because the patients did not have clinical follow-up and were unable to be reached by telephone. Follow-up information was available for 348 SCCs in 288 patients (median follow-up 3.15 years) (Table I); 77.0% (268/348) had at least 1 Brigham and Women's Hospital risk factor and 29.3% (102/348) met the conventional designation of high risk (stage T2b or greater).

Eight patients had local recurrences (2.30%; 8/348) (Supplemental Table II); 62.5% of these patients (5/8) were immunosuppressed and all were aged 60 years or older (8/8; 100%). The 5-year Kaplan-Meier local recurrence rates were 2.43% (95% confidence interval 1.08%-5.43%) for all SCC cases and 1.60% (95% confidence interval 0.50%-5.02%) for tumors with greater than or equal to 1 Brigham and Women's Hospital risk factor (Fig 1). Absolute local recurrence rates by Brigham and Women's Hospital stage and Brigham and Women's Hospital risk factors were low (Table II), with stage T1 cases demonstrating the highest absolute local recurrence rate (5/80; 6.25%).

Limitations of this study include its single-center, retrospective design and lack of direct comparison to conventional excision or Mohs micrographic surgery alone.

We contribute what is to our knowledge the largest published case series in which every tumor was evaluated with both hematoxylin-eosin and AE1/AE3 cytokeratin immunostains. Our local recurrence rates for SCCs with 1 Brigham and Women's Hospital risk factor or more compare favorably to published rates after Mohs micrographic surgery without immunohistochemical staining.[2] Improved local recurrence rates of challenging SCC may be attributed to enhanced margin interpretation and control with immunohistochemical use (Supplemental Fig 1). Stage T1 tumors limited to the dermis had the highest local recurrence rate, suggesting that characteristics other than Brigham and Women's Hospital high-risk features may increase the risk for local recurrence.

Leora Aizman, BS,[a] Christopher J. Miller, MD,[b] Allison M. Perz, BS,[c] Tess M. Lukowiak, BS,[d] Olivia G. Cohen, BS, MS,[e] Eric Bean, BS,[e] Michaela K. Hitchner, BS,[e] Jeremy R. Etzkorn, MD, MS,[b] Thuzar M. Shin, MD, PhD,[b] H. William Higgins, II, MD,[b] Cerrene N. Giordano, MD,[b] Justine V. Cohen, MD,[e] John T. Miura, MD,[f] and Joseph F. Sobanko, MD[b]

From George Washington University School of Medicine and Health Sciences, Washington, District of Columbia[a]; Department of Dermatology, Hospital of the University of Pennsylvania, Philadelphia[b]; Cooper Medical School of Rowan University, Camden, New Jersey[c]; Drexel University College of Medicine, Philadelphia, Pennsylvania[d]; University of Pennsylvania Perelman School of Medicine, Philadelphia[e]; and Department of Surgery, Hospital of the University of Pennsylvania, Philadelphia.[f]

Funding sources: None.

Conflicts of interest: None disclosed.

Reprints not available from the authors.

Correspondence to: Leora Aizman, BS, George Washington University School of Medicine and Health Sciences, 2300 I St NW, Washington, DC 20052

E-mail: leora.aizman@gmail.com

REFERENCES

1. Rowe DE, Carroll RJ, Day CL Jr. Prognostic factors for local recurrence, metastasis, and survival rates in squamous cell carcinoma of the skin, ear, and lip. Implications for treatment modality selection. *J Am Acad Dermatol*. 1992;26(6):976-990.
2. Marrazzo G, Zitelli JA, Brodland D. Clinical outcomes in high-risk squamous cell carcinoma patients treated with Mohs micrographic surgery alone. *J Am Acad Dermatol*. 2019;80(3):633-638.
3. Ruiz ES, Karia PS, Besaw R, et al. Performance of the American Joint Committee on Cancer Staging Manual, 8th Edition vs the Brigham and Women's Hospital tumor classification system for cutaneous squamous cell carcinoma. *JAMA Dermatol*. 2019;155(7):819-825.
4. Miller CJ, Sobanko JF, Zhu X, et al. Special stains in Mohs surgery. *Dermatol Clin*. 2011;29(2):273-286. ix.
5. Etzkorn JR, Sobanko JF, Elenitsas R, et al. Low recurrence rates for in situ and invasive melanomas using Mohs micrographic surgery with melanoma antigen recognized by T cells 1 (MART-1) immunostaining: tissue processing methodology to optimize pathologic staging and margin assessment. *J Am Acad Dermatol*. 2015;72(5):840-850.

