HOWARD UNIVERSITY

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CETLA

Center for Excellence in Teaching, Learning, and Assessment

CETLA Twentieth Anniversary Conference Proceedings

Conference Theme, "The Next Frontier: AI and Beyond."

CONFERENCE PROCEEDINGS - 2023

Morris Thomas, Ph.D., MBA, PMP, CETLA Director

CETLA's 20th Anniversary Conference

The Next Frontier: AI and Beyond

CETLA'S 20th ANNIVERSARY

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PREFACE

The Center for Excellence in Teaching, Learning, and Assessment (CETLA), celebrated a significant milestone, its Twentieth Anniversary. To commemorate this momentous occasion, we hosted a conference, “ The Next Frontier: AI and Beyond.” This conference was a platform for groundbreaking discussions, insightful presentations, and the exchange of innovative ideas. This document contain the conference proceedings.

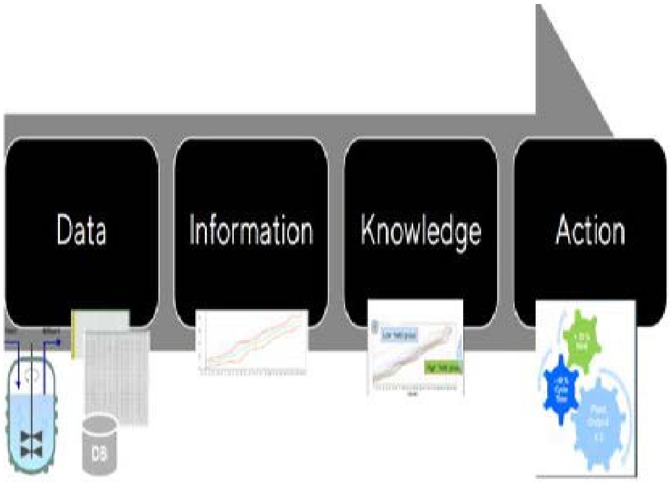
ARTIFICIAL INTELLIGENCE (AI) IN DRUG PRODUCT FORMULATION, DEVELOPMENT AND MANUFACTURE

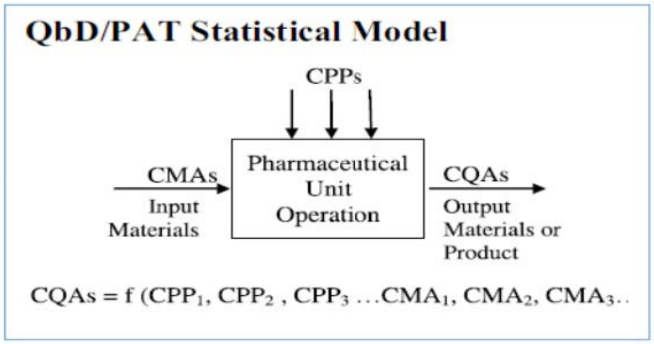
Emmanuel O. Akala, R.Ph., Ph.D.

Hollywood has long presented artificial intelligence (AI) as a futuristic concept far from reality, but technology has now eliminated the gap between science fiction and science fact. AI is here and here to stay; 50% of global healthcare companies plan to implement AI strategies by 2025 (1, 2). AI can mean wildly different things to different people. The FDA's Center for Drug Evaluation and Research (CDER) describes AI rather inclusively as "a branch of computer science, statistics, and engineering that uses algorithms or models that exhibit behaviors such as learning, making decisions, and making predict10ns" (2, 3). The National Academies of Sciences, Engineering, and Medicine issued a report on innovations in pharmaceutical manufacturing that highlighted Al's potential role in the measurement, modeling, and control used for pharmaceutical manufacturing (4).

The relatively new concept of quality by design (QbD) and process analytical technology (PAT) in pharmaceutical dosage form design and development are a subset of AI. QbD and PAT, which are already incorporated into automakers' production principles, involve designing and developing drug formulations and manufacturing processes that ensure predefined drug product specifications. It is believed that product and process understanding is a key element of QbD-PAT [5-7]. Thus an important part of QbD-PAT is to understand how process and formulation variables affect product characteristics and subsequent optimization of these variables vis-à-vis the final specifications as shown in Figures 1 A and 1 B (characteristics that are critical to quality from the patient's perspective are translated into the drug product critical quality attributes (CQAs) by establishing the relationship between formulation (CMA: critical material attributes) and manufacturing (CPP: critical process parameters) variables and CQAs to consistently deliver a drug product with such CQAs to the patient.

