from primary care physicians. Int J Technol Assess Health Care 2016 Jan;32(1-2):29-36. [doi: 10.1017/S0266462316000015] [Medline: 27472158]
12. Saigí-Rubió F, Torrent-Sellens J, Jiménez-Zarco A. Drivers of telemedicine use: comparative evidence from samples of Spanish, Colombian and Bolivian physicians. Implement Sci 2014 Oct 08;9:128 [FREE Full text] [doi: 10.1186/s13012-014-0128-6] [Medline: 25293651]
13. Villalba-Mora E, Casas I, Lupiañez-Villanueva F, Maghiros I. Adoption of health information technologies by physicians for clinical practice: the Andalusian case. Int J Med Inform 2015 Jul;84(7):477-485. [doi: 10.1016/j.ijmedinf.2015.03.002] [Medline: 25823578]
14. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 1989 Sep;13(3):319. [doi: 10.2307/249008]
15. Hu P, Chau P, Sheng O, Tam K. Examining the technology acceptance model using physician acceptance of telemedicine technology. J Manag 1999;16(2):91-112. [doi: 10.1080/07421222.1999.11518247]
16. Yarbrough AK, Smith TB. Technology acceptance among physicians: a new take on TAM. Med Care Res Rev 2007 Dec;64(6):650-672. [doi: 10.1177/1077558707305942] [Medline: 17717378]
17. Bagozzi R. The legacy of the technology acceptance model and a proposal for a paradigm shift. J Assoc Inf Syst 2007 Apr;8(4):244-254. [doi: 10.17705/1jais.00122]
18. Venkatesh V, Morris MG, Davis G, Davis FD. User acceptance of information technology: toward a unified view. MIS Q 2003;27(3):425-478. [doi: 10.2307/30036540]
19. Parasuraman A, Grewal D. The impact of technology on the quality-value-loyalty chain: a research agenda. J Acad Mark Sci 2000 Jan 01;28(1):168-174. [doi: 10.1177/0092070300281015]
20. Orruño E, Gagnon MP, Asua J, Ben Abdeljelil A. Evaluation of teledermatology adoption by health-care professionals using a modified Technology Acceptance Model. J Telemed Telecare 2011;17(6):303-307. [doi: 10.1258/jtt.2011.101101] [Medline: 21844171]
21. Zailani S, Gilani MS, Nikbin D, Iranmanesh M. Determinants of telemedicine acceptance in selected public hospitals in Malaysia: clinical perspective. J Med Syst 2014 Sep;38(9):111. [doi: 10.1007/s10916-014-0111-4] [Medline: 25038891]
22. Vidal-Alaball J, Garcia Domingo JL, Garcia Cuyàs F, Mendioroz Peña J, Flores Mateo G, Deniel Rosanas J, et al. A cost savings analysis of asynchronous teledermatology compared to face-to-face dermatology in Catalonia. BMC Health Serv Res 2018 Aug 22;18(1):650 [FREE Full text] [doi: 10.1186/s12913-018-3464-4] [Medline: 30134891]
23. Keshvari H, Haddadpoor A, Taheri B, Nasri M, Aghdak P. Survey determinant factors of telemedicine strategic planning from the managers and experts perspective in the health department, isfahan university of medical sciences. Acta Inform Med 2014 Oct;22(5):320-324 [FREE Full text] [doi: 10.5455/aim.2014.22.320-324] [Medline: 25568581]

Abbreviations

ANOVA: analysis of variance
EFA: exploratory factorial analysis
GP: general practitioner
ICT: information and communication technology
PU: perceived utility
TAM: Technological Acceptance Model
TD: teledermatology
TRA: theory of reasoned action

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Original Paper

Evaluating Web-Based Platforms and Traditional Methods for Recruiting Tattoo Artists: Descriptive Survey Research Study

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Abstract

Background: Almost one-third of US adults (29%) have a tattoo, and almost half (47%) of millennials reported having a tattoo. With more people getting tattoos, there is an increased risk of infectious diseases, skin infections, and allergic reactions. Tattoo artists can influence these health risks with their standards of practice, tattoo inks, and sterilization techniques. Although tattoos are becoming mainstream, it was unclear if tattoo artists would be a hard-to-reach population. Using social media sites represents a promising method for recruiting tattoo artists for Web-based survey studies.

Objective: The aim of this study was to evaluate various Web-based platforms and traditional methods for recruiting tattoo artists into a descriptive Web-based survey study.

Methods: Recruitment occurred via Facebook ads , Instagram, Twitter, website, Web-based advertisement, emails, and postcards mailed to tattoo shops.

Results: Recruitment methods resulted in 2332 respondents, of which 1845 answered question 1, “Are you a tattoo artist?” Only 1571 were tattoo artists. Facebook ads recruited the most study participants. Facebook accounted for 1228 (1228/1571, 78.17%) respondents who were tattoo artists. This number surpassed the next leading category of HTTP Referer unknown, which had 268 (268/1571, 17.06%). The Tattoo Survey 2015 website recruited 45 (45/1571, 2.86%) tattoo artists, whereas other Web-based sources contributed to the recruitment of 28 (28/1571, 1.78%) tattoo artists. Twitter and email had the lowest response rate with only 0.06% (1/1571) each.

Conclusions: Social media sites enhanced survey participation, making it easier to reach tattoo artists nationwide. Of the recruitment methods used, Facebook ads were the most effective option, both for cost and recruitment rates. This study’s findings extend those of the previous research studies that demonstrated the timeliness, ease, and effectiveness of using Facebook ads for recruitment.

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KEYWORDS

tattooing; ink; social media; internet; survey and questionnaires; United States; adult; skin diseases; advertising as topic

Introduction

Recruiting for a national study has changed in today's research climate with the continued reduction of home landline telephones. Accessing participants through the internet and social media has become a common substitute and an asset in national surveys. There are many social media platforms including Facebook, Instagram, Twitter, Pinterest, Snapchat, LinkedIn, and YouTube, all of which are potential sources for recruitment. Even with their potential for recruitment, it is important to understand the research limitations of social media based on the platforms' infrastructures, such as self-selection bias.

Facebook continues to be the primary social media platform used in the United States [1]. According to a recent survey, 68% of US adults use Facebook. The percentage increases in younger age groups with 88% of 18- to 29-year-olds using some type of social media and 78% in people aged 30 to 49 years [1]. As of September 2018, Facebook reported 1.49 billion daily active users and 2.27 billion monthly active users [2].

Following Facebook, Instagram is the next most used platform among US adults (35%) [1]. Instagram is used to share images and is widely used by tattoo artists. As of December 21, 2018, there have been over 19 million public posts using the hashtags #tattooist (4.4 million), #tattooer (3.4 million), or #tattooartist (11.4 million). There have been over 150 million public posts using #tattoo (103.4 million) or #tattoos (46.9 million) [3-7].

According to the New York survey service Harris Poll, almost one-third of US adults (29%) have a tattoo, and almost half (47%) of millennials reported having a tattoo [8]. With more people getting tattoos, there is an increased risk of skin infections, such as Methicillin-resistant *Staphylococcus aureus*, nontuberculous mycobacterial infections— *Mycobacterium chelonae* and *Mycobacterium abscessus*, and pseudoepitheliomatous hyperplasia [9-13]. Skin infections from tattoos can be a consequence of unsterile equipment, contaminated tattoo ink, or using tap water to dilute tattoo ink ([14]; Griffin et al, in press). "A person can have an allergic reaction to various components in the ink which can result in an itchy rash at the tattoo site or other skin condition including granulomas – small knots or bumps, or keloids – raised areas caused by overgrowth of scar tissue" [15].

In the original study, the recruitment goal was at least 461 tattoo artists who primarily tattooed in the United States, although 1315 participants were included in the study after all inclusion and exclusion criteria [15]. The purpose of this paper was to evaluate various Web-based platforms and traditional methods for recruiting tattoo artists into a descriptive Web-based survey study.

Methods

Study Overview

The study aimed to gain an understanding and describe the perceptions and opinions of tattoo artists regarding tattoo regulations in the United States. The study used a descriptive survey research design, and data were collected through a Web-based survey. Tattoo artists were recruited from September 2015 to February 2016. Tattoo artists were eligible to participate if they were aged 18 years and older and primarily tattooed in the United States [15].

Recruitment

Recruitment for the research study was conducted through various processes and platforms. Traditional advertising, Web-based marketing, Web-based advertisements, social media, snowball sampling, tattoo conventions, and tattoo registries were used.

Marketing strategies are prominent for selling products or services, and branding is an intricate part of marketing. According to North Star Marketing, brand consistency helps manage perceptions and eliminates brand confusion [16]. For consistency and branding, all recruiting materials, websites, and social media domains used *Tattoo Survey 2015* for easy recognition; this included the website, Tattoo Survey 2015; Facebook page, Tattoo Survey 2015; Twitter, Tattoo Survey 2015; and Instagram, Tattoo Survey 2015. Furthermore, a consistent image accompanied the websites and social media pages to maximize branding recognition. When appropriate, consistent hashtags (#) were used to accompany various Web-based posts and images. These included #TattooSurvey2015, #rockthesurvey, and #futureDrJessica.

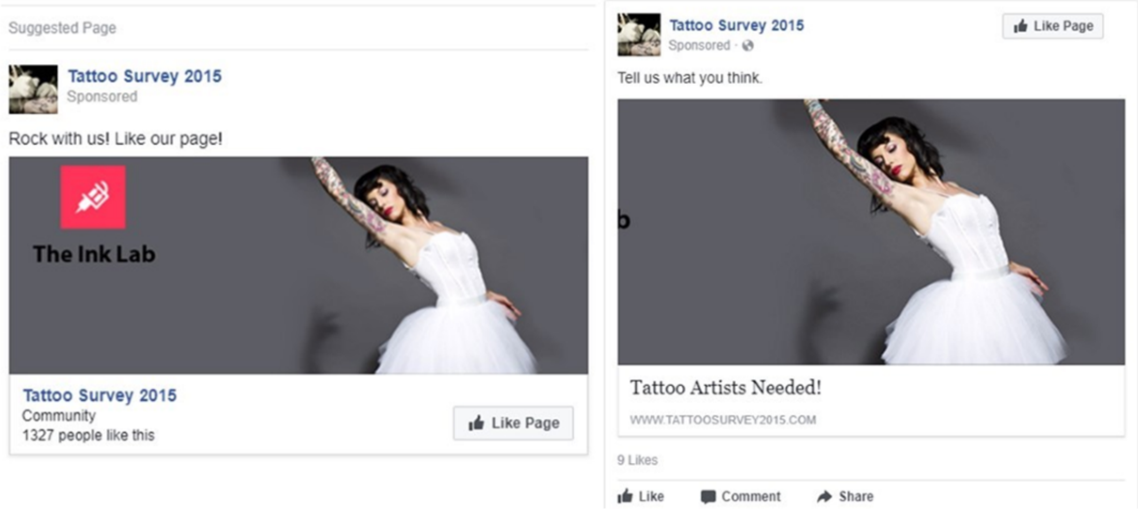
Tattoo Convention and Emails

A tattoo convention was attended in September 2015 in Tampa, Florida, for networking to recruit potential participants. Business cards were collected from the tattoo artists' booths and 131 emails were sent in October 2015 with an anonymous survey link and details regarding the research project. Tattoo artists were represented from 109 tattoo shops in 24 states. It was discovered at the tattoo convention that most tattoo artists used Instagram to advertise their tattoos and artwork. This detection was the determinant to include Instagram and Twitter in recruiting (in addition to Facebook) them.

