

Reducing Bias in Algorithms to Improve Demand for Your Services

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Marketing Science Institute

Webinar Series

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What We Will Talk About Today

- What is Algorithmic Bias?
- High Profile Examples of Algorithmic Bias
- How Algorithmic Discrimination in Service Can Impact Customer Demand
- Two Concrete Examples:
 - Loss Prevention in Retailing: Discrimination in Detecting Shoplifters
 - Small Business Loans
- What Can Organizations Do to Reduce Algorithmic Bias to Improve Customer Demand
- Takeaways About Algorithms

What is Algorithmic Bias?

- Systematically unfair algorithmic outcomes which arbitrarily advantages one group of constituents over another (Friedman and Nissenbaum 1996, Barocas and Selbst 2016, O'Neil 2016).
- Sources of algorithmic bias:
 - Biased or unrepresentative training data (Sweeney 2013; O'Neil 2016)
 - Algorithm design (Mullainathan and Obermeyer 2017; Obermeyer et. al. 2019)
- Algorithmic bias examples with consumer demand implications:
 - Face recognition technology (Buolamwini and Gebru 2018)
 - Services (Ukanwa and Rust 2020)
 - Medical care (Mullainathan and Obermeyer 2017)
 - Online ads (Lambrecht and Tucker 2019)
 - Online real estate services (Fu, Huang, Vir Singh, Srinivasan 2020)
- Algorithmic bias is often unintentional. All the more reason it needs urgent research.

Algorithmic Bias Has Media's Attention

DesignNews

Algorithms can drive inequality. Just look at Britain's school exam chaos

By Zamira Rahim, CNN

Updated 12:01 AM ET, Sun August 23, 2020

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Why it's totally unsurprising that Amazon's recruitment AI was biased against women

The Apple Card Is the Most High-Profile Case of AI Bias Yet

Apple Card users have alleged that its credit decision algorithm discriminates against women.

Wrongfully Accused by an Algorithm



There Are Policy Implications Too

4,666 views | Nov 17, 2019, 08:30am EST

Forbes

Will Machine Learning Algorithms Erase The Progress Of The Fair Housing Act?

TOM SIMONITE

BUSINESS 02.07.2020 07:00 AM

WIRED

Europe Limits Government by Algorithm. The US, Not So Much

A Dutch court halted a program to identify people more likely to commit benefits fraud. Critics said it discriminated against immigrants and low-income residents.

What Are Possible Downstream Effects of Algorithmic Bias on Consumer Demand?

Algorithmic Discrimination in Service Can Affect Demand

(Ukanwa and Rust 2020)

- Algorithmic discrimination in service can be **profitable**—in the short run.
- Algorithmic discrimination in service can be **unprofitable** in the long run due to word-of-mouth reducing consumer demand.
- Paradoxically, **word-of-mouth does not have to be negative.**
- Ignoring group information or proxies, higher variation in consumer data, and lower measurement error **can reduce algorithmic discrimination in service.**

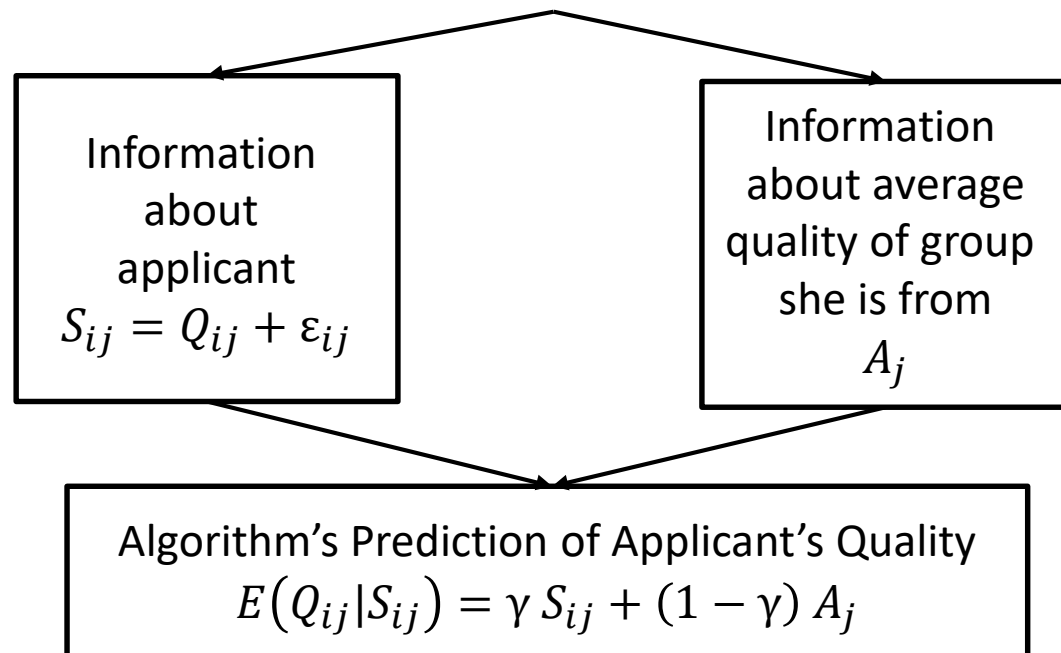
Example: Bank Loan Decision

Loan Applicant i from group $j \in \{L, H\}$



Information about Applicant i	
S_{ij}	A_j
Debt load	
Job history	
Bill payment record	
Income tax record	

Bank's Loan Program



Algorithmic Discrimination in Service Is...