https://doi.org/10.1016/j.jaad.2020.06.1012

Social media activity is associated with higher physician ratings by patients

To the Editor: Social media (SM) activity is increasing, including its use in health care decision making.[1] The effect of SM on physician ratings has been explored across specialties[2-4]; however, its impact on clinical practice has not been studied in dermatology. We evaluated factors associated with patient satisfaction across physician rating websites (PRWs), the prevalence of SM use, and the relationship between SM use and online physician ratings for dermatologists.

Table I. Data from online physician-rating websites, by social media presence

Websites	Social media presence		*P* value
	Yes (n = 180)	No (n = 204)	
Healthgrades, mean ± SD			
Overall rating	3.9 ± 1.2	3.4 ± 1.6	**.0005**
Number of ratings	13.4 ± 15.3	7.6 ± 9.2	**<.0001**
Number of comments	4.6 ± 8.2	2.2 ± 4.0	**.0002**
Vitals, mean ± SD			
Overall rating	4.0 ± 2.6	3.7 ± 1.5	.1673
Number of ratings	20.4 ± 19.8	13.9 ± 14.9	**.0002**
Number of comments	10.7 ± 16.0	5.8 ± 9.6	**.0001**
Google, mean ± SD			
Overall rating	4.6 ± 0.6	4.2 ± 1.0	**.0002**
Number of ratings	11.6 ± 18.3	3.5 ± 6.5	**<.0001**
Care philosophy, n			
Yes	41	21	**.0004**
No	141	195	
Wait time, minutes			
0-10	55	52	
10-15	87	87	
16-30	28	40	
>30	1	3	.4134
Castle Connolly, n			
Yes	56	47	**.0472**
No	131	173	

Bold values indicate statistical significance ($P < .05$).
SD, Standard deviation.

We identified fully trained members of the American Academy of Dermatology actively practicing in Manhattan between August 1 and November 1, 2018, from the Academy's online directory. Physician profiles were reviewed on 3 publicly available PRWs: Healthgrades.com (HG), Vitals.com (V), and Google.com (G) between March 12 and April 21, 2019. Data obtained included medical degree, graduation year, institution type, fellowship training, patient-reported wait times, presence of a care philosophy, and Castle Connolly status, as well as overall scores and numbers of ratings and comments. Physicians were searched on Google.com, and the first 10 results were reviewed for SM presence and personal and/or institutional websites. Differences between physician characteristics and online PRW score means were assessed using chi-square tests and *t* tests, respectively. Linear regression analysis was used to assess associations between ratings and SM presence, training, practice type, and graduation year.

Of the 412 dermatologists, 91% had MD degrees, 70% worked in private practice, and 65% were not fellowship trained. Nearly all (94.9%) had personal or institutional websites, and nearly half (45.6%) had SM presence. Facebook was the most widely used platform (35.9%), followed by Instagram (30.3%) and Twitter (25%) (Supplemental Table I; available via Mendeley at http://doi.org/10.17632/bf994yffxz.2).

The average number ± standard deviation of ratings per dermatologist was 11.0 ± 16.1 for HG, 19.4 ± 24.1 for V, and 9.5 ± 30.5 for G. The average overall score (range, 0-5) was 3.5 ± 1.6 for HG, 3.7 ± 2.1 for V, and 3.1 ± 2.1 for G. Dermatologists in private practice received more HG and G ratings ($P < .0001$) and more HG comments ($P < .05$) than those in academia. Dermatologists who graduated residency before 2000 had more HG and V ratings than those who graduated after ($P < .0001$) yet were less likely to use Instagram ($P < .05$). Dermatologists with SM presence had more ratings and comments on HG and V ($P < .001$) and higher overall scores on HG and G ($P < .001$). Dermatologists with professional websites had higher overall HG scores ($P < .0001$) (Table I). SM presence was associated with HG and G ratings after accounting for reported physician characteristics (Table II).

