Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

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Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Criterion 5 (original contributions of major significance). It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

414	426	17	5
Citing papers mapped	Citation edges	Home papers mapped	h-index (GS)

Filtering statement — methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper's authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar's known collaborators; *same-institution* citations are by authors affiliated with the scholar's institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar's own circle.

Known limitations — counsel must verify. (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight — re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar's own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

94.5% independent of 220 classified citing papers

Citation type	Count
Independent	208
Self-citation	5
Co-author	7
Same-institution	0

194 citing papers could not be classified (no author data) and are excluded from the percentages above.

C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total — the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing — how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner's choice of comparison field.

Contribution 1

Claim — Contribution 1

The researcher pioneered text-guided image colorization and advanced image-to-image translation through novel transformation and masking techniques, establishing a foundational framework for semantic visual synthesis.

The researcher's core contribution centers on the 2018 paper 'Coloring with words,' which introduced a method for guiding image colorization through text-based palette generation. This work serves as the foundation for a subsequent line of inquiry into semantic image manipulation and translation.

This line of work appears to address the challenge of integrating textual semantics with visual data to control image attributes. The titles suggest a progression from global color guidance to more complex structural transformations, including group-wise deep whitening-and-coloring and local mask-based translation, indicating an expansion from color-specific tasks to broader image-to-image translation problems.

The significance of this research is evidenced by substantial citation counts, with the core paper accumulating 161 citations and the 2019 follow-up on deep whitening-and-coloring reaching 201 citations. Furthermore, analysis of 220 citing papers reveals that 94.5% originate from independent researchers, demonstrating broad adoption and impact beyond the researcher's immediate academic circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 183 · **28 flagged influential by Semantic Scholar**

CORE PAPER

Coloring with words: Guiding image colorization through text-based palette generation

2018 · Proceedings of the european conference on computer vision (eccv), 431-447, 2018 · 161 citations (GS)

Field-normalised: 102 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2018 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Cartoon image processing: a survey	Hefei University of Technology	China	Background
2	Aesthetic-aware image style transfer	Microsoft Research, Tsinghua University & Beijing National Research Center for Information Science and Technology	China, United States	**Methodology**
3	Zoom-GAN: learn to colorize multi-scale targets	National University of Defense Technology, Northwestern Polytechnical University	China	**Methodology**
4	Learning to colorize near-infrared images with limited data	National University of Defense Technology, Northwestern Polytechnical University	China	—
5	Flexible portrait image editing with fine-grained control	Institute of Software, Chinese Academy of Sciences, Nanyang Technological University	China, Singapore	**Methodology**
6	C2ideas: Supporting creative interior color design ideation with a large language model	China Academy of Art, The Hong Kong University of Science and Technology,	China	Background

No.	Citing paper	Citing institution(s)	Country	S2
		The Hong Kong University of Science and Technology (Guangzhou)		
7	Multi-text guidance is important: Multi-modality image fusion via large generative vision-language model	Dalian Minzu University	China	—
8	Towards vivid and diverse image colorization with generative color prior	Tencent	China	Methodology
9	Unicolor: A unified framework for multi-modal colorization with transformer	City University of Hong Kong, University of Bath	China, United Kingdom	—
10	Image colorization: A survey and dataset	Nankai University, National University of Sciences and Technology, Saudi Electronic University	Australia, China, Pakistan	Methodology
11	Tag2pix: Line art colorization using text tag with secat and changing loss	Seoul National University	South Korea	Background
12	PalGAN: Image colorization with palette generative adversarial networks	SenseTime Research, Shanghai AI Laboratory, Tencent	China, United States	Methodology
13	Disentangled image colorization via global anchors	Tencent, The Chinese University of Hong Kong	China	—
14	Language-based colorization of scene sketches	City University of Hong Kong, Google, Sun Yat-sen University	China, United States	Methodology
15	De-Stijl: Facilitating graphics design with interactive 2D color palette recommendation	Adobe, Stony Brook University, University of Waterloo	Canada, United States	Background
16	Retrieve-then-adapt: Example-based automatic generation for proportion-related infographics	Microsoft Research Asia, Peking University	China	—
17	Color palette generation from digital images: A review	Beijing Institute of Graphic Communication, Wuhan Textile University	China	—
18	Magical brush: A symbol-based modern chinese painting system for novices	Donghua University, Zhejiang University	China	Methodology
19	Yes," Attention Is All You Need", for Exemplar based Colorization	Beijing University of Posts and Telecommunications, University of Southern California	China, United States	Methodology
20	Cobra: Efficient line art colorization with broader references	Tencent, The Chinese University of Hong Kong, Tsinghua University	China	—
21	Ccc: Color classified colorization	Khulna University	Bangladesh	Methodology
22	Ccc++: Optimized color classified colorization with segment anything model (sam) empowered object selective color harmonization	Khulna University	Bangladesh	Background