$$\text{Quality } (Q_{ij}) = 50$$

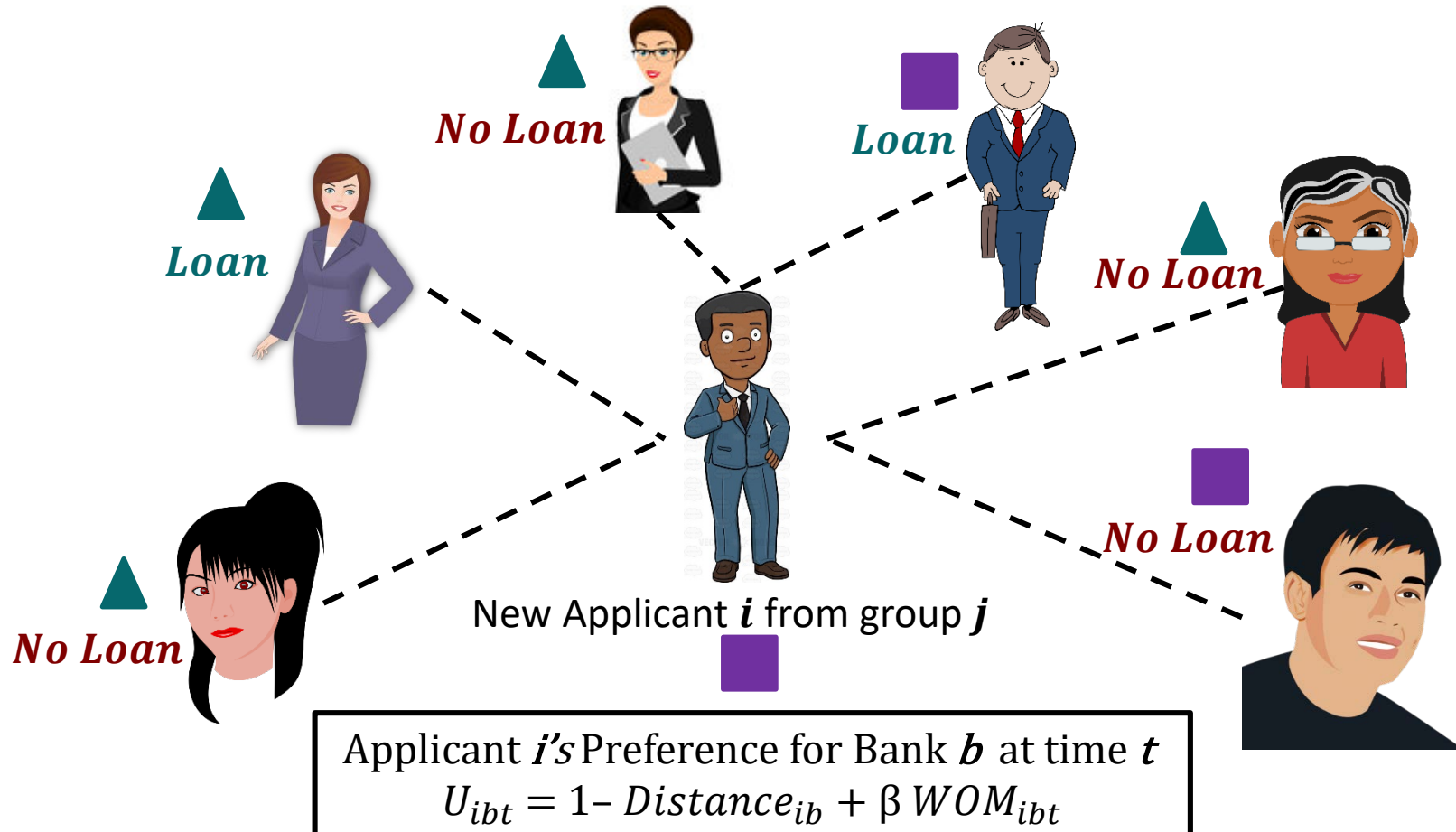
$$\text{Score } (S_{ij}) = 65$$



Group j	 L	 H
Group j's Average Quality, A_j	40	60
Applicant i's Predicted Quality, $E(Q_{ij} S_{ij})$	60	64
Bank's Minimum Score Criterion, S_j^{min}	68	63
Loan Decision	No Loan	Loan