SM has revolutionized information gathering in health care. We found that dermatologists with SM presence had more online ratings and higher overall scores on HG and G, suggesting that patients may feel more engaged with physicians who use SM. Private practitioners had more ratings on HG and V than academicians, perhaps due to higher patient

Table II. Linear regression analysis for overall ratings across physician-rating websites and social media presence, practice type, and graduation year

Physician information	Univariate parameter estimate (SD)	Univariate *P* value	Multivariate parameter estimate (SD)	Multivariate *P* value
Healthgrades overall rating (n = 381)				
Degree	0.004 (0.14)	.98	−0.005 (0.14)	>.99
Fellowship	−0.17 (0.15)	.43	−0.17 (0.15)	.26
Institution type	0.02 (0.17)	.21	0.01 (0.17)	.95
Graduation year	0.13 (0.15)	.46	0.14 (0.15)	.35
Website	−0.03 (0.01)	**<.05**	−0.03 (0.15)	**.03**
Social media presence	0.51 (0.15)	**<.0001**	0.34 (0.16)	**.03**
Website activity*				
Number of ratings	0.02 (0.01)	**<.001**	0.02 (0.01)	**<.01**
Number of comments	0.01 (0.02)	**<.05**	0.01 (0.02)	.53
Vitals overall rating (n = 388)				
Degree	0.02 (0.21)	.91	0.11 (0.22)	.61
Fellowship	0.18 (0.22)	.41	0.16 (0.23)	.49
Institution type	0.11 (0.23)	.64	0.03 (0.25)	.91
Graduation year	−0.39 (0.21)	.07	−0.34 (0.22)	.13
Website	−0.04 (0.02)	.08	−0.03 (0.02)	.14
Social media presence	0.29 (0.21)	.17	0.25 (0.24)	.3
Website activity*				
Number of ratings	0.02 (0.01)	**<.01**	−0.02 (0.02)	.25
Number of comments	0.01 (0.01)	.08	0.03 (0.01)	**<.04**
Google overall rating (n = 272)				
Degree	−0.04 (0.10)	.68	0.01 (0.11)	.93
Fellowship	0.21 (0.11)	**<.05**	0.16 (0.11)	.14
Institution type	0.15 (0.12)	.21	0.02 (0.13)	.91
Graduation year	0.11 (0.10)	.26	0.07 (0.10)	.5
Website	0.08 (0.07)	.28	0.01 (0.08)	.93
Social media presence	0.38 (0.20)	**<.0001**	0.34 (0.12)	**<.01**
Website activity*				
Number of ratings	0.004 (0.003)	.17	0.001 (0.003)	.78
Number of comments	—	—	—	—

Bold values indicate statistical significance ($P < .05$).
SD, Standard deviation.
*Number of ratings and comments on Healthgrades, Vitals, and Google, respectively.

volume and greater likelihood of using systems that encourage patient ratings. Physicians who have been in practice longer had more reviews, likely due to higher cumulative patient volume. Study limitations include geographic constraint and reliance on a single measurement occasion.

In conclusion, patient ratings, SM presence, practice setting, and duration of practice contribute to higher ratings, more comments, and higher overall scores for dermatologists.

Shadi Damanpour, MD,[a] Roya Nazarian, BA,[b] Alana Deutsch, BA,[a] H. Dean Hosgood, PhD,[c] Jaehwan Kim, MD, PhD,[a] and Beth N. McLellan, MD[a]

From the Department of Medicine, Division of Dermatology, Albert Einstein College of Medicine and Montefiore Medical Center, Bronx, New York[a]; Icahn School of Medicine at Mount Sinai, New York, New York[b]; and Department of Epidemiology and Population Health, Albert Einstein College of Medicine and Montefiore Medical Center, Bronx, New York.[c]

Funding sources: None.

Conflicts of interest: None disclosed.

IRB approval status: Not applicable.

Reprint requests: Beth N. McLellan, MD, 3411 Wayne Avenue Dermatology Suite, 2nd Floor, Bronx, NY 10467

E-mail: bmclella@montefiore.org

REFERENCES

1. Riemer C, Doctor M, Dellavalle RP. Analysis of online ratings of dermatologists. *JAMA Dermatol.* 2016;152(2):218-219.