Facebook

Facebook ads were the predominantly used Web-based advertisements. In total, there were 6 Facebook ad campaigns used for various purposes. A campaign was used to promote the Facebook page to increase *Likes* of the page (Figure 1). The target audience was individuals that had an interest in tattoos, located in the United States, and aged 18 years and older. This campaign had the fewest selection criteria. The second campaign was to promote the Tattoo Survey 2015 website that directed individuals who clicked on the advertisement to the website (Figure 1). The remaining 4 campaigns were used to send individuals directly to the Web-based survey.

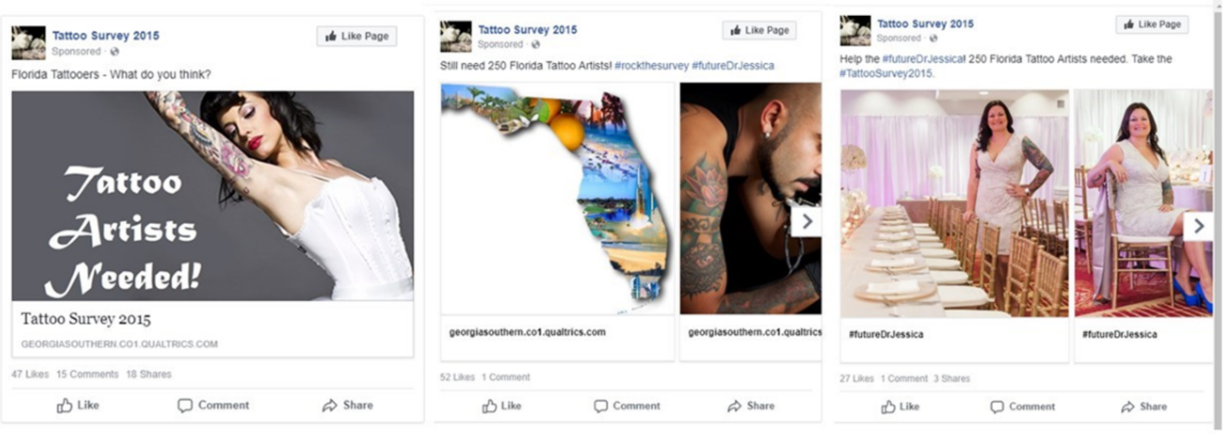
Figure 1. Facebook ads—Tattoo Survey 2015 Facebook page and website.



The target audience for campaign 3 (Figure 2) were individuals aged 18 years and older, located in the United States, with special interests, such as tattoo machines, tattoo ink, tattoo artist magazine, and tattooist. Campaigns 4, 5, and 6 (Figure 3) had the same target audiences, except they were specific to the Florida region. The campaigns used various images, headers, and hashtags. The Facebook ads were staggered at different time intervals between September 29, 2015, and January 6, 2016.

Figure 2. Facebook ad—take survey.

Figure 3. Facebook ads—Florida.



Instagram

Tattoo Survey 2015 Instagram (Figure 4) was created to network and recruit tattoo artists by *following* tattoo artists and receiving *followers* on Instagram. Tattoo Survey 2015 followed over 1300 tattoo artists and had about 100 followers during the study. Various images (n=25) were posted for recruitment from September 30, 2015, to January 23, 2016. The anonymous survey link was available in the biography section of the Instagram profile (the link was changed to the study results link once it concluded).

Twitter

Tattoo Survey 2015 Twitter (Figure 5) was created to network and recruit tattoo artists by *tweeting* information, *following* tattoo artists, and receiving *followers* on Twitter. Tattoo Survey 2015 followed about 90 tattoo artists and had about 17 followers during the study. Various tweets (n=32) were posted for recruitment from September 30, 2015, to February 2, 2016. The anonymous survey link was provided in a pinned tweet for easy access but also included multiple tweets (pinned tweet was changed to the study results link once it concluded).

Figure 4. Tattoo Survey 2015 Instagram account.

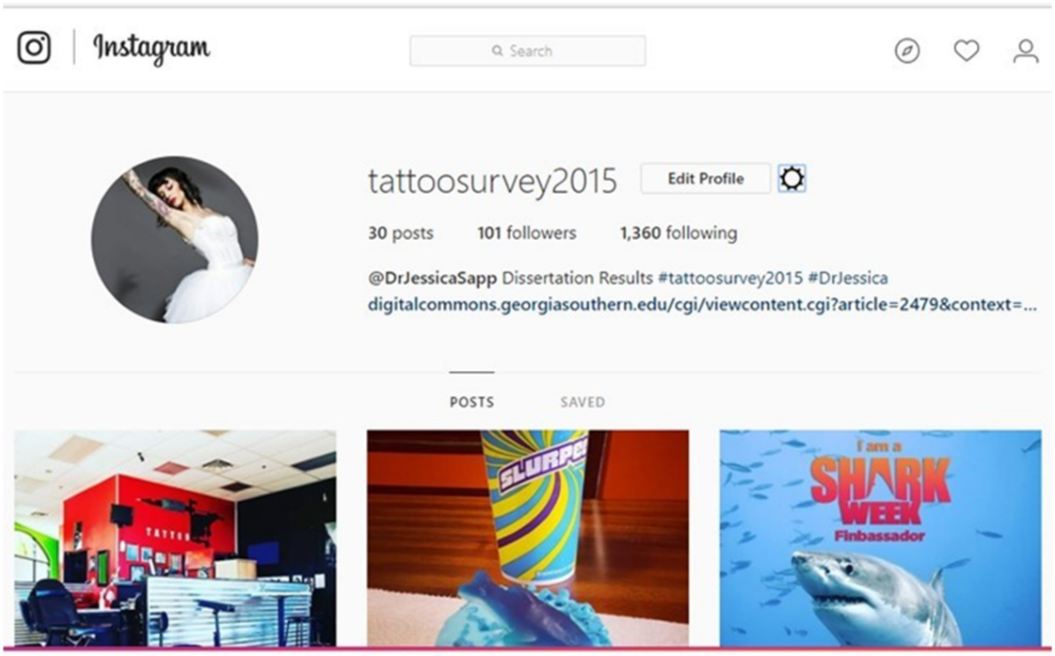


Figure 5. Tattoo Survey 2015 Twitter account.

Website

A website ([Figure 6](#)) was used to provide a central location to direct participants to complete the survey and provide valuable information including consent and research disclosures. The website furnished more details than the social media platforms. All social media pages (Facebook, Instagram, and Twitter) included links to the survey and website.

Website Advertisement

World Tattoo Events is a website that is considered the Web-based calendar for international tattoo conventions [17]. Tattoo conventions attract many tattoo artists. It would be expected that the primary audience for World Tattoo Events is the tattoo artists. As a result, a Web-based banner was displayed on the website ([Figure 7](#)).

Figure 6. Tattoo Survey 2015 website.

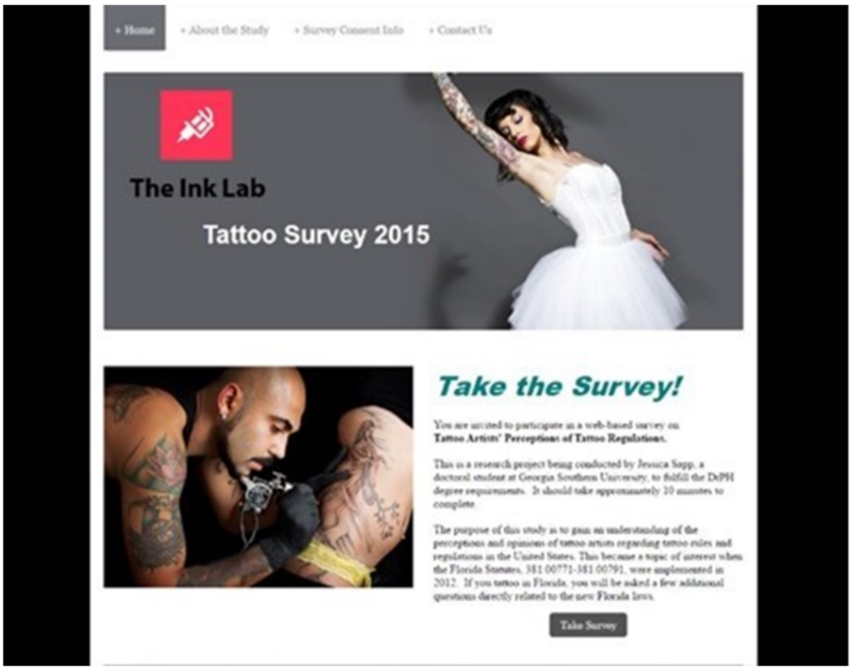


Figure 7. Website advertisement on World Tattoo Events homepage.