$$\text{Discrimination } (D_i) = \text{Difference in Predicted Quality} = 4$$

Demand Effects From The Service Decision



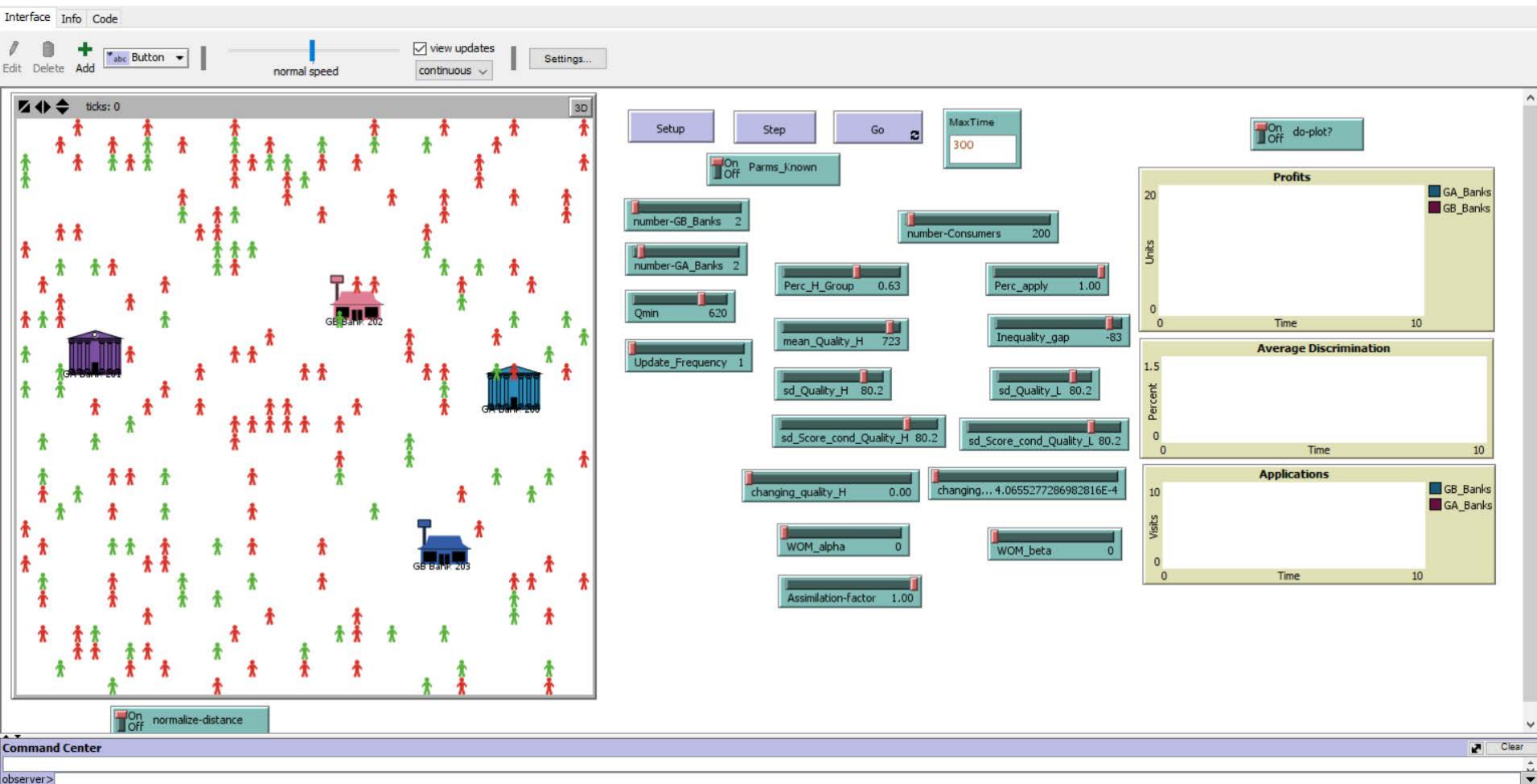
WOM_{ibt} = Word-of-mouth measure based on proportion of Applicant i 's network that received a loan from Bank b .

Distance_{ib} = Distance between Applicant i and Bank b

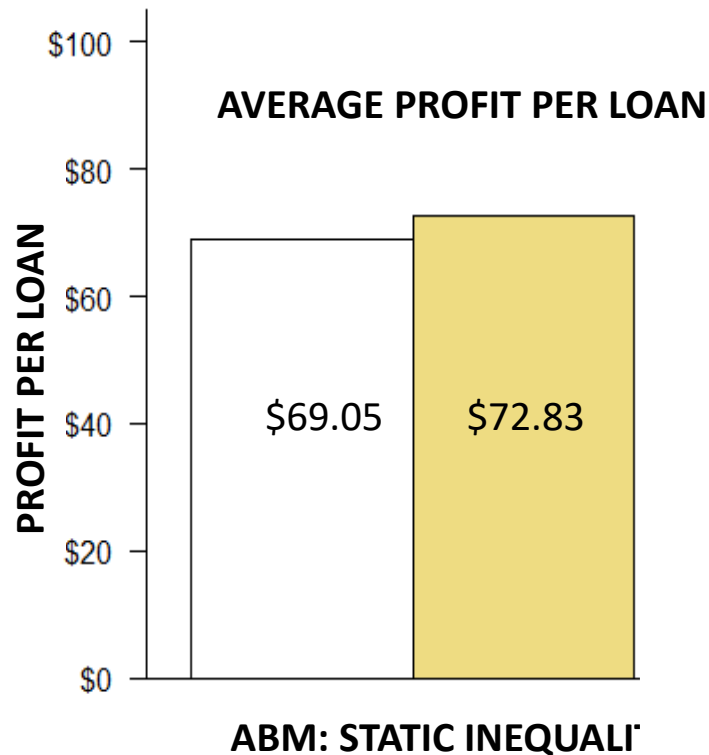
Which Service Approach Is Optimal?

	Group-Aware Service	Group-Blind Service
Minimum Service Criterion, S_j^{min}	One per group	One for everyone
Use of group information in prediction about applicant	Uses	Ignores
Service Decision: When to serve consumer?	If consumer surpasses criterion for group	If consumer surpasses criterion for everyone

Agent-Based Model of Bank Lending



Discrimination Can Be Profitable in the Short-Run ...



 GROUP-BLIND
 GROUP-AWARE

p-value	t-stat
< 0.001	16.496

...But Unprofitable in the Long-Run



 GROUP-BLIND
 GROUP-AWARE

p-value	t-stat
< 0.001	9.752

Why Profit Reverses In Long Run?

- Word-of-mouth facilitates consumer social learning over time.
- Regardless of whether word-of-mouth is positive/neutral/negative, it informs consumers about probability of receiving service.
- L-group has tougher service criterion at Group-Aware firms. Over time, L-group learns they are more likely to receive service at Group-Blind firms.
- H-group has easier time receiving service. Given sufficient H-group interest, combined demand is greater at Group-Blind firms.

An Example:

Loss Prevention in Retailing:
Discrimination in Detecting
Shoplifters

USING AI SYSTEMS TO DETECT SHOPLIFTERS

If the system spots behavior it deems suspicious, it alerts store personnel via an app. Then it's up to staffers to take action.

Japanese communications giant NTT East made headlines last summer with AI Guardsman, a camera that uses technology similar to Vaakeye's to analyze shoppers' body language for signs of possible theft. AI Guardsman's developers said the camera cut shoplifting losses by 40 percent.