2. Donnally CJ 3rd, Li DJ, Maguire JA Jr, et al. How social media, training, and demographics influence online reviews across three leading review websites for spine surgeons. *Spine J*. 2018;18(11):2081-2090.
3. Trehan SK, Daluiski A. Online patient ratings: why they matter and what they mean. *J Hand Surg Am*. 2016;41(2):316-319.
4. Dorfman RG, Mahmood E, Ren A, et al. Google ranking of plastic surgeons values social media presence over academic pedigree and experience. *Aesthet Surg J*. 2019;39(4):447-451.

https://doi.org/10.1016/j.jaad.2020.06.1015

Machine learning for precision dermatology: Advances, opportunities, and outlook

To the Editor: With the explosion of big data in medicine driven by the advent of electronic medical records, next-generation sequencing, multi-omics, and noninvasive imaging techniques, dermatology is a field at the precipice of an artificial intelligence (AI) revolution. However, to the majority of clinicians, machine learning (ML) is a magical black box that is powerful but inaccessible. Here, we review the latest advances in ML applied to dermatologic diagnosis and treatment and highlight key discoveries with translational potential. ML is an AI technique that focuses on designing machines (or computers) that mimic human pattern recognition and problem solving.[1] With the rise of big data and data science, ML and AI already affect our daily lives in innumerable ways. Comparatively, clinical medicine has been slower to integrate ML into daily practice.[2] ML has typically been considered a tool well outside of a typical clinician's purview. At the same time, there is now an enormous demand for high-quality research that is advancing health care using ML and AI.[3] ML is a natural fit for translation into dermatology because dermatology is a specialty that is heavily reliant on visual evaluation and pattern recognition.

We searched the literature for high-quality studies published within the last 5 years describing the latest advances in ML applied to precision dermatology (Supplemental Table I; available via Mendeley at http://doi.org/10.17632/8w4dkfbdpk.1). Because digital photography is so prevalent, many ML studies in dermatology focus on lesion image analysis[4-7] and classification.[8,9] However, we also find that ML is now also being applied to electronic medical records, patient laboratory data, and genomic data from next-generation sequencing to study the genetic basis of diseases; to identify associations between comorbidities, risk factors, and disease prognosis; and to design and predict responses to pharmacologic therapies (Supplemental Table I). Applications span the prediction of adverse drug reactions[10] to responses to therapy in oncologic dermatology[11] and autoimmune and rheumatologic skin disease.[12] Together, these landmark studies outline a promising generalized framework that leverages gene expression data and multi-omics for biomarker discovery in autoimmune skin diseases and for biologics and immunotherapies in general (Fig 1, *A* and *B*). The convergence of ML and next-generation sequencing represents a golden opportunity to advance precision dermatology, and multidisciplinary collaborations between ML

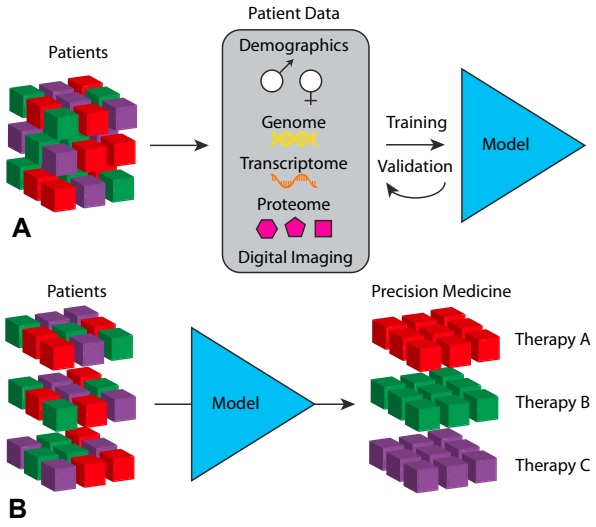

Fig 1. Machine learning for precision medicine. **A**, Schematic showing the training and validation of a machine learning model from multimodal input patient data, such as clinical images, patient demographics, and multi-omics. **B**, Application of the machine learning model to choose individually tailored therapies for specific disease states.