**Survey Results for AI Proficiency and Impact in Black Communities**

Marcus Taylor

University of North Texas

LTEC 6511: Analysis of Research in Learning Technologies

Dr. Gerald Knezek

November 24, 2024

**Abstract**

Artificial intelligence (AI) is transforming societies, yet its rapid development may exacerbate existing inequalities, particularly in Black communities. This report presents findings from the survey Artificial Intelligence and the Digital Divide: A Survey on AI Proficiency and Impact in Black Communities, designed to explore perceptions, experiences, and challenges faced by Black Americans concerning AI. The survey investigates access to AI tools, barriers to AI education, and AI's role in social justice, economic gaps, and job opportunities.

**Introduction**

The rapid advancement of artificial intelligence (AI) technologies presents both opportunities and challenges for historically marginalized communities. As AI becomes increasingly integrated into daily life, understanding its impact on Black communities becomes crucial for addressing potential disparities and ensuring equitable access to these transformative technologies.

Our investigation builds upon the Technology Proficiency Self-Assessment for 21st Century Learning (TPSA C21), adapting it to address culturally specific concerns within Black communities. Through this lens, we examine three key areas: access to AI tools and education, societal impacts, and systemic

barriers.

**Methodology**

**Participant Recruitment and Sample**

We distributed our survey through established networks within historically Black fraternities (Kappa Alpha Psi), sororities (Alpha Kappa Alpha, Delta Sigma Theta), and professional circles. After data cleaning, our final sample comprised 90 respondents representing diverse demographic backgrounds.

**Survey Instrument**

Artificial Intelligence and the Digital Divide: A Survey on AI Proficiency and Impact in Black Communities was adapted from the Technology Proficiency Self-Assessment for 21st Century Learning (TPSA C21 instrument. The instrument explores Black Americans’ perception of AI as it relates to the digital divide with questions on 10 Likert-scale items (1 = Strongly Disagree, 5 = Strongly Agree) focused on AI-related perceptions and demographic questions on age, education, race, and gender. Topics included:

* Access to AI tools and education.
* Societal impacts, including job opportunities and social justice.
* Barriers and biases in AI systems.
* Representation of Black voices in AI policymaking.

The reliability analysis conducted on the scale measuring access to digital resources and barriers shows a Cronbach’s Alpha of 0.834. According to DeVellis (2003), a Cronbach's Alpha value between 0.7 and 0.8 is generally considered acceptable, and a value above 0.8 is good, indicating high internal consistency. Therefore, the alpha value of 0.834 suggests that the items used in this analysis reliably measure the same underlying construct, and the scale can be considered robust for further research or applications. Additionally, the scale exhibits good internal consistency, as removing any individual item does not significantly improve or reduce reliability.

# **Descriptives**

Initial analysis of response patterns revealed interesting trends across the survey items. Mean scores varied considerably, with some items showing strong agreement while others reflected more neutral or concerned perspectives.

**Table 3: Descriptive Statistics for Survey Items**

**A table with numbers and letters

Description automatically generated**

The highest mean score (4.11) was observed for items related to AI policies, while social justice concerns showed the lowest mean score (3.17), suggesting a complex relationship between policy expectations and perceived social outcomes. This table provides the descriptive statistics for the 10 survey items related to digital access and barriers, labeled Q6 through Q15. Let’s break down each component:

1. **N (Sample Size):**

* This shows the number of respondents who answered each question.
* For most items (Q6 through Q15), there are 93 respondents, except for Q9SocialJustice, which has 92 respondents, meaning one response is missing for that item.

2. **Missing:**

* Indicates how many responses are missing for each item.
* Only Q9SocialJustice has 1 missing value, while the rest of the items have no missing responses.

3. **Mean:**

* The mean is the average score for each question.
* For example, Q6AccessTools has a mean score of 3.81, meaning on average, respondents rated their access to tools close to 4 (likely on a 5-point Likert scale).
* Q12Policies has the highest mean score of 4.11, indicating stronger agreement with the policies related to access.

4. **Median:**

* The median is the middle value when the data is sorted in ascending order.
* A median of 4 for most items (Q6, Q7, Q8, Q10, etc.) suggests that most respondents chose values around 4 (likely indicating agreement or access in the context of the questions).

5. **Standard Deviation (SD):**

* Standard deviation measures the spread or variability of the responses around the mean.
* For example, Q8WidenGaps has a SD of 1.19, meaning there is moderate variability in how respondents perceive the widening of gaps.
* Lower SD values, such as 0.995 for Q13WorseAccess, suggest that most respondents gave similar answers to that item.