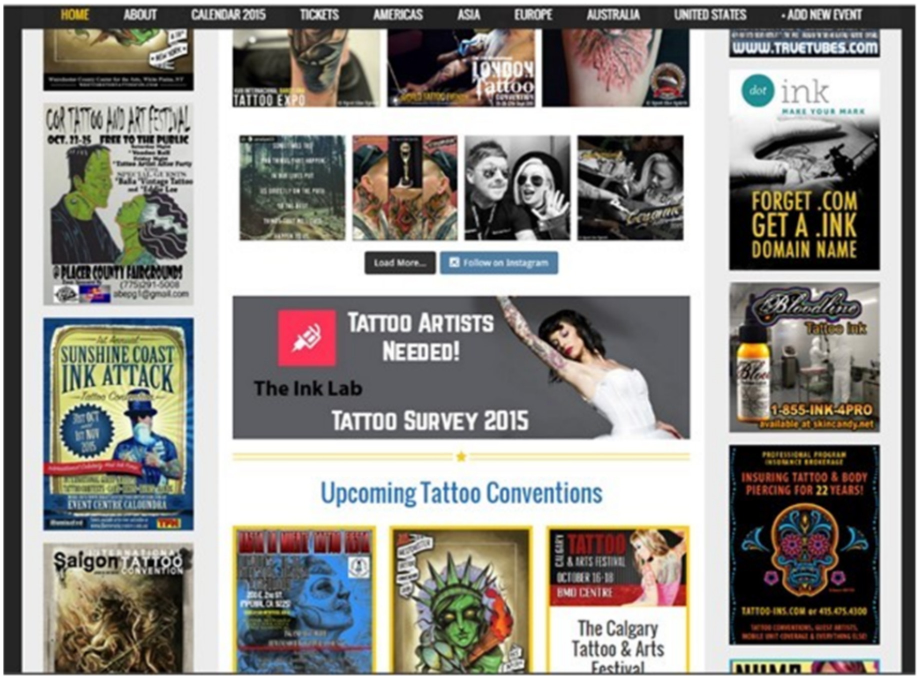


Figure 8. Tattoo Survey 2015 postcard (front and back).

Postcards

The Florida Department of Health has a Web-based registry of tattoo shop inspections [18]. This registry was used to obtain addresses of tattoo establishments throughout Florida. Over 400 postcards (Figure 8) were distributed to local tattoo establishments via mail, and digital versions were posted on the Web. Because there were only about 10 respondents who were tattoo artists in the 4 weeks following the mailout, no additional postcards were mailed for recruitment.

Snowball Sampling

Snowball sampling has evolved with technology developments and social networking sites [19,20]. People continue to increase Web-based interactions and use social media platforms for daily conversation [21]. Snowball sampling included not only word-of-mouth, but also viral interactions, such as Facebook postings, repostings, and sharing through friend networks.

Measures

Qualtrics software was used for the survey tool. Qualtrics provided built-in embedded data including HTTP Referer [22]. The HTTP Referer data were used to determine the Web page the respondent was on when he or she clicked the survey link. This information was collected to determine the frequency of recruitment sources and descriptive characteristics among participants based on the referrer source. Demographics were self-reported by study participants in the Web-based survey.

Facebook ads manager includes standard metrics that were used to assess Facebook ads performance. Similar to the previous studies using Facebook ads [23-27], reach, unique clicks, costs, cost per click, and daily budget were examined. Duration (number of days) of Facebook ads was also reviewed. Facebook measures reach as the number of people who saw the ad at least once. Impressions are the number of times the ad was on screen, which can include multiple views by the same person. Unique clicks are the number of people who clicked on the ad.

Results

Recruitment methods resulted in 2332 respondents, of which 1845 answered question 1, "Are you a tattoo artist?" Only 1571 were tattoo artists (ie, answered *yes*). In the original study, there were 1315 study participants after all exclusions [15].

Recruitment

With the various recruitment methods, Facebook recruited the most study participants (Table 1). For the recruitment sample, Facebook accounted for 1228 (1228/1571, 78.17%) respondents who were tattoo artists. This number dominated all recruitment efforts and surpassed the next leading category of referrer unknown, which had 268 (268/1571, 17.06%). The Tattoo Survey 2015 website recruited 45 (45/1571, 2.86%) tattoo artists, whereas other Web-based sources recruited 28 (28/1571, 1.78%). Twitter and email had the lowest response rate with only 0.06% (1/1571) each.

Facebook Ads

Facebook ads were the major contributor to recruiting tattoo artists in the Web-based survey. The Take Survey ad (campaign 3) had the best response with 3234 unique clicks and a reach of 92,799. This resulted in a US $0.09 cost per click. There were 6 campaigns with a combined 7129 unique clicks and a reach of 282,664. All Facebook ads cost US $1353.01. Table 2 displays the performance of each Facebook ad.

Participant Characteristics

Of the 1571 tattoo artists (Table 3), the majority were recruited through Facebook (1228/1571, 78.17%). Most of the participants were male (808/1571, 51.43%) and had been tattooing for 1 to 10 years (793/1571, 50.48%). Almost half of the participants were aged 25 to 44 years (674/1571, 42.90%). The majority of respondents were full-time tattoo artists (867/1571, 55.19%) and tattooed in a tattoo shop (1013/1571, 64.48%) but did not own a tattoo shop (952/1571, 60.59%).

Table 1. Recruitment referrer source for participants who answered *yes* to question 1 (*Are you a tattoo artist?*) (N=1571).

Referrer source	Frequency, n (%)
Facebook	1228 (78.17)
Twitter	1 (0.06)
Website	45 (2.86)
Email	1 (0.06)
Other Web-based source	28 (1.78)
Referrer unknown	268 (17.06)
Total	1571 (100.00)

Table 2. Facebook ads.

Facebook ads	Clicks	Reach	Cost, US $	Cost per click, US $	Daily budget, US $	Duration, days
Tattoo survey[a]	3527	92,799	319.88	0.09	5	63
Tattoo survey 2015 Facebook page	452 (page likes)	6318	49.99	0.11	5	10
Tattoo Survey 2015 website	148	18,470	49.99	0.34	5	10
Florida tattooers[a]	514	43,979	219.75	0.43	10	22
300 Florida[a]	1924	75,524	375.74	0.20	10	35
FL250[a]	708	39,047	287.70	0.41	350[b]	25

[a]Facebook ads directly linked to the Web-based survey.

[b]Lifetime budget of US $350 was used instead of a daily budget.

Table 3. Descriptive characteristics of study sample based on the referrer source (N=1571).

Variables	Facebook (n=1228), n (%)	Twitter (n=1), n (%)	Website (n=45), n (%)	Email (n=1), n (%)	Other Web-based source (n=28), n (%)	Referrer unknown (n=268), n (%)
Gender						
Male	639 (52.04)	0 (0)	20 (44)	0 (0)	14 (50)	135 (50.4)
Female	29 (2.36)	0 (0)	4 (9)	0 (0)	2 (7)	9 (3.4)
Missing	560 (45.60)	1 (100)	21 (47)	1 (100)	12 (43)	124 (46.3)
Age (years)						
18-24	74 (6.03)	0 (0)	4 (9)	0 (0)	4 (14)	9 (3.4)
25-34	273 (22.23)	0 (0)	4 (9)	0 (0)	6 (21)	52 (19.4)
35-44	258 (21.01)	0 (0)	9 (20)	0 (0)	4 (14)	68 (25.4)
45-54	60 (4.86)	0 (0)	5 (11)	0 (0)	1 (4)	12 (4.5)
55-64	2 (0.16)	0 (0)	1 (2)	0 (0)	0 (0)	1 (0.4)
65-74	0 (0)	0 (0)	0 (0)	0 (0)	1 (4)	0 (0)
>75	0 (0)	0 (0)	1 (2)	0 (0)	0 (0)	0 (0)
Missing	561 (45.68)	1 (100)	21 (47)	1 (100)	12 (43)	126 (47.0)
How long tattooing (years)						
<1	52 (4.23)	0 (0)	3 (7)	0 (0)	4 (14)	9 (3.4)
1-5	358 (29.15)	1 (100)	10 (22)	0 (0)	9 (32)	53 (19.8)
6-10	277 (22.56)	0 (0)	7 (16)	1 (100)	6 (21)	71 (26.5)
11-15	159 (12.95)	0 (0)	4 (9)	0 (0)	2 (7)	37 (3.0)
16-20	77 (6.27)	0 (0)	5 (11)	0 (0)	1 (4)	21 (7.8)
>20	88 (7.17)	0 (0)	7 (16)	0 (0)	3 (11)	17 (6.3)
Missing	217 (17.67)	0 (0)	9 (20)	0 (0)	3 (11)	60 (22.4)
Employment status of tattooer						
Full-time tattoo artist	689 (56.11)	0 (0)	26 (58)	1 (100)	11 (39)	140 (52.2)
Part-time tattoo artist	109 (8.88)	0 (0)	5 (11)	0 (0)	3 (11)	24 (9.0)
Intermittent tattoo artist	112 (9.12)	0 (0)	3 (7)	0 (0)	4 (14)	23 (8.6)
Tattoo as a hobby	132 (10.75)	1 (100)	1 (2)	0 (0)	5 (18)	24 (9.0)
Missing	186 (15.15)	0 (0)	10 (22)	0 (0)	5 (18)	57 (21.3)
Location of tattooing						
Tattoo shop	812 (66.12)	0 (0)	29 (64)	1 (100)	14 (50)	157 (58.6)
Tattoo convention	286 (23.29)	0 (0)	12 (27)	1 (100)	4 (14)	60 (22.4)
Home	308 (25.08)	0 (0)	8 (18)	0 (0)	12 (43)	74 (27.6)
Other	75 (6.11)	1 (100)	3 (7)	0 (0)	1 (4)	18 (6.7)
Own a tattoo shop						
Yes	292 (23.78)	0 (0)	16 (36)	0 (0)	3 (11)	57 (21.3)
No	751 (61.16)	1 (100)	20 (44)	1 (100)	21 (75)	158 (59.0)
Missing	185 (15.07)	0 (0)	9 (20)	0 (0)	4 (14)	53 (19.8)

Discussion

Principal Findings

The acceptance of tattoos has shifted greatly since tattoos were often associated with deviant behaviors in previous decades [28]. The tattoo community is more than people who have tattoos. On the basis of the previous literature, it is not easy to be considered a part of the tattoo community [28]. Having a tattoo does not automatically include individuals into the tattoo community. Even tattoo artists have a hierarchy, although tattoo artists may be accepted based on a shared profession. There is a devotion in the tattoo community that extends beyond having a tattoo, such as emphasizing the talent and elevating the profession to admired pieces of art.

Although tattoos are becoming mainstream, it was unclear if tattoo artists would be a hard-to-reach population. There is a paucity of research related to tattoo artists in the United States, so it was difficult to compare the recruitment efforts of other studies, including using social media or Web-based resources. The response to the Web-based survey was a surprise considering most of the responses occurred in the first 6 weeks of distribution, mainly from Facebook.

As so many tattoo artists use Instagram, it was expected that Instagram would have been effective in recruitment efforts. Instagram is readily used by tattoo artists to showcase their artwork, tattoos, and establish a Web-based portfolio. Instagram is beneficial because it is free for users and eliminates the added expenses for website domains and hosting. This is also a benefit for tattoo artists because they can develop their brand based on their name or alias, which is independent of a tattoo establishment. This is especially helpful for tattooists that do not own a tattoo establishment. However, the limitations of Instagram may have hindered its use, ultimately making it an ineffective recruiting tool in this study.