One challenge that faces pharmaceutical drug product development scientists is the selection of a set of conditions (formulation and process variables) that will result in a drug product with a desirable combination of properties. Essentially, this situation involves simultaneous optimization of several response variables (the desirable combination of properties), which depend upon several independent variables (formulation and process variables) (9, 10). In a conventional experimental technique, the procedure holds all but one variable constant while changing one variable at a time. However, we know that the properties of pharmaceutical products are influenced by several variables. Thus, changing one factor at a time approach is not only time-consuming but also limited concerning information on the interaction effects of variables on drug product properties [10,11]. An efficient way of planning and optimizing such experiments involves the principles of Design of Experiments (DOE). The important property of DOE is that while several factors are varied simultaneously, each factor may be evaluated independently. Box and his co-workers have been quoted as saying that "if the factors do act additively, the DOE design does the job with much more precision than the one-factor-at-a-time method and if the factors do not act additively, DOE, unlike the one factor-at-a-time design, can detect and estimate interactions that measure this non-additivity" [11, 12].





A B

Figures IA and IB show AI in action: Link input critical material attributes (CMAs) and critical process parameters (CPPs) to output critical quality attributes (CQAs) for a unit operation/the whole drug product formulation and development processes (Ref 8).

Our laboratory has developed nanotechnology platforms for breast cancer treatments (HER2+ and triple-negative breast cancers) and HIV/AIDS cure using a dispersion polymerization technique at room temperature and numerical and graphical optimizations. In an optimization problem, the response surface method (RSM) or response surface modeling (RSM) design is used. The efforts in our laboratory involving AI will be illustrated with two projects:
(1). Computer Optimization of Biodegradable Nanoparticles Fabricated by Dispersion Polymerization Using D-Optimal Mixture Experimental Design.

The objective of this project is to generate mathematical models to predict nanoparticle size and percent yield as a function of the formulation variables and to optimize particle size and percent yield by numerical and graphical optimizations. Aided by statistical software, a D-optimal mixture experimental design was used to vary the components (crosslinker, initiator, stabilizer, and macromonomers) to obtain twenty nanoparticle formulations (Poly-L-Lactide (PLLA)-based nanoparticles) and thirty formulations (poly-ε-caprolactone-based nanoparticles). Table 1 shows the data for PLLA-based nanoparticles. With the mixture design, the response determined by any possible component mixtures can be identified by a point in the experimental domain called the design space. When working with three different variables (components), the experimental domain corresponds to an equilateral triangle with the vertices corresponding to the pure components while different points within the design space correspond to a mixture of components.

Scheffe polynomial models were generated to predict particle size (nm), zeta potential, and yield (%) as functions of the composition of the formulations. Simultaneous optimizations were carried out on the response variables. Solutions were returned from simultaneous optimization of the response variables for component combinations to (i) minimize nanoparticle size; (ii) maximize the surface negative zeta potential; and (iii) maximize percent yield to make the nanoparticle fabrication an economic proposition. Following simultaneous numerical optimization of nanoparticle size and percent yield of poly-L-lactide-based nanoparticles, four solutions were returned. Three of the solutions were used to fabricate nanoparticles to compare the predicted values with the actual laboratory values. The observations from the confirmation experiments are within the confirmation 95% prediction intervals showing the confirmation of the models. Paclitaxel anticancer drug was then loaded to the optimized formulation. Figure 2 shows the graphical optimization.