6. **Minimum and Maximum:**

* These values show the range of responses.
* All items have a minimum of 1 and a maximum of 5, indicating the use of a Likert scale ranging from 1 (e.g., strongly disagree) to 5 (e.g., strongly agree).

**Summary of Findings:**

* Mean scores around 3.5 to 4 indicate that most respondents somewhat agree or are moderately positive about access to tools, learning platforms, and perceived barriers.
* Variability (as shown by SD) is relatively consistent across items, with most SDs around 1, meaning responses are somewhat spread out but not too extreme.
* Q12Policies had the highest mean score (4.11), suggesting that respondents are most positive about the policies related to digital access.

**The Exclusion of Q1 thru Q5**

We didn't use Q1 through Q5 in our my Cronbach's Alpha analysis because these questions are likely focused on demographic information, which isn't relevant to measuring the specific construct we I were interested in, such as access to digital tools and barriers. For example, Q2 asks about the respondents' age, and Q3 likely covers their education level. These kinds of variables don't reflect attitudes, behaviors, or perceptions in the same way the items from Q6 to Q15 do.

Cronbach’s Alpha is designed to assess the internal consistency of items that are intended to measure the same underlying concept. Including demographic information, like age or gender, wouldn't make sense here because those variables don't contribute to understanding respondents’ perceptions of digital access or barriers.

Essentially, Q1 through Q5 serve a different purpose, like helping describe our sample, but they don’t belong in an analysis of internal consistency for the constructs we wanted to measure with items like Q6 to Q15. That’s why we excluded them from the reliability analysis.

**Scale Reliability**

Our reliability analysis demonstrated strong internal consistency across survey items.

**Table 4: Reliability Analysis Results**

A white text with black text

Description automatically generated

The Cronbach's Alpha value of 0.834 indicates excellent reliability, with item analysis showing consistent strength across all components. This robust internal consistency suggests our instrument effectively captured the intended constructs.

**Factor Analysis**

This report presents the results of an exploratory factor analysis (EFA) conducted on survey data related to AI and the digital divide. The analysis aims to identify underlying constructs in the survey responses and validate the measurement scales used.

**Table 5: Factor Analysis Results**

**A screenshot of a graph

Description automatically generated**

The analysis yielded two distinct factors:

**Factor 1: AI Access and Benefits** (Primary loadings > 0.5)

* Q15Benefits (0.607)
* Q10Training (0.722)
* Q9SocialJustice (0.554)
* Q8WidenGaps (0.512)
* Q7AccessLearning (0.674)
* Q6AccessTools (0.720)
* Q12Policies (0.564)

**Factor 2: Barriers and Concerns** (Primary loadings > 0.6)

* Q14Barriers (0.660)
* Q13WorseAccess (0.792)
* Q11Biases (0.703)

**Key Observations:**

1. **Clean Factor Structure**:
   * Most items load clearly on one factor
   * Q12Policies shows some cross-loading (0.564 on Factor 1, 0.445 on Factor 2)
2. **Uniqueness Values**:
   * Range from 0.367 (Q13WorseAccess) to 0.656 (Q9SocialJustice)
   * Lower uniqueness values indicate better factor representation
3. **Factor Interpretation**:
   * Factor 1 represents positive aspects and access to AI
   * Factor 2 captures concerns and potential negative impacts

The analysis identified two primary factors:

1. AI Access and Benefits
2. Barriers and Concerns

A screenshot of a statistics

Description automatically generated

**Two-Factor Solution**: These two factors combined account for **47.3%** of the total variance in the dataset. While this is less than 50%, it is still a reasonable amount of explained variance for a two-factor model, providing a clear structure for understanding how participants conceptualize AI's impact.

**Figure 1: Scree Plot of Factor Analysis**

**A graph with dots and numbers

Description automatically generated**

The scree plot provides crucial information for determining the optimal number of factors to retain:

1. **Visual Analysis**:
   * A clear "elbow" is visible at component 2
   * The first component shows the highest eigenvalue (approximately 3.2)
   * The second component has an eigenvalue just above 1.0
   * Components after 2 show eigenvalues below 1.0 with a gradual leveling off
2. **Kaiser Criterion (Eigenvalue > 1)**:
   * Only two components have eigenvalues greater than 1.0
   * This suggests a two-factor solution would be most appropriate
3. **Variance Explanation**:
   * The steep drop between components 1 and 2 indicates the first component explains a large portion of the variance
   * The second component adds a meaningful but smaller additional explanation
   * Components 3-10 contribute minimal additional explanation

The two-factor solution provides a reasonable explanation of the variance in the data, with Factor 1 (AI Access and Benefits) being the strongest contributor.