Email and Twitter both had a poor response rate. Emails can be cluttered with promotions, so this may influence the lack of response from email recruitment, especially if the recipient feels it was unsolicited. Tattoo artists may also prioritize their emails for clients or appointment inquiries. On the basis of the business cards that were collected from the tattoo artists' booths at the tattoo convention, Twitter handles were not included as frequently as Instagram or Facebook. This could be an indicator that Twitter is not as popular among tattoo artists. In addition, no paid advertisements were used on Twitter or Instagram.

Social media sites enhanced participation because it was an electronic platform that was easily distributed to reach tattoo artists nationwide. *Social media may represent increased access to survey respondents* [29] and is less costly than traditional recruitment methods [30]. The study sample included respondents from all 50 states. Of the recruitment methods used, Facebook ads were the most effective option, both for cost and recruitment rates. The cost per click rates varied between US $0.09 and US $0.43 for all Facebook ads that were directly linked to the Web-based survey. For the 2 advertisements targeting *page likes* that began in September and October, the cost per click rates were US $0.11 and US $0.10, respectively.

Overall, Facebook ads are promising for recruiting tattoo artists for a Web-based survey. Out of 2332 respondents, 1571 were tattoo artists. It is assumed that the remaining 761 respondents were not tattoo artists. All advertisements and recruiting materials specifically stated *tattoo artists* in the messages. The response from non–tattoo artists may indicate the benefit of using Facebook ads to recruit persons with tattoos or those interested in tattoos. This study's findings extend findings of the previous research studies that demonstrated the timeliness, ease, and effectiveness of using Facebook ads for recruitment.

Limitations

Use of social media leads to various limitations in research. This study's limitations include accessing only those with social media accounts during the specified timeframe, September 2015 to February 2016. Even though there was a large sample size, the results cannot be generalized, especially considering only tattoo artists were recruited. Using targeted Facebook ads may produce different outcomes with various populations. Also, race was not captured in the demographics of the Web-based survey, so it cannot be determined if this study's recruitment efforts had results similar to that of other studies where whites were more likely than ethnic minorities to respond to Facebook ads [31], although Facebook use among races is similar [1].

Although Instagram can be resourceful for tattoo artists, it has limitations for research and recruitment. At the time of this study, Instagram did not allow active website links in the text portion of image posts. Instagram only permits hyperlinks in the bio section of an Instagram profile. A website address can be provided in the text, but a person would have to either *copy and paste* the website address to go to the website or go to the profile to *click* on the hyperlink. This creates extra steps and reduces the ease of participation for Web-based surveys or recruitment efforts.

Public Health Implications

More people are getting tattoos, which is driving it into the mainstream culture. The technique used to create a tattoo involves opportunities for harmful health effects, such as infectious diseases, skin infections, and allergic reactions. Although there are health risks associated with tattoos, it is important to recognize the potential for integrating tattoo artists in skin health promotion.

Tattoo artists inspect a person's skin before tattoo placement, which is an opportune time to identify skin or mole irregularities that should be seen by a physician. Using sunscreen is essential in tattoo maintenance to help preserve ink colors and details in a tattoo, so this could be discussed along with using sunscreen for skin cancer prevention. Tattoo artists can spend many hours with a client in 1 tattooing session, so it is possible to have a conversation for 5 to 15 min about skin health promotion.

Using community members, such as hairstylists or clergy, has shown to be effective with various health topics. This concept could be extended to tattoo artists to reach more people for skin cancer prevention. Future research could explore tattoo artists' perceptions of engaging with clients about skin health topics. Using social media shows promise to reach this population.

Conclusions

Public health is dynamic and challenging, especially with the constant changes that occur in social norms and way of living. Technology has revolutionized lifestyles, and, as a result, has become embedded into daily activities. As practitioners, it is critical to evolve and encompass these digital tools to reach more people to improve their quality of life.

Although it cannot be expected to reach everyone through social media, Facebook ads showed to be effective in recruiting participants (ie, tattooers) for a Web-based tattoo survey.

Overall, Facebook ads seem to be an acceptable option to reach this target population. In addition, it appears to be effective in reaching younger populations (ie, aged 18-49 years).

As social media platforms offer new features, it is important to reassess the use of Facebook ads along with other sites, such as Instagram. Since this study, Instagram has added video options, which demonstrates how quickly technology changes, which may reveal different impacts in the future. Continued research is needed for tattoo artists and tattoo consumers because of limited literature and studies for this population.

Acknowledgments

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Conflicts of Interest

None declared.

References

1. Smith A, Anderson M. Pew Research Center. 2018. Social Media Use in 2018 URL: http://assets.pewresearch.org/wp-content/uploads/sites/14/2018/03/01105133/PI_2018.03.01_Social-Media_FINAL.pdf [accessed 2018-04-05] [WebCite Cache ID 6yStMK1kE]
2. Facebook Newsroom. 2018. Company Info URL: https://newsroom.fb.com/company-info/ [accessed 2018-04-05] [WebCite Cache ID 74puCqQnf]
3. Instagram. Instagram Search: #tattooist URL: https://www.instagram.com/explore/tags/tattooist/ [accessed 2018-12-21]
4. Instagram. Instagram Search: #tattooer URL: https://www.instagram.com/explore/tags/tattooer/ [accessed 2018-12-21]
5. Instagram. Instagram Search: #tattooartist URL: https://www.instagram.com/explore/tags/tattooartist/ [accessed 2018-12-21]
6. Instagram. Instagram Search: #tattoo URL: https://www.instagram.com/explore/tags/tattoo/ [accessed 2018-12-21]
7. Instagram. Instagram Search: #tattoos URL: https://www.instagram.com/explore/tags/tattoos/ [accessed 2018-12-21]
8. Shannon-Missal L. The Harris Poll. 2016. Tattoo Takeover: Three in Ten Americans Have Tattoos, and Most Don't Stop at Just One URL: https://theharrispoll.com/tattoos-can-take-any-number-of-forms-from-animals-to-quotes-to-cryptic-symbols-and-appear-in-all-sorts-of-spots-on-our-bodies-some-visible-in-everyday-life-others-not-so-much-but-one-thi/ [accessed 2018-04-05] [WebCite Cache ID 6yRe6bEwg]
9. Centers for Disease Control and Prevention (CDC). Methicillin-resistant Staphylococcus aureus skin infections among tattoo recipients--Ohio, Kentucky, and Vermont, 2004-2005. MMWR Morb Mortal Wkly Rep 2006 Jun 23;55(24):677-679 [FREE Full text] [doi: 10.1097/01.inf.0000240350.61108] [Medline: 16791134]
10. Centers for Disease Control and Prevention (CDC). Tattoo-associated nontuberculous mycobacterial skin infections--multiple states, 2011-2012. MMWR Morb Mortal Wkly Rep 2012 Aug 24;61(33):653-656 [FREE Full text] [doi: 10.1111/j.1468-3083.2011.04359.x] [Medline: 22914227]
11. Ricciardo B, Weedon D, Butler G. Mycobacterium abscessus infection complicating a professional tattoo. Australas J Dermatol 2010 Nov;51(4):287-289. [doi: 10.1111/j.1440-0960.2010.00659.x] [Medline: 21198529]
12. Kazlouskaya V, Junkins-Hopkins JM. Pseudoepitheliomatous hyperplasia in a red pigment tattoo: a separate entity or hypertrophic lichen planus-like reaction? J Clin Aesthet Dermatol 2015 Dec;8(12):48-52 [FREE Full text] [Medline: 26705448]
13. Kluger N. Cutaneous complications related to tattoos: 31 cases from Finland. Dermatology 2017;233(1):100-109 [FREE Full text] [doi: 10.1159/000468536] [Medline: 28441655]
14. Dieckmann R, Boone I, Brockmann SO, Hammerl JA, Kolb-Mäurer A, Goebeler M, et al. The risk of bacterial infection after tattooing. Dtsch Arztebl Int 2016 Oct 7;113(40):665-671 [FREE Full text] [doi: 10.3238/arztebl.2016.0665] [Medline: 27788747]
15. Sapp JL. Georgia Southern University. 2016. Evaluation of Tattoo Artists' Perceptions of Tattoo Regulations in the United States URL: http://digitalcommons.georgiasouthern.edu/etd/1410
16. Lynch A, Ickes B, Kindred C, Morgan C, Seevers J, Croft L, et al. North Star Marketing. The Difference Between a Good Brand and a Great Brand? Consistency URL: https://www.northstarmarketing.com/2015/05/07/the-difference-between-a-good-brand-and-a-great-brand-consistency/ [accessed 2018-04-05] [WebCite Cache ID 6yRcqtxOm]
17. World Tattoo Events. URL: https://www.worldtattooevents.com/ [accessed 2018-04-05] [WebCite Cache ID 6yRjOKwUA]
18. Florida Department of Health. Inspection Reports and Data: Tattoos URL: http://www.floridahealth.gov/statistics-and-data/eh-tracking-and-reporting/tattoos.html [accessed 2018-04-05] [WebCite Cache ID 6yRj6z9iy]
19. Dusek GA, Yurova YV, P. Ruppel CP. Using social media and targeted snowball sampling to survey a hard-to-reach population: a case study. Int J Doctoral Stud 2015;10:279-299 [FREE Full text] [doi: 10.28945/2296]
20. Baltar F, Brunet I. Social research 2.0: virtual snowball sampling method using Facebook. Internet Res 2012 Jan 27;22(1):57-74. [doi: 10.1108/10662241211199960]