Table 1: Composition and response of D-optimal mixture experimental design for the fabrication of stealth poly-L-lactide-based nanoparticles

Standard Order	**Run Order**	**A: Crosslinking Agent (mmol)**	B: Initiator System (mmol)	C: Stabilize (PEG-MMA) (mmol)	D: Macromonomer (mmol)	Response 1(Particle Size: nm)	Response 2(Percent Yield %)
9	1	0.048	0.359	0.304	0.289	297.6	56.87
8	2	0.056	0.285	0.215	0.445	306.6	28.99
1	3	0.087	0.377	0.091	0.445	261.5	62.39
5	4	0.018	0.565	0.214	0.204	270.6	35.26
19	5	0.087	0.377	0.091	0.445	268.1	58.82
12	6	0.042	0.452	0.259	0.247	286.4	31.88
20	7	0.018	0.565	0.214	0.204	295.8	61.08
17	8	0.087	0.183	0.304	0.426	326.4	31.13
14	9	0.018	0.312	0.304	0.367	290.3	41.19
15	10	0.053	0.415	0.148	0.384	322.3	45.15

3	11	0.055	0.625	0.115	0.204	293.1	47.87
4	12	0.087	0.183	0.304	0.426	322.9	34.18
13	13	0.036	0.522	0.163	0.279	320.7	43.08
2	14	0.018	0.446	0.091	0.445	313.1	24.43
11	15	0.087	0.500	0.091	0.321	273.3	43.32
16	16	0.018	0.446	0.091	0.445	293.8	35.08
18	17	0.055	0.625	0.115	0.204	305.9	39.22
6	18	0.018	0.234	0.304	0.445	320.9	35.98
7	19	0.018	0.625	0.091	0.265	295.6	44.71
10	20	0.087	0.394	0.198	0.321	314.9	37.59

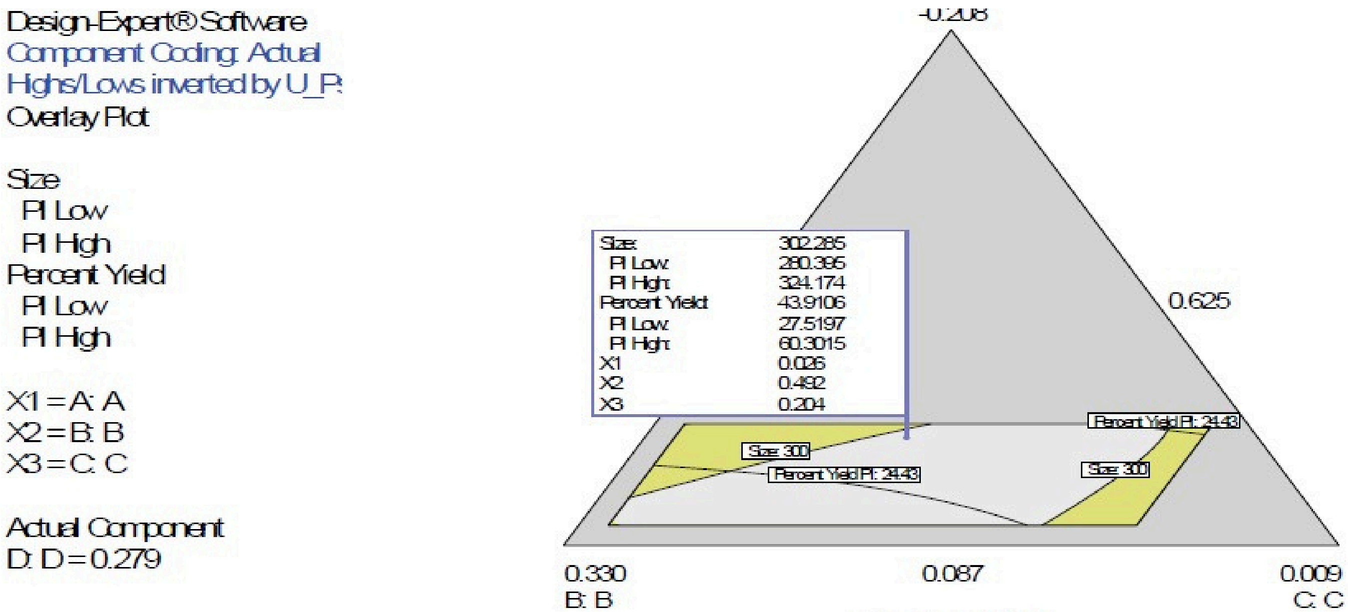


Figure 2. Simultaneous graphical optimization (overlay plot) of the design space variation in particle size and % yield as functions of the mixture composition. A = crosslinking agent; B = initiators; C = stabilizer and D = macromonomer.