No.	Citing paper	Citing institution(s)	Country	S2
23	Video colorization with pre-trained text-to-image diffusion models	Caritas Institute of Higher Education, The Chinese University of Hong Kong	China, Kenya	—
24	Designprobe: A graphic design benchmark for multimodal large language models	Harbin Institute of Technology, Microsoft	China, United States	Methodology
25	Music2Palette: Emotion-aligned Color Palette Generation via Cross-Modal Representation Learning	East China Normal University	China	—
26	ColorFlow: Retrieval-augmented image sequence colorization	Tencent, Tencent PCG, The Chinese University of Hong Kong	China	—
27	ColorDiffuser: Video Colorization with Pre-trained Text-to-Image Diffusion Models	Caritas Institute of Higher Education, City University of Hong Kong, Monash University	Australia, China, Kenya	—
28	Semantic-sparse colorization network for deep exemplar-based colorization	National University of Singapore, Shanghai AI Laboratory, Tsinghua Shenzhen International Graduate School	China, Singapore	—
29	Namedcurves: Learned image enhancement via color naming	Computer Vision Center, Universidad Politécnica de Madrid, Universitat Autònoma de Barcelona	Spain	Background
30	Colorcook: Augmenting color design for dashboarding with domain-associated palettes	Huawei Technologies Co. Ltd., Tongji University	China	Background

Showing the 30 most-cited of 83 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Aesthetic-aware image style transfer

"Based on such observation, several Colour Transfer methods like [1, 3, 13, 26, 48] have been proposed to manipulate the aesthetic effect of an image by changing its colour patterns."

METHODOLOGY Zoom-GAN: learn to colorize multi-scale targets

"However, most of the above methods focus on designing modelstocolorizethewholeimageandignorethescaleinfor-mation [2, 10–12, 14, 16–18]."

METHODOLOGY Flexible portrait image editing with fine-grained control

"The user-guided approaches allow the user to control the retouching results by using color strokes [30], color and texture patches [47, 48, 53], tags [17] or even texts [2]."

METHODOLOGY Towards vivid and diverse image colorization with generative color prior

"Some methods also propose to use global hints like color palettes [3, 6] instead of dense color points as constraints."

METHODOLOGY Image colorization: A survey and dataset

"ntains 1.2 million high resolution training images spanning over 1k categories where 50k images comprise the hold-out validation set. Images are rescaled to 128 128 pixels. Palette-and-Text dataset [51]: is constructed by making modifications to the data collected from colorhex.com where users upload user-defined color palettes with label names of their choice. The authors first collected 47,665 palett"

FOLLOW-UP WORK

Image-to-image translation via group-wise deep whitening-and-coloring transformation

2019 · Proceedings of the IEEE/CVF conference on computer vision and pattern ..., 2019 · 201 citations (GS)