21. Statista. Daily Time Spent on Social Networking by Internet Users Worldwide From 2012 to 2017 (in Minutes) URL: https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/ [accessed 2018-04-07] [WebCite Cache ID 6yRjtrLTw]
22. Qualtrics. Embedded Data URL: https://www.qualtrics.com/support/survey-platform/survey-module/survey-flow/standardelements/embedded-data/ [accessed 2018-04-05] [WebCite Cache ID 6yRdMle9s]
23. Reiter PL, Katz ML, Bauermeister JA, Shoben AB, Paskett ED, McRee AL. Recruiting young gay and bisexual men for a human papillomavirus vaccination intervention through social media: the effects of advertisement content. JMIR Public Health Surveill 2017 Jun 2;3(2):e33 [FREE Full text] [doi: 10.2196/publichealth.7545] [Medline: 28576758]
24. Carter-Harris L, Bartlett ER, Warrick A, Rawl S. Beyond traditional newspaper advertisement: leveraging Facebook-targeted advertisement to recruit long-term smokers for research. J Med Internet Res 2016 Dec 15;18(6):e117 [FREE Full text] [doi: 10.2196/jmir.5502] [Medline: 27306780]
25. Hudnut-Beumler J, Po'e E, Barkin S. The use of social media for health promotion in Hispanic populations: a scoping systematic review. JMIR Public Health Surveill 2016 Jul 11;2(2):e32 [FREE Full text] [doi: 10.2196/publichealth.5579] [Medline: 27400979]
26. Adam LM, Manca DP, Bell RC. Can Facebook be used for research? Experiences using Facebook to recruit pregnant women for a randomized controlled trial. J Med Internet Res 2016 Sep 21;18(9):e250 [FREE Full text] [doi: 10.2196/jmir.6404] [Medline: 27655184]
27. Laws RA, Litterbach EK, Denney-Wilson EA, Russell CG, Taki S, Ong KL, et al. A comparison of recruitment methods for an mhealth intervention targeting mothers: lessons from the growing healthy program. J Med Internet Res 2016 Dec 15;18(9):e248 [FREE Full text] [doi: 10.2196/jmir.5691] [Medline: 27634633]
28. DeMello M. Bodies of Inscription: A Cultural History of the Modern Tattoo Community. Durham, North Carolina: Duke University Press; 2000.
29. Murphy J, Link MW, Childs JH, Tesfaye CL, Dean E, Stern M, et al. American Association for Public Opinion Research. 2014. Social Media in Public Opinion Research: Report of the AAPOR Task Force on Emerging Technologies in Public Opinion Research URL: http://www.aapor.org/AAPOR_Main/media/MainSiteFiles/AAPOR_Social_Media_Report_FNL.pdf [accessed 2018-04-05] [WebCite Cache ID 6ySygtKAR]
30. Whitaker C, Stevelink S, Fear N. The use of Facebook in recruiting participants for health research purposes: a systematic review. J Med Internet Res 2017 Dec 28;19(8):e290 [FREE Full text] [doi: 10.2196/jmir.7071] [Medline: 28851679]
31. Guillory J, Wiant KF, Farrelly M, Fiacco L, Alam I, Hoffman L, et al. Recruiting hard-to-reach populations for survey research: using Facebook and Instagram advertisements and in-person intercept in LGBT bars and nightclubs to recruit LGBT young adults. J Med Internet Res 2018 Dec 18;20(6):e197 [FREE Full text] [doi: 10.2196/jmir.9461] [Medline: 29914861]

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Original Paper

Transparent, Reproducible, and Open Science Practices of Published Literature in Dermatology Journals: Cross-Sectional Analysis

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Abstract

Background: Reproducible research is a foundational component for scientific advancements, yet little is known regarding the extent of reproducible research within the dermatology literature.

Objective: This study aimed to determine the quality and transparency of the literature in dermatology journals by evaluating for the presence of 8 indicators of reproducible and transparent research practices.

Methods: By implementing a cross-sectional study design, we conducted an advanced search of publications in dermatology journals from the National Library of Medicine catalog. Our search included articles published between January 1, 2014, and December 31, 2018. After generating a list of eligible dermatology publications, we then searched for full text PDF versions by using Open Access Button, Google Scholar, and PubMed. Publications were analyzed for 8 indicators of reproducibility and transparency—availability of materials, data, analysis scripts, protocol, preregistration, conflict of interest statement, funding statement, and open access—using a pilot-tested Google Form.

Results: After exclusion, 127 studies with empirical data were included in our analysis. Certain indicators were more poorly reported than others. We found that most publications (113, 88.9%) did not provide unmodified, raw data used to make computations, 124 (97.6%) failed to make the complete protocol available, and 126 (99.2%) did not include step-by-step analysis scripts.

Conclusions: Our sample of studies published in dermatology journals do not appear to include sufficient detail to be accurately and successfully reproduced in their entirety. Solutions to increase the quality, reproducibility, and transparency of dermatology research are warranted. More robust reporting of key methodological details, open data sharing, and stricter standards journals impose on authors regarding disclosure of study materials might help to better the climate of reproducible research in dermatology.

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KEYWORDS

reproducibility of findings; data sharing; publishing, open access; dermatology

Introduction

Scientific research is currently facing a *reproducibility crisis*, with an estimated 50% to 90% of research having been suggested to be irreproducible [1-3]. Supporting the notion of this crisis, the Reproducibility Project: Cancer Biology experienced failure of 32 of 50 replication attempts, in part owing to insufficient reporting of information necessary to reproduce the original study [4]. One study included in this large-scale project was conducted by Baker and Dolgin [5].

Aiming to better understand the causes of melanoma, the authors conducted whole-genome sequencing of 25 human telomerase reverse transcriptase–immortalized metastatic melanoma cells and reported that 6 different *PREX2* gene mutations are common to melanoma cells. They additionally asserted that PREX2 mutations can increase the rate of tumor incidence compared with controls [5]. However, attempts to replicate these findings failed. In one such attempt, Berger et al [6] obtained samples of human skin cells used in the original study and assiduously copied the study's experimental conditions. They found that the median tumor-free survival was only 1 week, whereas the original study found that 70% of mice remained tumor-free at 9 weeks. These results ultimately made it impossible to determine whether PREX2 mutations influenced the rate of tumor incidence compared with control.

Reproducible research is a foundational component for scientific advancement [7]; however, many published works often lack essential reproducibility-related elements, such as openly shared data files, materials, and protocols [8,9] Equally problematic in terms of the lack of information sharing is the rate at which trials are prospectively registered before study commencement. For example, Nankervis et al [10] found that only 5% of eczema randomized controlled trials (RCTs) were preregistered, registered correctly, and registered with enough accessible information to assess whether the primary outcome aligned with the original registration. Preregistration can protect against selective outcome reporting bias and aid in reducing the prevalence of spurious and misleading results [11-13]. In addition, the dissemination of raw datasets from clinical research through Web-based repositories allows complex issues to be reanalyzed for confirmation or refutation by replication studies [14]. Furthermore, data sharing allows for further clarification through open discussion and helps to legitimize the quality and integrity of research outcomes [15,16]. Clinical trials are now required to include a data sharing plan in the trial registration as a condition to be considered for publication in journals that are members of the International Committee of Medical Journal Editors [17]. Journals following this policy in dermatology include *JAMA Dermatology*, *Dermatology*, *American Journal of Clinical Dermatology*, and *Journal of Surgical Dermatology*, among others. Optimizing good statistical practices—as well as using methods that promote reproducibility and transparency—could ultimately increase reproducibility within the dermatology literature. As questionable findings or false leads impinge scientific advancements, researchers and physicians must advocate for efficient scientific methods that bolster reproducible research [18,19].

As little is known about the extent of reproducible literature within dermatology journals, further investigation is warranted. We therefore explored the current state of reproducibility-related research practices in a random sample of publications from the field of dermatology. Our study examined specific indicators of reproducibility and transparency, building upon similar studies, to provide baseline data for subsequent investigations [8,9,20].

Methods

Overview

This cross-sectional analysis evaluating indicators of reproducibility and transparency was based on the methodology of Hardwicke et al [8], with slight modifications. To promote transparency and clarity of our research, all protocols, data, and appropriate materials are available on Open Science Framework [21]. This analysis did not include human subjects and was not subject to institutional review board oversight [22]. This investigation was reported using the guidelines for conducting meta-research as detailed by Murad and Wang [23] and, when necessary, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines [24]. Our primary objective was to evaluate for the presence of specific indicators of reproducibility and transparency in the published dermatology literature.

Journal and Publication Selection

On June 6, 2019, one author (DT) searched the National Library of Medicine (NLM) catalog for journals in the field of dermatology using the subject terms tag "Dermatology [ST]." To be included, journals had to be (1) MEDLINE indexed and (2) published in the English language. One investigator (DT) used the electronic ISSN to extract the list of journals. The same journal search string of ISSNs was then used in PubMed on June 7, 2019, to collect all publications published between January 1, 2014, and December 31, 2018. A random sample of 300 publications were selected for our analysis using Excel's random number function. Our search string and the complete list of publications returned from our search are available for reference [25].

Data Extraction

Before data extraction, 2 investigators (MA and AN) completed training (conducted by DT) to ensure reliability between investigators. This training session (which was recorded and is available for reference [26]) involved reviewing study objectives, study design, study protocol, and the data extraction form. After completion of training, MA and AN extracted data from the 300 randomly sampled publications in a blinded and independent manner. Data extraction began on June 10, 2019, and concluded on June 30, 2019. Investigators held a final consensus meeting to resolve any discrepancies. DT was available for adjudication, if necessary. Publications were separated into 2 categories: (1) those that contained empirical data and (2) those that lacked empirical data. Our dataset is available on a Web-based repository [27].

Specific Indicators of Reproducibility and Transparency

A pilot-tested Google Form similar to that created by Hardwicke et al [8] was used for data extraction. This form prompted investigators to identify the presence of prespecified indicators considered necessary to reproduce a study [28]. Information extracted from each publication varied according to the study design. Studies with empirical data were assessed for the following indicators: materials availability, data availability, analysis scripts, protocol, preregistration, conflict of interest

(COI) statement, funding statement, and open access. Nonempirical studies were only assessed for the presence of 3 indicators: COI, funding statement, and open access. Furthermore, despite case reports and case series often providing empirical data, previous studies have demonstrated that key methodological information needed to reproduce these study types is commonly absent or is insufficient [9]. Thus, we decided to omit these study types from certain assessments. Table 1 details the 8 queried indicators of reproducibility and transparency, their importance, and a description of study designs included in each analysis.

Table 1. Indicators of reproducibility and transparency. Analysis of variables within each publication was dependent upon the study type classification.

Indicators of reproducibility and transparency	Study types included for analysis of reproducibility indicator	Usefulness for reproducing the medical literature
Materials available	Empirical studies[a]	Having access to all materials (eg, stimuli, survey instruments, and computer code/software used for data collection or running experiments) increases the feasibility by which researchers are able to replicate a study using identical methodology
Raw data	Empirical studies[b]	Sharing of data in their unaltered, digital form facilitates validation of study outcomes and helps prevent forms of bias, such as selective outcome reporting
Analysis scripts available	Empirical studies[b]	Having access to well-documented, step-by-step instructions detailing data preparation and analysis can help to increase the clarity of data interpretation. In addition, thorough analysis scripts can help limit inadvertent computations and misrepresentation of study findings in replication studies
Protocol available	Empirical studies[b]	To completely and accurately reproduce a study, the full protocol must be available in its entirety. Slight alterations to the original study protocol have the potential to influence study outcomes, thereby hindering reproducibility
Preregistration	Empirical studies[b]	Publications restricted behind a paywall contribute to the irreproducible environment of biomedical research. One way to circumvent this obstacle is through study preregistration. Making available study methods, hypotheses, and analysis scripts could potentially help increase the transparency of biomedical research while simultaneously mitigating reporting bias, data dredging, and p-hacking
Disclosure of conflicts of interest	All eligible studies[c]	Disclosure of authors' financial conflicts of interest might help facilitate the publication of the most robust and unbiased research possible
Funding source	All eligible studies[c]	Funding sources help make costly study designs possible by providing resources to conduct experiments. The transparency of biomedical research is enhanced by disclosure of funding sources
Open access	All studies included in random sampled[d]	Open access increases the availability of pertinent information for study reproduction. Failing to make available complete records of the study's protocol, data, and analyses hinders a comprehensive evaluation of the given study

[a]Empirical studies refers to studies with empirical data including clinical trial, cohort, case control, chart review, and cross-sectional; even though case studies and case series often include empirical data, this category excludes these study types owing to the inherent difficulty surrounding their reproduction, as discussed by Wallach et al [9]. Meta-analyses and commentaries were also excluded from this analysis as materials are not typically included (n=114).