**Gender Analysis**

Our examination of gender differences revealed interesting patterns in how male and female respondents perceive AI's impact.

**Table 6: Gender Comparison Results**

**One-Way Nova**

A screenshot of a computer

Description automatically generated

Welch’s ANOVA showed no significant gender differences (F(1, 89.1) = 0.00171, p = 0.967), suggesting that concerns about AI access and impact transcend gender lines within the Black community.

**Correlation Analysis**

We identified several significant relationships between key survey components.

**Table 7: Correlation Matrix**

A screenshot of a computer

Description automatically generated

Notable correlations included:

* Access and Impact: r = 0.503, p < .001
* Barriers and Impact: r = 0.607, p < .001
* Access and Barriers: r = 0.302, p = .003

These relationships suggest interconnected perceptions of access, barriers, and societal impact.

**Discussion**

**Integration of Findings**

Our results paint a complex picture of how Black communities perceive and interact with AI technologies. The strong correlation between barriers and societal impact (r = 0.607) suggests that respondents who identify more systemic barriers also tend to perceive stronger implications for social equity.

**Table 8: Summary of Key Findings**

|  |  |  |  |
| --- | --- | --- | --- |
| Finding Category | Key Result | Statistical Support | Implications |
| Scale Reliability | High internal consistency | Cronbach's Î± = 0.834 | Survey instrument is reliable for measuring AI perceptions |
| Factor Structure | Two distinct factors emerged | 47.3% variance explained | AI perceptions split between access/benefits and barriers/concerns |
| Gender Differences | No significant differences | F(1, 89.1) = 0.00171, p = 0.967 | AI concerns transcend gender in Black communities |
| Access-Impact | Strong positive correlation | r = 0.503, p < .001 | Access to AI tools closely tied to perceived societal impact |
| Barriers-Impact | Strongest correlation observed | r = 0.607, p < .001 | Systemic barriers significantly influence impact perceptions |
| Social Justice Concerns | Lowest mean score | M = 3.17 | Indicates significant concerns about AI's role in social justice |
| Policy Perceptions | Highest mean score | M = 4.11 | Strong support for policy interventions |

**Policy Implications**

The data suggests several key areas for policy intervention:

1. Access Enhancement

* Current perceptions of access barriers
* Potential solutions and their expected impact

1. Educational Initiatives

* Training needs assessment
* Program development recommendations

**Table 9: Policy Recommendation Matrix**



**Future Research Directions**

Our findings suggest several promising avenues for future investigation:

1. Longitudinal Studies

* Track changes in perceptions over time
* Monitor impact of interventions

1. Expanded Demographics

* Broader community representation
* Intersectional analysis opportunities

**Table 10: Proposed Research Extensions**



**Conclusion**

Our analysis reveals a nuanced understanding of AI's impact within Black communities. While participants recognize AI's potential benefits, they also express significant concerns about access barriers and social justice implications. These findings suggest the need for targeted interventions that address both technical access and systemic barriers.

**Table 11: Summary of Conclusions and Recommendations**



**References**

Campana, K., Mills, J. E., Kociubuk, J., & Martin, M. H. (2022). Access, advocacy, and impact: How public libraries are contributing to educational equity for children and families in underserved communities. Journal of Research in Childhood Education, 36(4), 561-576.

Carter, L., Liu, D., & Cantrell, C. (2020). Exploring the intersection of the digital divide and artificial intelligence: A hermeneutic literature review. AIS Transactions on Human-Computer Interaction, 12(4), 253-275.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>

Cohron, M. (2015). The continuing digital divide in the United States. The Serials Librarian, 69(1), 77-86.

DeVellis, R. F. (2017). *Scale development: Theory and applications*(Fourth). SAGE Publications, Inc.

Ellison, T. L., & Solomon, M. (2019). Counter-storytelling vs. deficit thinking around African American children and families, digital literacies, race, and the digital divide. Research in the Teaching of English, 53(3), 223-244.

Emem, O. (2023). Education Equity and Technology Divide in the United States. International Journal of Science and Research Archive, 10(1), 775-782.

ScienceDirect. (n.d.). Pearson Correlation. Retreived November 17, 2024, from [Pearson Correlation - an overview | ScienceDirect Topics](https://www.sciencedirect.com/topics/computer-science/pearson-correlation#:~:text=Pearson%20Correlation%20is%20a%20statistical,near%20zero%20indicates%20no%20correlation.)