Jerome Williams, a professor and senior administrator at Rutgers University's Newark campus, has written extensively on race and retail environments. He said that unless training data is carefully controlled, a theft-detection algorithm might wind up unfairly targeting people of color, who are routinely stopped on suspicion of shoplifting more often than white shoppers.

“The people who get caught for shoplifting is not an indication of who's shoplifting,” Williams said. “It's a function of who's being watched and who's being caught, and that's based on discriminatory practices.”

Williams said black shoppers who felt they had been unfairly scrutinized in stores previously might be more likely to appear nervous in subsequent shopping experiences — a potentially risky proposition if a system misidentifies anxiety as suspicious behavior. Still, he praised Vaakeye's focus on body language. “I think it's a good approach,” he said. “You shouldn't racially profile. You should behaviorally profile.”

3 Blacks Win \$1 Million in Bauer Store Incident

A Federal District Court jury in nearby Greenbelt, Md., ordered the Eddie Bauer company today to pay \$1 million in damages over an incident in which three young black men were detained on suspicion of shoplifting.

One youth, who was forced to remove his shirt in the incident two years ago, Alonzo Jackson, received the bulk of the award: \$850,000 in compensatory and punitive damages. His friends, Rasheed Plummer and Marco Cunningham, were awarded \$75,000 each. All live in the Maryland suburbs of the capital. "We're pleased," Donald Temple, a Washington lawyer for Mr. Jackson and Mr. Plummer, said today. "We've educated the public, and the country will benefit as a result."

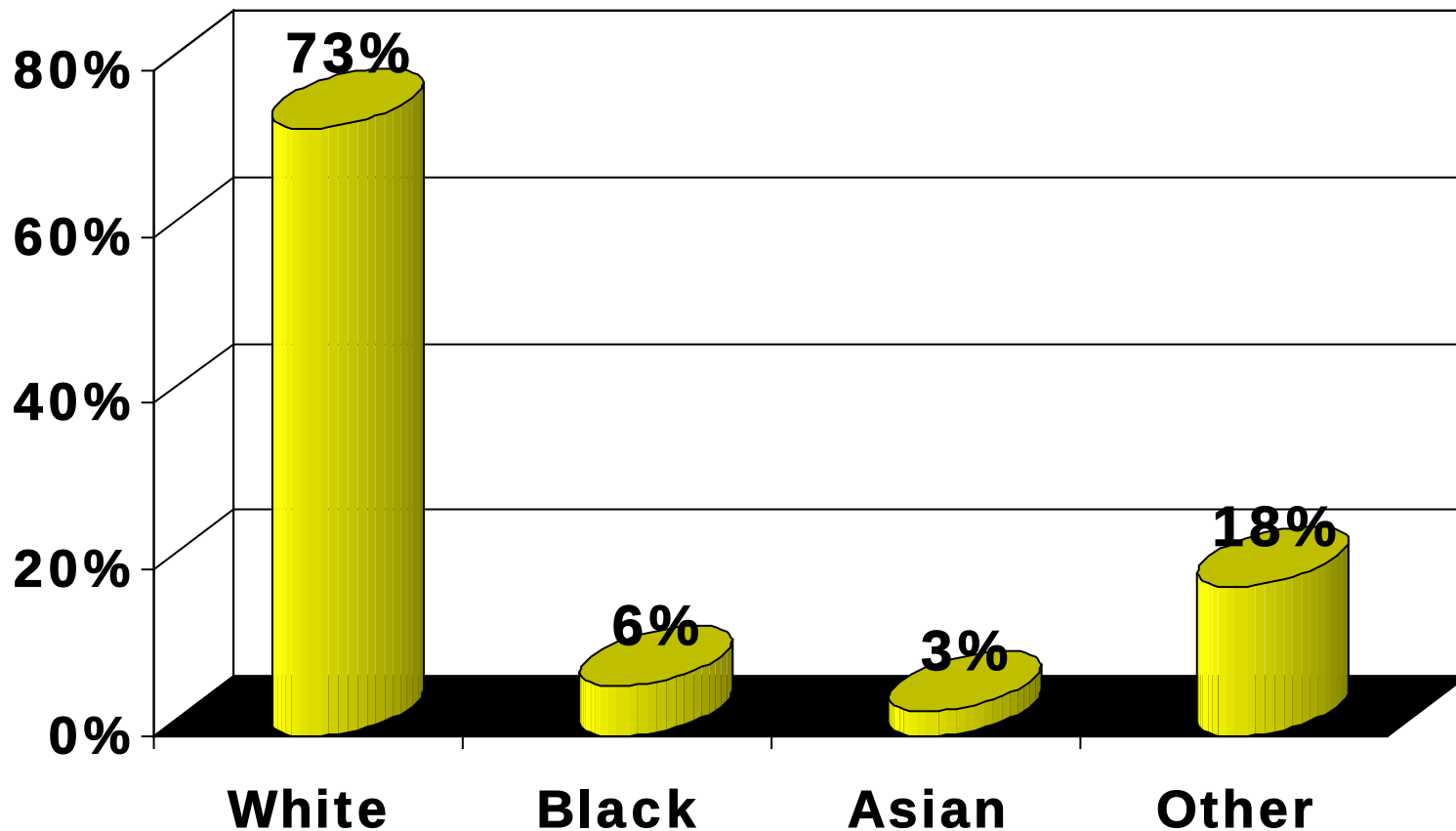
The case attracted widespread attention as a civil rights issue, and prompted a public apology by Eddie Bauer, a giant clothing retailer based in Redmond, Wash. Mr. Jackson, now 18, Mr. Plummer, 19, and Mr. Cunningham, who is now 20, were shopping at a Bauer outlet store in Fort Washington, Md., a largely black and middle-class community, on Oct. 20, 1995, when they were confronted by two uniformed Prince Georges County police officers who were moonlighting as security guards.