[b]Empirical studies (clinical trial, cohort, case control, secondary analysis, chart review, commentary [with data analysis], and cross-sectional) excluding case reports and case series. Meta-analyses were included in this analysis (n=127).

[c]All empirical and nonempirical studies were included in this analysis (n=280).

[d]All publications included in random sample were included in this analysis (n=300).

Assessing Open Access

We employed a systematic process to determine the public's ability to access full text PDF versions of publications included in our sample. First, a search using the publication's title, digital object identifier, and/or PubMed ID on Open Access Button [29] was performed. If this search yielded no return, investigators then performed this same search process using Google Scholar and PubMed. Publications were determined to be inaccessible and paywall restricted if a full text version was unobtainable.

Attempts of Replication and Citation in Research Synthesis

To evaluate whether a publication with empirical data was cited in a systematic review and/or meta-analysis, we used Web of Science [30], following previous studies [8,9,20]. We determined the citing publications to be either a replication study or a meta-analysis or systematic review by individually screening the title, abstract, or the full text when necessary.

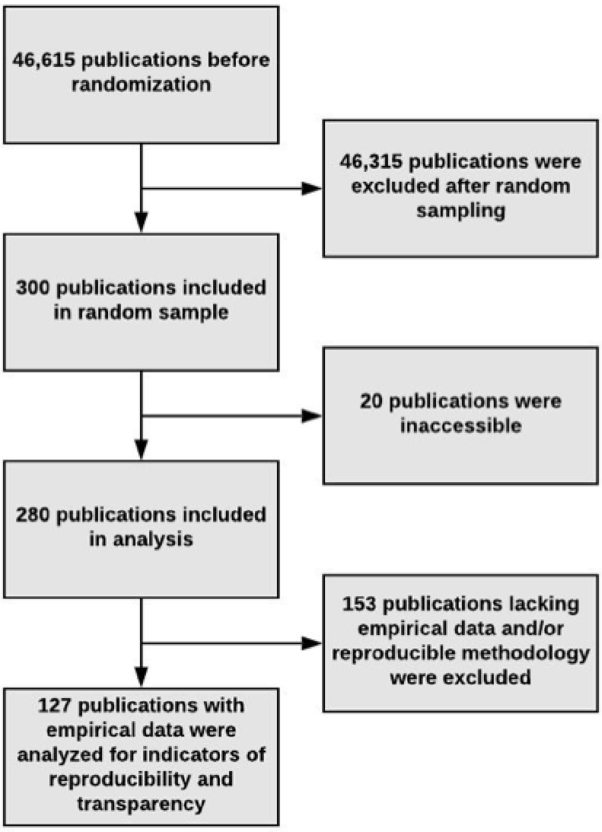
Statistical Analysis

We presented outcomes as percentages with associated 95% CIs, calculated using the Wilson binomial proportion confidence interval method. Descriptive statistics, medians, and upper and lower quartiles were reported using functions available in Microsoft Excel.

Results

Our search of the NLM catalog returned 100 dermatology journals. In all, 46 of these journals met the inclusion criteria and accounted for 46,615 publications from 2014 to 2018. Data were extracted from a random sample of 300 publications. A total of 280 were deemed eligible and accessible, whereas the remaining 20 were inaccessible (Figure 1).

Figure 1. Flow diagram for included and excluded studies.



Sample Characteristics

Our final analysis of 280 dermatology publications included 127 publications (45.4%) with empirical data from reproducible study designs and 153 publications (54.6%) that lacked empirical data or were inherently difficult to reproduce. The median 5-year journal impact factor was 2.719. Journal impact factors were inaccessible for 21 publications. Tables 2 and 3 provide additional characteristics for our sample of dermatology publications.

Table 2. Reproducibility and transparency characteristics for a sample of publications in dermatology journals.

Characteristics	Value, n (%)
Study design[a]	
Publications with nonempirical data	69 (24.6)
Meta-analysis	9 (3.2)
Commentary with reanalysis	4 (1.4)
Cost effectiveness	0 (0.0)
Clinical trial	14 (5.0)
Case study	68 (24.3)
Case series	16 (5.7)
Cohort	17 (6.1)
Case control	0 (0.0)
Survey	8 (2.9)
Laboratory	53 (18.9)
Multiple	0 (0.0)
Other	22 (7.9)
Funding source[a]	
University	6 (2.1)
Hospital	0 (0.0)
Public	19 (6.8)
Private/industry	22 (7.9)
Nonprofit	6 (2.1)
No funding statement listed	125 (44.6)
No external funding received	77 (27.5)
Mixed	25 (9.0)
Test subjects[a]	
Animals	11 (3.9)
Humans	178 (63.6)
Both	0 (0.0)
Neither	91 (32.5)
Country of journal publication[a]	
United States	233 (83.2)
Japan	0 (0.0)
United Kingdom	8 (2.9)
France	11 (3.9)
India	6 (2.1)
Canada	1 (0.4)
Other[b]	21 (7.5)
Country of corresponding author[a]	
United States	75 (26.8)
China	9 (3.2)
United Kingdom	9 (3.2)
Germany	16 (5.7)

Characteristics	Value, n (%)
Japan	26 (9.3)
France	12 (4.3)
Canada	5 (1.8)
Italy	11 (3.9)
India	10 (3.6)
Spain	16 (5.7)
Other[c]	91 (32.5)

[a]All empirical and nonempirical studies included in this study (n=280): editorials, commentaries (without reanalysis), simulations, news, and reviews.

[b]Brazil, Ireland, New Zealand, and Switzerland.

[c]Argentina, Australia, Austria, Belgium, Brazil, Croatia, Czech Republic, Denmark, Hungary, Iran, Ireland, Israel, Netherlands, Nigeria, Pakistan, Poland, Portugal, Scotland, Singapore, Slovakia, South Korea, Sweden, Switzerland, Taiwan, Turkey, and Ukraine.

Table 3. Additional sample characteristics and Google Form response rates from sampled dermatology publications.

Characteristics and Google Form response	Response rate, n (%)	95% CI
Data availability statement (n=127)		
Data availability statement provided, the data (or some of the data) are available	14 (11.0)	6.7-17.7
Data availability statement provided, the statement declares the data are not available	0 (0.0)	0.0-0.0
No data availability statement provided	113 (89.0)	82.4-93.3
Means by which additional data are available (n=14)		
Personal/institutional website	1 (7.1)	—[a]
Supplementary information hosted by the journal	12 (85.8)	—
Online third-party repository	0 (0.0)	—
Upon request from the corresponding author(s)	1 (7.1)	—
Accessibility of additional data (n=14)		
All data files were successfully accessed and downloaded	11 (78.6)	—
One or more data files could not be accessed or downloaded	3 (21.4)	—
Data files containing all raw numerical data	3 (21.4)	—
Data files without all raw numerical data	8 (57.1)	—
Materials availability statement (n=114)		
Materials availability statement provided, some materials are available	23 (20.2)	13.8-28.5
Materials availability statement provided, materials are not available	0 (0.0)	0.0-0.0
No materials availability statement provided	91 (79.8)	71.5-86.2
Means by which supplemental materials are available (n=23)		
Personal/institutional website	0 (0.0)	—
Supplementary information hosted by the journal	23 (100)	—
Online third party	0 (0.0)	—
Upon request from the corresponding author(s)	0 (0.0)	—
Accessibility of additional materials (n=23)		
Materials availability provided, all supplemental materials were accessible	21 (91.3)	—
Materials availability statement provided, but the materials were not accessible	2 (8.7)	—
Protocol availability statement (n=127)		
Protocol availability statement provided	3 (2.4)	0.8-6.7
No protocol availability statement provided	124 (97.6)	93.3-99.2
Accessibility of additional protocols (n=3)		
Full protocol was available using provided link	3 (100)	—
Full protocol was not available using provided link	0 (0.0	—
Hypotheses were included in the linked protocol	0 (0.0	—
Methods were included in the linked protocol	3 (100)	—
Analysis plans were included in the linked protocol	3 (100)	—
Analysis script availability statement (n=127)		
Analysis script provided, declares that the analysis scripts (or some of the analysis scripts) are available	1 (0.8)	0.1-4.3
Analysis script statement provided, declares that the analysis scripts are not available	0 (0.0)	0.0-0.0
No analysis script statement provided	126 (99.2)	95.7-99.9
Preregistration statement (n=127)		
Statement provided, declaring study was preregistered	3 (2.4)	3.0-6.7
Statement provided, declaring the study was not preregistered	0 (0.0)	0.0-0.0

Characteristics and Google Form response	Response rate, n (%)	95% CI
No preregistration statement provided	124 (97.6)	93.3-99.2
Accessibility of publication registration (n=3)		
Preregistration was accessible	3 (100)	—
Preregistration was not accessible	0 (0.0)	—
Number of studies preregistered on ClinicalTrials.gov	2 (66.7)	—
Number of studies preregistered on GlaxoSmithKline Clinical Study Register: gsk-clinicalstudyregister.com	1 (33.3)	—
Conflicts of interest statement (n=280)		
Disclosure statement provided, author(s) declare one or more conflicts of interest	30 (10.7)	7.6-14.9
Disclosure statement provided, author(s) declare that there are no conflicts of interest	203 (72.5)	67.0-77.4
No conflicts of interest statement provided	47 (16.8)	12.9-21.6
Open access (n=300)		
Publication found via Open Access Button (openaccessbutton.org)	65 (21.7)	17.4-26.7
Publication found via Google Scholar and/or PubMed	136 (45.3)	39.8-51.0
Publication determined to be paywall restricted	99 (33)	27.9-38.5

[a]Not applicable.