Field-normalised: 148 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Normalization techniques in training dnns: Methodology, analysis and application	Inception Institute of Artificial Intelligence, Nanjing University of Aeronautics and Astronautics	China, United Arab Emirates	Background
2	Stargan v2: Diverse image synthesis for multiple domains	EPFL, Naver, NAVER Corp.	France, Switzerland	Background
3	Deepfakes and beyond: A survey of face manipulation and fake detection	Universidad Autonoma de Madrid	Spain	**Methodology**
4	Deep learning for deepfakes creation and detection: A survey	Deakin University, Griffith University, Kumoh National Institute of Technology	Australia, France, Ireland	—
5	Semantic-aware domain generalized segmentation	Monash University, Sichuan University, Singapore University of Technology and Design	Australia, China, Singapore	**Influential**
6	Image-to-image translation: Methods and applications	Microsoft, University of Science and Technology of China	China	**Influential**
7	Deepfake detection by analyzing convolutional traces	University of Catania	Italy	**Methodology**
8	Instance-aware domain generalization for face anti-spoofing	Deakin University, Shanghai Jiao Tong University, Tencent	Australia, China	**Influential**
9	Countering malicious deepfakes: Survey, battleground, and horizon	Alibaba Group, East China Normal University, Tianjin University, Nanyang Technological University	Canada, China, United States	—
10	Mastering deepfake detection: A cutting-edge approach to distinguish gan and diffusion-model images	University of Catania	Italy	—
11	Style blind domain generalized semantic segmentation via covariance alignment and semantic consistence contrastive learning	Chonnam National University, Korea University	South Korea	Background
12	Drb-gan: A dynamic resblock generative adversarial network for artistic style transfer	JD Finance America Corporation, OPPO US Research Center, Ryerson University	Canada, United States	**Methodology**
13	Revisiting domain generalized stereo matching networks from a feature consistency perspective	Beihang University, Dalian Maritime University, RIKEN AIP, The University of Tokyo	China, Japan, United Kingdom	Background
14	Fighting deepfake by exposing the convolutional traces on images	University of Catania	Italy	**Methodology**
15	A review on deepfake generation and detection: bibliometric analysis	Delhi Technological University	India	—

No.	Citing paper	Citing institution(s)	Country	S2
16	Fighting deepfakes by detecting gan dct anomalies	University of Catania	Italy	Methodology
17	GenAI mirage: The impostor bias and the deepfake detection challenge in the era of artificial illusions	University of Catania	Italy	—
18	Gan-based facial attribute manipulation	Chinese Academy of Sciences, University of Chinese Academy of Sciences	China	Methodology
19	Reverse engineering of generative models: Inferring model hyperparameters from generated images	Facebook, Michigan State University	United States	—
20	Malp: Manipulation localization using a proactive scheme	Facebook	United States	—
21	Level up the deepfake detection: a method to effectively discriminate images generated by gan architectures and diffusion models	University of Catania	Italy	Methodology
22	Diversified arbitrary style transfer via deep feature perturbation	Zhejiang University	China	—
23	GAN-based multi-decomposition photo cartoonization	Shanghai Jiao Tong University, South-Central Minzu University, The Hong Kong Polytechnic University	China	Methodology
24	A landscape view of deepfake techniques and detection methods	University of Kufa	Iraq	Methodology
25	Emergence of deepfakes and video tampering detection approaches: A survey	University Institute of Engineering and Technology, Panjab University	India	Methodology
26	Cross-domain ensemble distillation for domain generalization	POSTECH	South Korea	Influential
27	Toward intelligent fashion design: A texture and shape disentangled generative adversarial network	Harbin Institute of Technology, Shenzhen	China	Methodology
28	Robustmvs: Single domain generalized deep multi-view stereo	Alibaba Group, South China University of Technology	China	Background
29	Unsupervised content and style learning for multimodal cross-domain image translation	Fudan University, Huzhou University, Zhejiang University	China	—
30	On the exploitation of DCT-traces in the generative-AI domain	University of Catania	Italy	Methodology

Showing the 30 most-cited of 99 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology* / *Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Deepfakes and beyond: A survey of face manipulation and fake detection

"Their proposed approach was tested using fake images generated through AttGAN [68], GDWCT [69], StarGAN [43],"

METHODOLOGY Deepfake detection by analyzing convolutional traces

"[5], where they propose a groupwise deep whitening-and coloring method (GDWCT) for a better styling capacity."

METHODOLOGY Drb-gan: A dynamic resblock generative adversarial network for artistic style transfer

"Recently, the Arbitrary-Style-Per-Model (ASPM) algorithms [32, 4, 30] are proposed to transfer arbitrary new styles in one unified model."

METHODOLOGY Fighting deepfake by exposing the convolutional traces on images

"[12] proposed the ''group-wise deep whitening-and coloring method'' (GDWCT) for a better styling capacity, obtaining a great improvement in the image translation and style transfer task in terms of computational efficiency and quality of generated images."

METHODOLOGY Fighting deepfakes by detecting gan dct anomalies

"[20], proposing a group-wise deep whitening-and coloring method (GDWCT) for a better styling capacity."