Testimony revealed that **one of the officers, Robert Sheehan, had become suspicious after noticing that Mr. Jackson's shirt looked new.** In fact, it was: Mr. Jackson had bought it at the store the previous day.

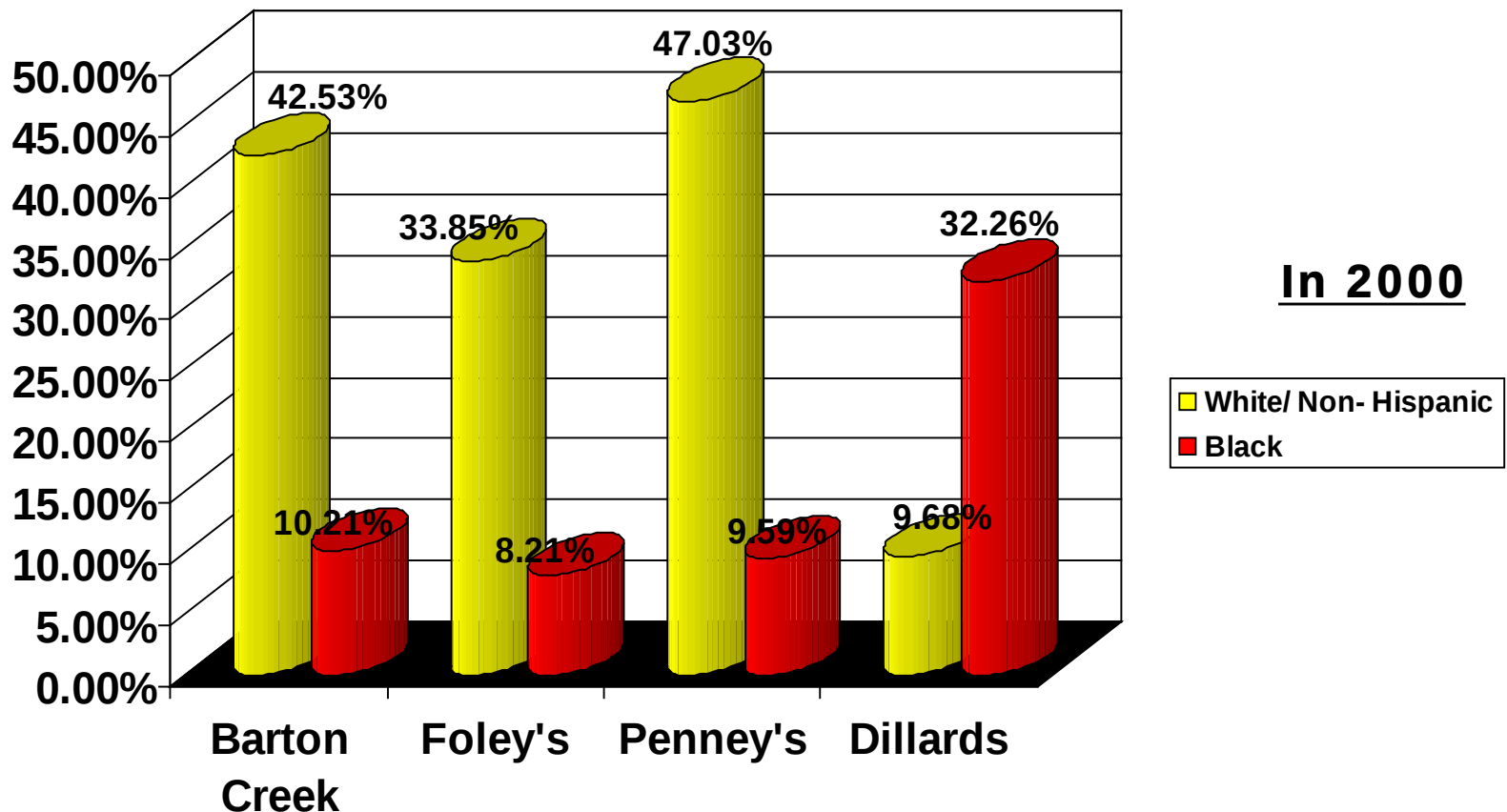
Mr. Jackson could not immediately produce a receipt, so the shirt was confiscated, despite a cashier's recollection of selling a shirt to him the day before, according to testimony.



Barton Creek Square Mall Demographics



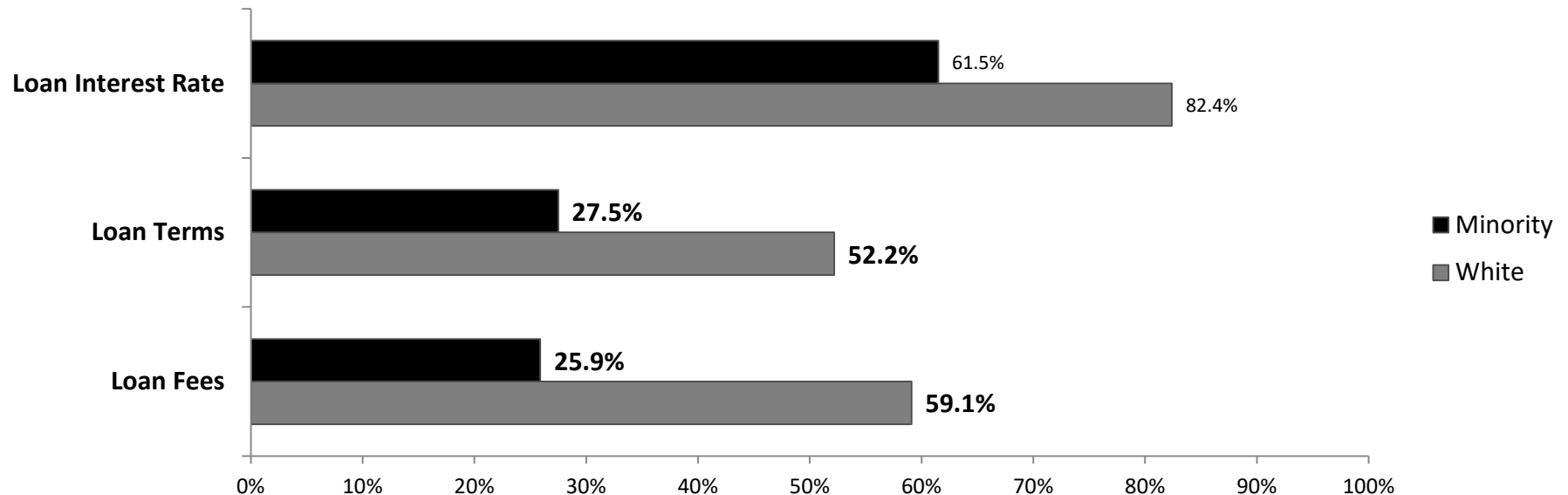
Shoplifting / Theft Data and Criminal Trespass Warnings