(2). Computer Optimization of Stealth Biodegradable Polymeric Dual-Loaded Nanoparticles for Cancer Therapy using Central Composite Face-Centered Design We used the central composite face-centered design (CCF) in three independent factors and seventeen runs (Tables 2 and 3).

Table 2: Values of the factors used in the fabrication of nanoparticles using central composite face-centered design (CCF).

Experiment No	Run Order	Crosslinker (mmol)	PEG (mmol)	Stirring Speed (rpm)	Macromonomer (mmol)	Initiator System (mmol)
1	6	0.373	0.898	100	0.28	0.594
2	17	0.466	0.898	100	0.28	0.594
3	12	0.373	1.123	100	0.28	0.594
4	11	0.466	1.123	100	0.28	0.594
5	16	0.373	0.898	300	0.28	0.594
6	9	0.466	0.898	300	0.28	0.594
7	15	0.373	1.123	300	0.28	0.594
8	7	0.466	1.123	300	0.28	0.594
9	8	0.373	1.0105	200	0.28	0.594
10	13	0.466	1.0105	200	0.28	0.594
11	4	0.4195	0.898	200	0.28	0.594
12	3	0.4195	1.123	200	0.28	0.594
13	10	0.4195	1.0105	100	0.28	0.594
14	1	0.4195	1.0105	300	0.28	0.594
15	2	0.4195	1.0105	200	0.28	0.594
16	5	0.4195	1.0105	200	0.28	0.594
17	14	0.4195	1.0105	200	0.28	0.594

Table 3: Data on nanoparticle properties (Response variables to the factors shown in Table 3, where P = paclitaxel, and G = 17AAG; ε = standard deviation).

Exp. No	Run Order	Particle Size (nm)	Drug Loading P (%)	Drug Loading G (%)	Encapsulation Efficiency (Paclitaxel) (%)	Encapsulation Efficiency (17-AAG) (%)	Release Time Drug (Paclitaxel) (h)	Release Time Drug (17- AAG) (h)
1	6	291.7	1.53	0.83	98.76	97.99	50.7	24.3
2	17	298.4	1.62	0.89	98.47	97.61	48	48
3	12	267.5	1.64	0.88	90	90.49	60.8	24
4	11	270.6	1.76	0.95	99.75	98.8	74	59
5	16	228.6	1.58	0.88	99.95	99.37	49	49
6	9	261.2	1.53	0.85	95.85	93.77	49	25
7	15	217.1	1.99	0.98	99.87	98.93	48	48
8	7	260.8	1.79	0.93	99.93	98.98	72	72
9	8	229	1.57	0.95	92.45	91.75	48	24
10	13	289.6	1.71	0.85	97.3	95.25	48	32
11	4	286.1	1.72	0.9	89.78	91.5	72	36
12	3	255.3	1.94	0.86	97.91	95.68	68	48
13	10	250.3	1.85	0.97	99.22	97.63	71	24
14	1	288.7	1.65	0.92	97.02	97.58	74	48.3
15	2	249.4	1.78	1	94.47	96.88	70	28
16	5	235.6	1.87	0.96	96.98	97.75	73	24
17	14	232.4	1.87	1	98.69	97.04	69	22
□	-	□0.2 - □ 10.6	□0.02 -□ 0.015	□0.01 -□ 0.003	□0.029 - □0.002	□0.450 - □0.118	□0.031 - □0.037	□0.029 -□ 0.046

:

A DoE approach was used to systematically investigate the effects of PEG concentration, stirrer speed, and crosslinker concentration on nanoparticle properties. The macromonomer and the initiator system were held constant, making the experimental design a central composite face-centered design (CCF) in three independent factors and seventeen runs including three replicates of the center points to provide an estimate of replicate error: the replicated experiments enable the performance of a lack of fit test. The response variables are nanoparticle size, paclitaxel drug loading, 17-AAG drug loading, paclitaxel encapsulation efficiency, 17-AAG encapsulation efficiency, release time for paclitaxel, and release time for 17-AAG. The formation of nanoparticles was confirmed by scanning electron microscopy, which revealed fairly monodispersed, spherical nanoparticles (Figure 3).