Eight Indicators of Reproducibility and Transparency

Among the 280 eligible publications, 201 (71.8%) were publicly available, whereas the remaining 79 (28.2%) were only available through a paywall. We classified the 20 publications for which full text PDF versions were unattainable as being paywall restricted. Thus, a total of 99 publications (of 300; 33.0%) were classified as being unavailable to the public. Only 23 publications (out of 114, 20.2%) provided a statement indicating that additional materials were available. Only 3 publications (out of 127, 2.4%) provided a protocol availability statement. All 3 of these statements provided a valid link to a Web-based protocol. Almost all publications lacked data availability statements. A total of 14 publications (out of 127, 11.0%) included data availability statements; however, only 11 of these data statements were linked to supplemental data files. Of the 11 accessible supplemental data files, only 3 provided access to complete and unmodified raw datasets. In addition, only 1 publication (out of 127, 0.8%) provided an analysis script or code. Our analysis revealed only 3 publications (of 127, 2.4%) were prospectively registered. A total of 233 publications (out of 280, 83.2%) provided a COI statement. Of these 280 publications, 30 (10.7%) indicated that 1 or more authors had a COI, and 203 (72.5%) declared the author(s) did not have a COI. The remaining 47 publications (out of 280, 16.8%) failed to provide a COI statement. Furthermore, 155 (out of 280, 55.4%) publications reported a funding source, whereas 125 (44.6%) publications did not receive external funding. Finally, 23 publications (out of 114, 20.2%) included in our analysis were cited in a subsequent data synthesis or review paper (Table 4). No publication included in our analysis was cited in a replication study.

Table 4. Number of times sampled publications have been cited in a meta-analysis and/or systematic review article.

Citation frequency	Value, n (%)
No citation	91 (79.8)
A single citation	15 (13.2)
1 to 5 citations	8 (7.0)
Greater than 5 citations	0 (0.0)

Discussion

Principal Findings

Our findings suggest that the current climate of dermatology research does not encourage reproducible and transparent research practices. Few studies provided access to datasets, analysis scripts, or complete study protocols. These findings are congruent with previous reports that found that studies often fail to promote transparent and reproducible research practices [9], and they align with a study published in *Nature* that found that 90% of more than 1500 researchers agreed that biomedical science is facing a significant reproducibility crisis [1]. This environment of poor research practice is problematic for clinicians and researchers who might seek to validate or reproduce a study in its entirety. As scientists and clinicians continue to make medical advances, studies must be readily reproducible to ensure proper validation of results and to allow for sustained progression in clinical practice. In the following text, we describe 2 practices in the field of dermatology—study protocols and preregistration—that were commonly omitted by researchers. We follow with actionable recommendations for research funders, journals, and researchers that, if implemented successfully, might help better the climate of reproducible research in published dermatology literature.

Most studies included in our sample did not provide additional materials or complete study protocols. Precisely outlining methodology is essential for study reproducibility [31], whether this information is provided within the publication or in supplementary materials [32]. The *Journal of the American Academy of Dermatology*'s (*JAAD*) instructions to authors state, "submissions of research articles should be accompanied by a supplementary document that includes the protocol and statistical analysis plan; this should be labeled 'For editor/reviewer reference only' and is *not for publication*" (emphasis ours) [33]. The *British Journal of Dermatology* (*BJD*) author guidelines state, "The editorial team has found that providing the study protocol facilitates acceptance of the paper if it is available. Therefore, the *BJD* encourages submission of the protocol at the time of manuscript submission, with the protocol identified as a 'Supplementary file for review.' Submission of the trial protocol is also strongly encouraged for industry-sponsored trials." [34] *JAMA Dermatology* guidance states, "authors of manuscripts reporting clinical trials must submit trial protocols (including the complete statistical analysis plan) along with their manuscripts… and that if the manuscript is accepted, the protocol and statistical analysis plan will be published as a supplement [35]." The widespread variability in guidance provided by these 3 prominent dermatology journals—which ranges from nonpublication of study protocols by *JAAD* to protocol publication upon article acceptance by *JAMA Dermatology*—suggests differing views toward implementing reproducible research practices within the field. *BJD* does not require protocol submission but simply encourages it. As journals are the final arbiters of studies that move on to publication, they have a high degree of influence on the climate of reproducibility and transparency in dermatology research. We highly recommend that dermatology journals adopt stronger requirements for submitting authors to promote greater transparency and reproducibility.

According to the Food and Drug Administration Amendments Act, established in 2007, all applicable RCTs must be registered before participant enrollment [22]. Although the number of preregistered RCTs has increased, other study designs have not shown as much improvement. Boccia et al found that only 1109 cancer observational studies were registered on ClinicalTrials.gov across an 11-year period [36]. In addition, systematic reviews have a preregistration platform, the International Prospective Register of Systematic Reviews (PROSPERO), which has increased in usage exponentially since its inception in 2011 [37]. These study designs are preregistered solely at the authors' discretion, with few journals or funders having concrete guidance on the subject. Of the 3 journals discussed above, only *BJD* mentions registering systematic reviews, stating that authors are required to preregister on PROSPERO [34]. Transparent research practices such as prospective registration can help mitigate unethical research practices by providing access to date-stamped protocol details and informing the public about current clinical trials being performed [38]. For example, P-hacking (using different statistical analyses until a nonsignificant finding is found to be significant) [39] and HARKing (forming study hypothesis after results have been calculated) [40] might be avoided if investigators disclose the expected statistical analyses that will be used throughout the study before its commencement. It should be noted that HARKing can be beneficial to the scientific process by generating important discoveries during post hoc analyses [41-43] In addition, previous studies have shown that reviewers often encourage authors to add hypotheses post hoc as part of the peer review process [44]. However, the crossover into research misconduct occurs when authors contend that these posthoc hypotheses were part of the original study design, thereby potentially decreasing the confidence of statistically significant outcomes [45].

Future Recommendations

Changes to the landscape of dermatology research are warranted; however, the optimal framework for doing so is unclear. Here, we offer recommendations for research stakeholders—including funding agencies, journals, and researchers—that may help increase the quality of reproducible research practices in dermatology, if implemented successfully.

With respect to funding, some foundations and governmental agencies have established measures to promote reproducibility and transparency of research for which they provide funding. A nonexhaustive list of these funders include the National Institutes of Health (NIH), the National Science Foundation, the Wellcome Trust, and the Bill and Melinda Gates Foundation. As one example, the Gates Foundation, which funds approximately 2000 to 2500 research articles per year totaling US $5 billion [46], has established an open access policy requiring that all research data and manuscripts resulting from its funds be *promptly and broadly disseminated* [47]. To further its goals for widespread dissemination, the foundation has launched its own open access journal, *Gates Open Research.* Currently, research funded by the foundation is not eligible for publication in some of the world's most renowned journals, such as *Nature*, *Science*, *Proceedings of the National Academy of Sciences*, and *New England Journal of Medicine* owing to these funding restrictions [48]. The NIH has established the Rigor and Reproducibility Initiative, embedding requirements that submitted grant applications outline strategies for more reproducible research [49]. Strategies such as these are the first steps toward adoption of more transparent and reproducible research practices.

For journals, we recommend consideration of adopting stricter standards on the disclosure of study materials, raw datasets, protocols, and analysis scripts. Journals should consider requiring that authors share all study materials on public repositories, such as Open Science Framework. With essential study materials publicly available, outcomes may be reproduced and validated with greater ease. A recent survey found that open access to study data increased the public's trust and confidence in research outcomes [50]. Depositing all study materials and data before publication may increase the public's faith and confidence in the literature published in journals with such requirements.

Finally, for researchers, we believe a need exists to train and equip principal investigators to adopt more reproducible and transparent research practices. This goal may be best accomplished through continuing education, academic conferences, webinars, and journal clubs. A need also exists to train and equip the next generation of scientists. Given the apprenticeship nature of many biomedical laboratories, principal investigators should take the lead in fostering such cultures within their laboratories and instilling such practices with mentees. Courses on open science are being developed across the country, many posted on the Open Science Framework [51]. The National Institutes of General Medical Sciences has posted several Web-based training modules to increase the overall rigor and reproducibility of medical research [52]. As these courses continue to expand at universities and with funders, continued development and uptake of such training may help reverse the scant nature of reproducibility and transparency of research in the dermatology literature.

Strengths and Limitations

Our study has many strengths, but some limitations are present. Regarding strengths, all materials, protocols, analysis plans, and raw data from our study are publicly available on Open Science Framework. In addition, we implemented numerous measures to ensure the reliability of study outcomes by (1) using a blinded, double data extraction technique—the gold standard for meta-research practices [53] and (2) providing thorough training of each investigator to ensure reliability of results between investigators. Regarding limitations, data extraction was limited to the content of the full-text PDFs and available supplemental materials for each publication. Additional materials may be attainable by contacting the corresponding author. Furthermore, this study focused specifically on publications in dermatology journals. Thus, the results from this study may not be generalizable to other subjects or years of publication. For the aforementioned reasons, interpretation of our findings should be considered a lower bound estimate of reproducibility of publications in dermatology journals.

In conclusion, the rate of disclosure of study materials, data, protocols, and analysis scripts of sampled dermatology publications is unacceptably low. Without implementing and adhering to more robust reporting standards and open science practices, reproducibility-related factors of dermatologic research may remain poor.

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Conflicts of Interest

None declared.