Another Example:

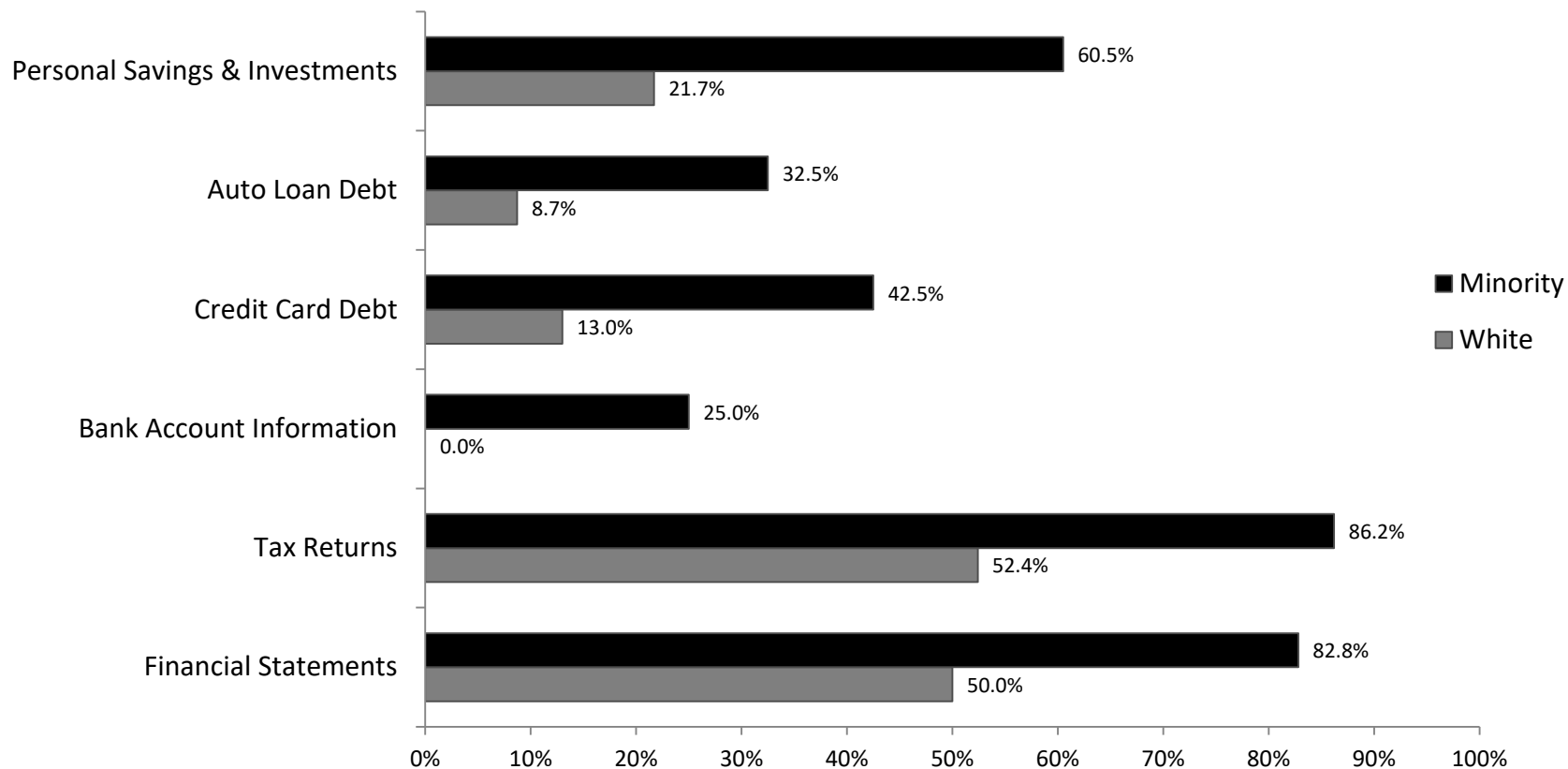
Bank Lending for Small Businesses

Results: *Information Provided*



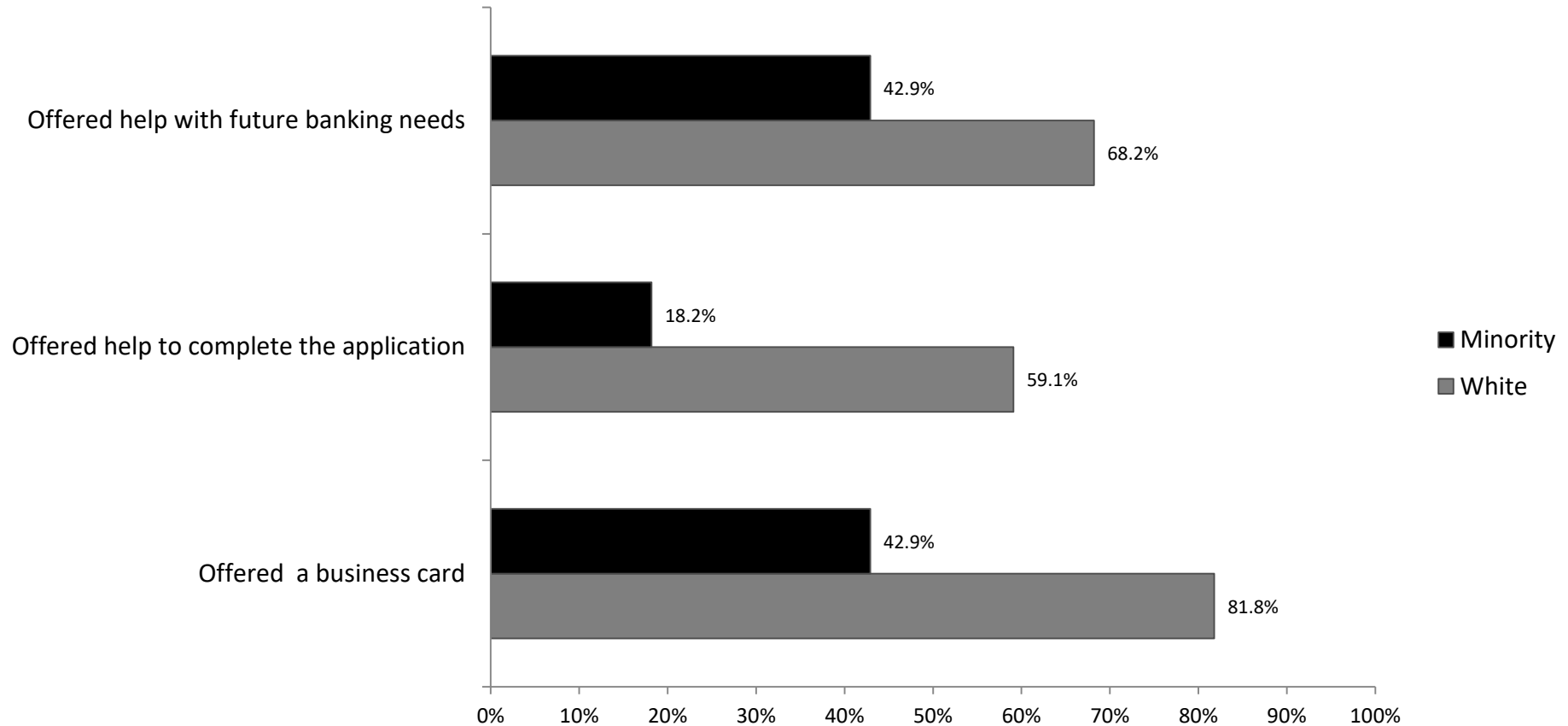
*Bolded values represent significant chi-square differences ($p < .05$)

Results: *Information Requested*



*All significant chi-square differences ($p < .05$)

Results: *Encouragement and Assistance*



*All significant chi-square differences ($p < .05$)

Key Lessons Learned From Marketplace Examples in Reducing Algorithmic Bias To Improve Demand

- Retailing
 - Using algorithms for detecting shoplifting has potential benefits
 - Caution: Be mindful that algorithms that build on using behaviors of shoppers may lead to wrong conclusions
- Banking
 - Using algorithms for identifying loan applicants likely to be most profitable for banks has potential benefits.
 - Caution: Be mindful that certain indicators, such as geography, may lead to racial bias (car insurance rates, assigning franchisee to most profitable locations, etc.

How Organizations Can Reduce Algorithmic Bias To Improve Demand

- Algorithm Design
 - Consider including word-of-mouth considerations in algorithm design (Ukanwa and Rust 2020).
 - Consider ignoring group information and group proxies in design (Ukanwa and Rust 2020).
 - Apply Fairness, Accountability, Transparency, and Ethics (FATE) standards to design/testing/auditing of algorithms (Lee, Resnick, and Barton 2019).
- Training Data
 - Use high variation in the data. (Buolamwini and Gebru 2018, Ukanwa and Rust 2020).
 - Reduce measurement error by investing in measurement tools (Ukanwa and Rust 2020).
- Diversify the builders of algorithms and datasets (Williams, Lopez, Shafto, Lee 2019).

Algorithms Have Many Potential Issues ...

- They can amplify and propagate existing societal biases
- They can be black boxes, obscuring the decision-making process.
- Their complexity could potential make it more difficult to challenge decisions.
- Automation bias create beliefs that “the machine is right”.

... But, Algorithms Present an Immense Opportunity to Improve Lives

- They enable evidence-based decision-making.
- They are faster and more efficient at processing “big data”
- They can provide greater transparency behind decisions.
- Algorithms can always be examined, improved, and fixed.
- With the right design, data, and policies in place, algorithms can actually lead to fairer outcomes than we have today.

Where You Can Find Us To Learn More ...