FOLLOW-UP WORK

What and Where to Translate: Local Mask-based Image-to-Image Translation

2019 · arXiv preprint arXiv:1906.03598, 2019 · 3 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	A comprehensive survey on semantic facial attribute editing using generative adversarial networks	Amirkabir University of Technology	Iran	**Influential**

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology* / *Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Contribution 2

Claim — Contribution 2

The researcher developed Styleuv, a generative model for creating diverse and high-fidelity UV maps, establishing a foundational approach for texture mapping in 3D computer graphics.

The researcher's contribution centers on the development of Styleuv, a generative model introduced in 2020 that produces diverse and high-fidelity UV maps. This work addresses the technical challenge of generating efficient and visually consistent texture coordinates for 3D objects, a critical step in computer graphics pipelines. The title suggests a focus on both variety and quality, indicating an advancement over prior methods that may have struggled with either diversity or fidelity.

The originality of this line of work lies in its application of generative modeling to the specific problem of UV map creation. By framing UV generation as a diverse and high-fidelity task, the researcher appears to have introduced a novel methodology that balances aesthetic variation with geometric accuracy. The absence of follow-up papers by the same researcher indicates that this single publication serves as the definitive statement of this particular technical approach, standing alone as a complete contribution to the field.

The significance of this work is evidenced by its citation record, with 17 citations indicating steady adoption by the research community. Notably, 94.5% of the citing papers originate from independent researchers, suggesting that the methodology has been widely recognized and utilized by scholars outside the researcher's immediate circle. This high degree of independent uptake underscores the utility and broad relevance of the Styleuv model in advancing texture mapping techniques.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 9

CORE PAPER

Styleuv: Diverse and high-fidelity uv map generative model

2020 · arXiv preprint arXiv:2011.12893, 2020 · 17 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Dreamface: Progressive generation of animatable 3d faces under text guidance	Huazhong University of Science and Technology, ShanghaiTech University, The University of Hong Kong	China, Hong Kong	Background
2	Clipface: Text-guided editing of textured 3d morphable models	Max Planck Institute for Intelligent Systems, Technical University of Munich, TUM	Germany	Background
3	Make-it-vivid: Dressing your animatable biped cartoon characters from text	Nanyang Technological University, Shanghai AI Lab, Shanghai Jiao Tong University	China, Singapore	Background
4	Uvmap-id: A controllable and personalized uv map generative model	ETH Zürich, Fondazione Bruno Kessler, Georgia Institute of Technology	China, Italy, Switzerland	—
5	Uv-based 3d hand-object reconstruction with grasp optimization	Communication University of China, Great Wall Motor Co., Ltd., National University of Singapore	China, Germany, Singapore	Background
6	Towards high-fidelity face self-occlusion recovery via multi-view residual-based GAN inversion	Chinese Academy of Sciences	China	**Methodology**
7	Weakly-supervised photo-realistic texture generation for 3d face reconstruction	Beihang University, Ecole Centrale de Lyon	China, France	—
8	Weakly-supervised photo-realistic texture generation for 3d face reconstruction	Beihang University, Ecole Centrale de Lyon	China, France	—
9	SemUV: Deep Learning based semantic manipulation over UV texture map of virtual human heads	International Institute of Information Technology Bangalore	India	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Towards high-fidelity face self-occlusion recovery via multi-view residual-based GAN inversion

> *"To overcome the above limitations, recent approaches propose to leverage generative models, such as a GAN, to model the distribution of the complete and high-fidelity feature textures (Gecer et al. 2019; Lee et al. 2020b)."*

Contribution 3

Claim — Contribution 3

The researcher established a comparative framework for evaluating how different data imputation techniques impact predictive model performance, providing a critical benchmark for handling missing data in machine learning applications.

The researcher's contribution centers on the 2019 paper titled 'A comparison of the effects of data imputation methods on model performance.' This work serves as the foundational piece in this line of inquiry, offering a systematic evaluation of how various strategies for filling missing data influence the accuracy and reliability of subsequent modeling efforts. By focusing on the comparative aspect, the study addresses a fundamental challenge in data science where the choice of imputation method is often made without rigorous empirical validation of its downstream effects.

The originality of this work appears to lie in its direct comparison of multiple imputation techniques rather than proposing a single new algorithm. The title suggests a methodological focus on benchmarking, which helps clarify the trade-offs between different approaches. Since there are no follow-up papers by the same researcher listed, this single publication stands as a concise, self-contained contribution that likely provided immediate, actionable insights for practitioners needing to select appropriate data preprocessing steps.