References

1. Baker M. 1,500 scientists lift the lid on reproducibility. Nature 2016 May 26;533(7604):452-454. [doi: 10.1038/533452a] [Medline: 27225100]
2. Freedman LP, Cockburn IM, Simcoe TS. The economics of reproducibility in preclinical research. PLoS Biol 2015 Jun;13(6):e1002165 [FREE Full text] [doi: 10.1371/journal.pbio.1002165] [Medline: 26057340]
3. Salman R, Beller E, Kagan J, Hemminki E, Phillips RS, Savulescu J, et al. Increasing value and reducing waste in biomedical research regulation and management. Lancet 2014 Jan 11;383(9912):176-185 [FREE Full text] [doi: 10.1016/S0140-6736(13)62297-7] [Medline: 24411646]
4. Center for Open Science. Reproducibility Project: Cancer Biology URL: https://cos.io/rpcb/ [accessed 2019-06-28]
5. Baker M, Dolgin E. Cancer reproducibility project releases first results. Nature 2017 Jan 18;541(7637):269-270. [doi: 10.1038/541269a] [Medline: 28102271]
6. Berger MF, Hodis E, Heffernan TP, Deribe YL, Lawrence MS, Protopopov A, et al. Melanoma genome sequencing reveals frequent PREX2 mutations. Nature 2012 May 9;485(7399):502-506 [FREE Full text] [doi: 10.1038/nature11071] [Medline: 22622578]
7. Munafò MR, Nosek BA, Bishop DV, Button KS, Chambers CD, Percie du Sert N, et al. A manifesto for reproducible science. Nat Hum Behav 2017 Jan 10;1(1):s41562–016–0021. [doi: 10.1038/s41562-016-0021]
8. Hardwicke TE, Wallach JD, Kidwell M, Ioannidis J. An empirical assessment of transparency and reproducibility-related research practices in the social sciences (2014-2017). MetaArXiv 2019 [FREE Full text] [doi: 10.31222/osf.io/6uhg5]
9. Wallach JD, Boyack KW, Ioannidis JP. Reproducible research practices, transparency, and open access data in the biomedical literature, 2015-2017. PLoS Biol 2018 Nov;16(11):e2006930 [FREE Full text] [doi: 10.1371/journal.pbio.2006930] [Medline: 30457984]
10. Nankervis H, Baibergenova A, Williams HC, Thomas KS. Prospective registration and outcome-reporting bias in randomized controlled trials of eczema treatments: a systematic review. J Invest Dermatol 2012 Dec;132(12):2727-2734 [FREE Full text] [doi: 10.1038/jid.2012.231] [Medline: 22832489]
11. Chalmers I, Glasziou P. Avoidable waste in the production and reporting of research evidence. Lancet 2009 Jul 4;374(9683):86-89. [doi: 10.1016/S0140-6736(09)60329-9] [Medline: 19525005]

12. Weber WE, Merino JG, Loder E. Trial registration 10 years on. Br Med J 2015 Jul 6;351:h3572. [doi: 10.1136/bmj.h3572] [Medline: 26149708]
13. Cook C, Checketts JX, Atakpo P, Nelson N, Vassar M. How well are reporting guidelines and trial registration used by dermatology journals to limit bias? A meta-epidemiological study. Br J Dermatol 2018 Jun;178(6):1433-1434. [doi: 10.1111/bjd.16135] [Medline: 29150841]
14. Peng RD, Dominici F, Zeger SL. Reproducible epidemiologic research. Am J Epidemiol 2006 May 1;163(9):783-789. [doi: 10.1093/aje/kwj093] [Medline: 16510544]
15. Warren E. Strengthening research through data sharing. N Engl J Med 2016 Aug 4;375(5):401-403. [doi: 10.1056/NEJMp1607282] [Medline: 27518656]
16. Groves T, Godlee F. Open science and reproducible research. Br Med J 2012 Jun 26;344:e4383. [doi: 10.1136/bmj.e4383] [Medline: 22736475]
17. Taichman DB, Sahni P, Pinborg A, Peiperl L, Laine C, James A, et al. Data sharing statements for clinical trials: a requirement of the international committee of medical journal editors. Ethiop J Health Sci 2017 Jul;27(4):315-318 [FREE Full text] [Medline: 29217933]
18. Scherer RW, Langenberg P, von Elm E. Full publication of results initially presented in abstracts. Cochrane Database Syst Rev 2007 Apr 18(2):MR000005. [doi: 10.1002/14651858.MR000005.pub3] [Medline: 17443628]
19. Nuzzo R. How scientists fool themselves - and how they can stop. Nature 2015 Oct 8;526(7572):182-185. [doi: 10.1038/526182a] [Medline: 26450039]
20. Iqbal SA, Wallach JD, Khoury MJ, Schully SD, Ioannidis JP. Reproducible research practices and transparency across the biomedical literature. PLoS Biol 2016 Jan;14(1):e1002333 [FREE Full text] [doi: 10.1371/journal.pbio.1002333] [Medline: 26726926]
21. OSF.io. 2019 Jun 7. Dermatology Reproducibility Project protocol URL: https://osf.io/qang3/ [accessed 2019-10-01]
22. eCFR — Code of Federal Regulations. 2018 Jul 19. Electronic Code of Federal Regulations URL: https://www.ecfr.gov/cgi-bin/retrieveECFR?gp=&SID=83cd09e1c0f5c6937cd9d7513160fc3f&pitd=20180719&n=pt45.1.46&r=PART&ty=HTML#se45.1.46_1102 [accessed 2019-11-04]
23. Murad MH, Wang Z. Guidelines for reporting meta-epidemiological methodology research. Evid Based Med 2017 Aug;22(4):139-142 [FREE Full text] [doi: 10.1136/ebmed-2017-110713] [Medline: 28701372]
24. PRISMA. URL: http://www.prisma-statement.org/ [accessed 2019-06-29]
25. OSF.io. 2019 Jun 7. pubmed_result URL: https://osf.io/c7a4t/ [accessed 2019-10-01]
26. OSF.io. 2019 Jun 7. Data Extraction Video URL: https://osf.io/jczx5/ [accessed 2018-10-01]
27. OSF.io. 2019 Jun 7. Reproducibility Data - Dermatology URL: https://osf.io/ev38h/ [accessed 2019-10-01]
28. OSF.io. 2019 Jun 7. Collection Form - Google Forms URL: https://osf.io/3nfa5/ [accessed 2019-10-01]
29. Open Access Button. URL: https://openaccessbutton.org/ [accessed 2019-08-31]
30. Web of Science. URL: http://webofknowledge.com [accessed 2019-08-31]
31. Niven DJ, McCormick TJ, Straus SE, Hemmelgarn BR, Jeffs L, Barnes TR, et al. Reproducibility of clinical research in critical care: a scoping review. BMC Med 2018 Feb 21;16(1):26 [FREE Full text] [doi: 10.1186/s12916-018-1018-6] [Medline: 29463308]
32. Goodman SN, Fanelli D, Ioannidis JP. What does research reproducibility mean? Sci Transl Med 2016 Jun 1;8(341):341ps12. [doi: 10.1126/scitranslmed.aaf5027] [Medline: 27252173]
33. Elsevier. Guide for Authors URL: https://www.elsevier.com/journals/journal-of-the-american-academy-of-dermatology/0190-9622/guide-for-authors [accessed 2019-08-08]
34. Wiley Online Library. British Journal of Dermatology Author Guidelines URL: https://onlinelibrary.wiley.com/page/journal/13652133/homepage/forauthors.html [accessed 2019-08-03]
35. JAMA Network. Instructions for Authors URL: https://jamanetwork.com/journals/jamadermatology/pages/instructions-for-authors [accessed 2019-08-08]
36. Boccia S, Rothman KJ, Panic N, Flacco ME, Rosso A, Pastorino R, et al. Registration practices for observational studies on ClinicalTrials.gov indicated low adherence. J Clin Epidemiol 2016 Feb;70:176-182. [doi: 10.1016/j.jclinepi.2015.09.009] [Medline: 26386325]
37. Page MJ, Shamseer L, Tricco AC. Registration of systematic reviews in PROSPERO: 30,000 records and counting. Syst Rev 2018 Feb 20;7(1):32 [FREE Full text] [doi: 10.1186/s13643-018-0699-4] [Medline: 29463298]
38. Zarin DA, Tse T, Williams RJ, Rajakannan T. Update on trial registration 11 years after the ICMJE policy was established. N Engl J Med 2017 Jan 26;376(4):383-391 [FREE Full text] [doi: 10.1056/NEJMsr1601330] [Medline: 28121511]
39. Head ML, Holman L, Lanfear R, Kahn AT, Jennions MD. The extent and consequences of p-hacking in science. PLoS Biol 2015 Mar;13(3):e1002106 [FREE Full text] [doi: 10.1371/journal.pbio.1002106] [Medline: 25768323]
40. Kerr NL. HARKing: hypothesizing after the results are known. Pers Soc Psychol Rev 1998;2(3):196-217. [doi: 10.1207/s15327957pspr0203_4] [Medline: 15647155]
41. Aguinis H, Vandenberg RJ. An ounce of prevention is worth a pound of cure: improving research quality before data collection. Annu Rev Organ Psychol Organ Behav 2014 Mar 21;1(1):569-595 [FREE Full text] [doi: 10.1146/annurev-orgpsych-031413-091231]

42. Bamberger P, Ang S. The quantitative discovery: what is it and how to get it published. Acad Manag Disc 2016;2(1):1-6. [doi: 10.5465/amd.2015.0060]
43. Locke EA. The case for inductive theory building. J Manag 2007;33(6):867-890. [doi: 10.1177/0149206307307636]
44. Bedeian AG, Taylor SG, Miller AN. Management science on the credibility bubble: cardinal sins and various misdemeanors. Acad Manag Learn Educ 2010 Dec 1;9(4):715-725. [doi: 10.5465/amle.9.4.zqr715]
45. Murphy KR, Aguinis H. HARKing: How badly can cherry-picking and question trolling produce bias in published results? J Bus Psychol 2019 Feb;34(1):1-17. [doi: 10.1007/s10869-017-9524-7]
46. Bill & Melinda Gates Foundation. Foundation Fact Sheet URL: https://www.gatesfoundation.org/who-we-are/general-information/foundation-factsheet [accessed 2019-08-12]
47. Bill & Melinda Gates Foundation. Open Access Policy URL: https://www.gatesfoundation.org/How-We-Work/General-Information/Open-Access-Policy/Page-2 [accessed 2019-08-12]
48. van Noorden R. Gates Foundation research can't be published in top journals. Nature 2017 Jan 13;541(7637):270. [doi: 10.1038/nature.2017.21299] [Medline: 28102276]
49. National Institutes of Health. Rigors and Reproducibility URL: https://www.nih.gov/research-training/rigor-reproducibility [accessed 2019-08-12]
50. Pew Research Center. Trust and Mistrust in Americans' Views of Scientific Experts URL: https://www.pewresearch.org/science/2019/08/02/trust-and-mistrust-in-americans-views-of-scientific-experts/ [accessed 2019-08-08]
51. Open Science Framework. URL: https://osf.io/ [accessed 2019-08-31]
52. National Institute of General Medical Sciences. 2015. Clearinghouse for Training Modules to Enhance Data Reproducibility URL: https://www.nigms.nih.gov/training/pages/clearinghouse-for-training-modules-to-enhance-data-reproducibility.aspx [accessed 2019-08-12]
53. Higgins J, Green S. Cochrane Handbook for Systematic Reviews of Interventions. Chichester, UK: Wiley; 2006.

Abbreviations

BJD: British Journal of Dermatology
JAAD: Journal of the American Academy of Dermatology
NIH: National Institutes of Health
NLM: National Library of Medicine
PROSPERO: International Prospective Register of Systematic Reviews
RCT: randomized controlled trial

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