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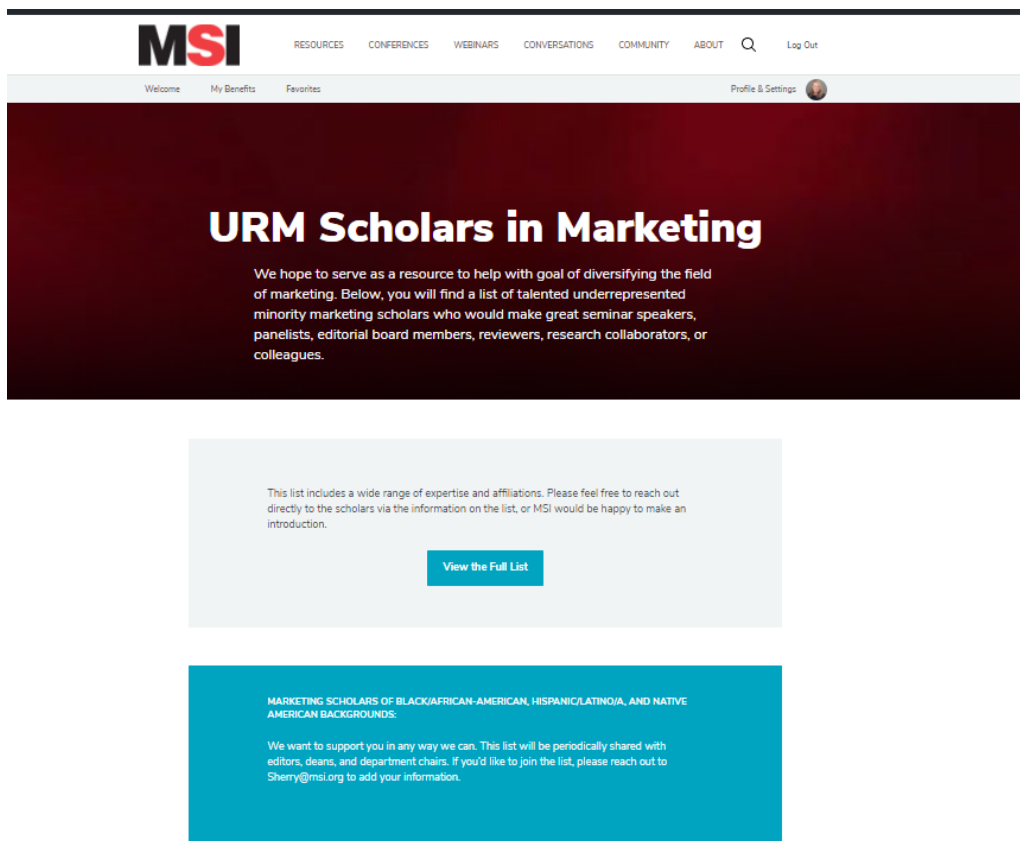
LinkedIn: www.linkedin.com/in/erick-m-mas-roman-4a1a5419/
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MSI Sponsorship of URM Scholars List

- **The Underrepresented Minority (URM) Scholars in Marketing list is a list of active marketing scholars in academia who also happen to self-identify as underrepresented minorities (Black/African-American, Latino/Hispanic, and Native American).**
- **MSI Sponsorship**
 - **Goal: to support diversification of the Marketing Academy**
 - **MSI sponsorship includes hosting and promotion**

MSI Sponsorship of URM Scholars List

www.msi.org/urm/



The screenshot shows the MSI URM Scholars in Marketing website. The header features the MSI logo and navigation links: RESOURCES, CONFERENCES, WEBINARS, CONVERSATIONS, COMMUNITY, ABOUT, a search icon, and Log Out. Below the header is a user profile bar with links for Welcome, My Benefits, Favorites, and Profile & Settings. The main content area has a dark red background with the title "URM Scholars in Marketing" in white. Below the title is a paragraph explaining the purpose of the list. A light blue box contains a paragraph about the list's scope and a "View the Full List" button. A teal box contains the title "MARKETING SCHOLARS OF BLACK/AFRICAN-AMERICAN, HISPANIC/LATINO/IA, AND NATIVE AMERICAN BACKGROUNDS:" followed by a paragraph about support and contact information.

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URM Scholars in Marketing

We hope to serve as a resource to help with goal of diversifying the field of marketing. Below, you will find a list of talented underrepresented minority marketing scholars who would make great seminar speakers, panelists, editorial board members, reviewers, research collaborators, or colleagues.

This list includes a wide range of expertise and affiliations. Please feel free to reach out directly to the scholars via the information on the list, or MSI would be happy to make an introduction.

[View the Full List](#)

MARKETING SCHOLARS OF BLACK/AFRICAN-AMERICAN, HISPANIC/LATINO/IA, AND NATIVE AMERICAN BACKGROUNDS:

We want to support you in any way we can. This list will be periodically shared with editors, deans, and department chairs. If you'd like to join the list, please reach out to Sherry@msi.org to add your information.

A special thank you to the marketing scholars who started this initiative: Aaron Barnes, Wendy De La Rosa, Aziza Jones, Erick Mas, Broderick Turner, Esther Uduehi, Kalinda Ukanwa, and Jared Watson.

MSI Sponsorship of URM Scholars List

URM Contacts

Name	Email	Current Affiliation	Current Title	Areas of Expertise (Substantive)	Areas of Expertise (Methodology)	Website	Area of Marketing	PhD Granting Institution	PhD Year	Classification Current Affiliation
Maria Albrecht	mariaalbrecht@alamos.com	University of Texas at Dallas	Marketing Lecturer	Strategic Models; Branding Architecture; Multicultural Advertising; Digital Marketing	Qualitative; Mixed methods; Interpretive sociology	Website	Consumer Behavior; Multicultural Marketing; Strategy	SMC University	2020	Research
Sidney Anderson	sidney.anderson@txstate.edu	Texas State University	Assistant Professor	Healthcare; service operations management	Structural equations modeling; big data	Website	Strategy	Florida State University	2018	Research
Demetra Andrews	demetra@ju.edu	Kelley School of Business (IUPUI)	Clinical Associate Professor of Marketing	Choice Confidence; Self-efficacy; Readiness/Willingness-to-Act	Experiments	Website	Consumer Behavior	University of Houston	2009	Balanced
Robert Aker	robertaker@gmail.com	Yale University	Assistant Professor of Marketing	Brand communities; consumption culture	Qualitative	Website	Consumer Behavior; Consumer Culture	University of Illinois at Urbana-Champaign	2000	Balanced

Questions or Comments?

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