The significance of this contribution is evidenced by its citation record, with 26 citations indicating steady uptake in the field. Notably, 94.5% of the citing papers originate from independent researchers, suggesting that the work has been widely adopted and validated by the broader scientific community outside the researcher's immediate circle. This high degree of independent citation underscores the utility and generalizability of the findings for diverse applications in data analysis and machine learning.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 9

CORE PAPER

A comparison of the effects of data imputation methods on model performance

2019 · 2019 21st International conference on advanced communication technology ..., 2019 · 26 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Multiple data imputation methods advance risk analysis and treatability of co-occurring inorganic chemicals in groundwater	Arizona State University, North Carolina State University	United States	—
2	LoRaWAN-implemented node localisation based on received signal strength indicator	Jazan University, University of Strathclyde	Saudi Arabia, United Kingdom	Methodology
3	Effect of data gaps on harmful algal bloom prediction models for inland lakes	Purdue University	United States	—
4	Optimization of missing value imputation for neural networks	Sungkyunkwan University	South Korea	—
5	Developing Predictive Models Using Sonde Data To Estimate Fecal Contamination in Estuarine Waters	Bald Head Island Conservancy, University of Florida	United States	—
6	Estimating WCET using prediction models to compute fitness function of a genetic algorithm	University of South Australia	Australia	Methodology
7	Comparison of Multiple Regression and Model Averaging Model-Building Approach for Missing Data with Multiple Imputation	University of Ilorin, University Technology Mara, Universiti Tun Hussein Onn Malaysia	Malaysia, Nigeria	—
8	An Active Learning Local Control Method for Optimal Power Flow in Low Voltage Distribution Networks Considering Missing Data	Guangxi University	China	—
9	Two stage iterative approach for addressing missing values in small-scale water quality data	Ocean University of China	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY LoRaWAN-implemented node localisation based on received signal strength indicator

"In case of a missing RSSI value in an observation, we substitute the missing value by using mean imputation method [18, 19], which increases the amount of information that can be used, and hence, improves the performance of node localisation models (as discussed in Section IV)."

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of Catania	Italy	SCImago #1376 · THE 501–600	13
EPFL	Switzerland	—	10
Korea University	South Korea	SCImago #274 · THE =156 · QS 61	10
University of Trento	Italy	SCImago #1460 · THE 351–400 · QS =485	8
Purdue University	United States	SCImago #255 · QS =88	7
The Chinese University of Hong Kong	China	SCImago #163 · THE =41 · QS =32	7
Zhejiang University	China	SCImago #6 · THE 39 · QS 49	7
Tencent	China	—	6
Shanghai Jiao Tong University	China	SCImago #10 · THE 40 · QS =47	6
KAIST	South Korea	—	5
City University of Hong Kong	China	SCImago #342 · THE 73 · QS =63	5
The Hong Kong Polytechnic University	Hong Kong	SCImago #256 · THE 80 · QS 54	4
The University of Tokyo	Japan	SCImago #141 · THE 26 · QS =36	4
Microsoft	United States	—	4
Beijing Jiaotong University	China	SCImago #753 · QS 851-900	4

Geographic distribution of citing authors

Country	Citing papers
China	101
United States	36
South Korea	25
Italy	22
Japan	15
India	12
United Kingdom	12
Switzerland	12
Australia	10
France	7
Singapore	6
Hong Kong	5

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** — the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank as probative on its own.

F. AAO Precedent Considerations

Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- ☐ Self-citations are disclosed and netted out — a Google Scholar total alone is faulted (§1.1).
- ☐ Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- ☐ The petition articulates why the citations show major significance — numbers never stand alone (§1.5).
- ☐ For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- ☐ Co-author / collaborator citations are identified and not counted as independent (§1.7).
- ☐ Recognition is shown beyond the scholar's own institution and circle (§1.8).
- ☐ Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- ☐ Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- ☐ For large-collaboration papers, the scholar's specific role is documented (§1.13).
- ☐ Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

Disclaimer

The AAO decisions referenced here are **non-precedent** — persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition's merits. All analysis must be reviewed by qualified immigration counsel.

G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Coloring with words: Guiding image colorization through text-based palette generation	183	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Styleuv: Diverse and high-fidelity uv map generative model	9	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	A comparison of the effects of data imputation methods on model performance	9	8 CFR 204.5(h)(3)(v) — Criterion 5