Seven response variables were evaluated for the nanoparticles: particle size, paclitaxel drug loading, 17-AAG drug loading, paclitaxel encapsulation efficiency, 17-AAG encapsulation efficiency, in vitro availability of paclitaxel and in vitro availability of 17-AAG. A typical response is shown in Figure 4. Analysis of variance (ANOVA) and Q2 (goodness of prediction) were used to select appropriate models relating the response variables to the nanoparticle formulation factors. The significance of the regression coefficient terms (factors) in the models was tested. Computer optimization was carried out to select the factor combination to minimize the particle size, to minimize the time (h) for maximum release of paclitaxel and 17-AAG, to maximize paclitaxel and 17-AAG loading efficiency, and to maximize paclitaxel and 17-AAG encapsulation efficiency. The data obtained are shown in Table 4. The optimization was successful, as shown by the validation data which lie within the confidence intervals of predicted values of the response variables. Crosslinker has the highest contribution (44.80%) to the optimized formulation followed by stirring speed (35.0%) and then PEG (20.15%). The selected factor combination is suitable for the fabrication of nanoparticles for in vivo evaluation of the nanoparticles loaded with paclitaxel and 17-AAG.

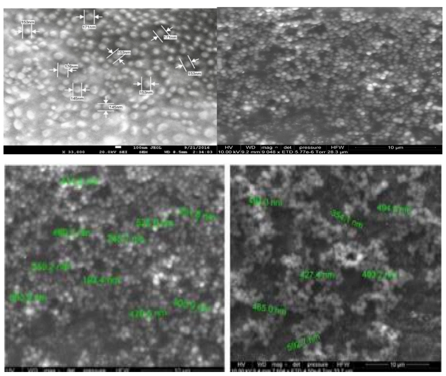


Figure 3: Typical scanning electron micrographs (SEM images) of polymeric drug-loaded nanoparticles fabricated in our laboratory.

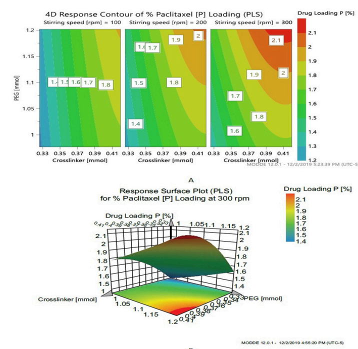


Fig. 4. Influence of PEG, stirring speed and crosslinker on % paclitaxel drug loading: A (Four dimensional plot); B (Response surface plot).

Table 4: Results of optimization of the data on central composite face-centered design (CCF) for the fabrication of paclitaxel and 17-AAG-loaded nanoparticles.

Optimizer

Setpoint

Selected setpoint: #20

The run with lowest log(D) is selected.

Alternative setpoints:

#	log(D)	Prob. of failure
16	-0.963	26%
17	-0.967	26%
18	-1.16	16%
19	-1.16	15%
20	-1.46	2.2%

Select best run

Optimizer settings

Objective | Setpoint (#20) | Alternative setpoints

	Response	Criterion	Value	Graph	log(D)	Prob. of failure	Cpk
1	Particle size	Minimize	241.967		-0.615121	0.02%	1.46743
2	Drug Loading P	Maximize	1.66389		-10	0.02%	1.37947
3	Drug Loading G	Maximize	0.95546		-10	0%	1.93563
4	EncapEffDrug P	Maximize	96.99		-10	1.7%	0.683567
5	EncapEffDrugG	Maximize	96.1165		-10	0.31%	1.50871
6	ReleaseTimeDrugP	Minimize	50.9236		-10	0.03%	1.66818
7	ReleaseTimeDrugG	Minimize	24.2931		-10	0.12%	1.20582

	Factor	Role	Value	Graph	Factor contribution
1	Crosslinker	Free	0.37303		44.8339
2	PEG	Free	1.00981		20.1506
3	Stirring speed	Free	215.075		35.0156
4	Macromonomer	Constant	0.28		
5	Initiator System	Constant	0.594		

3. Other AI applications in drug product formulation, development, and manufacture ongoing or under development in our laboratory are as follows:

- Process Analytical Technology to continuously improve processes and maintain control during manufacturing. It involves real-time process monitoring and predicting and correcting deviations in time. It gives engineers and operators actionable insights or even predictive warnings that allow them to correct process deviations before they cause quality or production issues.
- Finding meaning in –omics (Studying organisms as integrated systems (e.g. genomic, proteomic, or metabolomic pathways or cellular events) datasets (principal component analysis (PCA) for data summary/overview and partial least squares (PLS) and orthogonal PLS (OPLS) for regression analysis). The method requires a training data set consisting of samples (or objects) with a set of attributes and their class membership. One major goal is to extract biomarkers and understand the interplay between molecular and cellular components vis-à-vis drug product development.

CONCLUSION

We have shown, using two projects from our laboratory, how computer science and statistics use algorithms or models to achieve optimization (decisions and predictions) to handle many formulation and process variables to achieve drug product objectives. The beauty of it is that AI can help arrive at the combination of factors to achieve the desired objectives even when the objectives are competing (you want to reduce particle size, increase yield, prolong or reduce time for drug release, and maximize drug loading in the same pharmaceutical product at the same time).

ACKNOWLEDGMENTS

The author wishes to thank all members of my laboratory who participated in generating the data for the two projects discussed

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Use of GroupMe to Increase Student Engagement and Belonging

Joyvina Evans, Ph.D., MSPH, MSA

INTRODUCTION

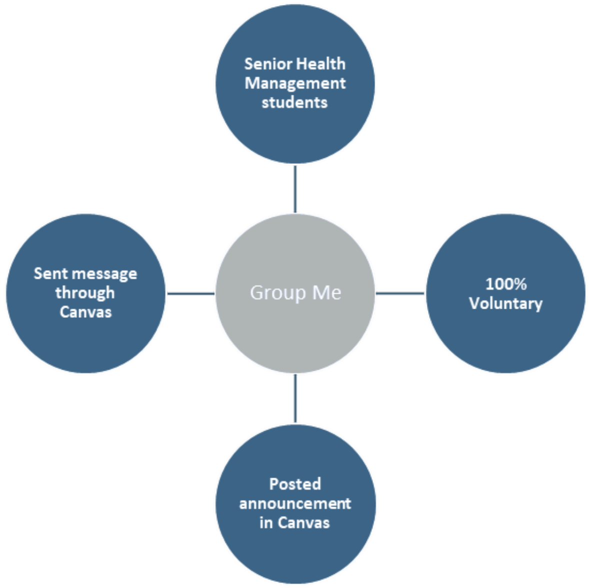
Faculty and student engagement is key in higher education. There is no universal or one-size-fits-all approach to communication. Tang and Hew (2020) suggest that instructor-facilitated use of instant messaging apps shows positive learning environments and creates more engagement and connection among faculty and students. The purpose was to assess if a course-specific GroupMe would be helpful in a course that had limited meeting dates.

WHAT IS GROUPME?

GroupMe is a free messaging application (app) founded in 2010. It replicates text messaging, as it allows the sending and receiving of messages in a text format. The app allows users to share photos, add calendar events, and share locations. The app works on iOS, Android, Windows, and the World Wide Web. GroupMe has been used in numerous personal and professional settings, such as hospital emergency rooms and university-led GroupMe. After attending a workshop at the Association of University Programs in Health Administration, I wanted to know if GroupMe would work for undergraduate students at Howard University. Therefore, I decided to implement it in one of my Fall courses.

INVITATION

At the beginning of Fall 2023, an email and announcement were posted inviting 25 students enrolled in the Health Management Internship course to scan a QR code linked to GroupMe. Students were informed that joining GroupMe was wholly voluntary and that no grades were associated with participation. Additionally, they were told that no information would be shared via GroupMe, providing users with an unfair advantage. The primary goal of the Health Management Internship is for the students to complete 120 hours of experience at a site. As such, the course met once a month. GroupMe was used to supplement and allow discussion and share experiences, content, and encouragement between months. All 25 students joined the GroupMe.



HEALTH MANAGEMENT INTERNSHIP GROUPME

Students and faculty initiated the GroupMe conversations. Faculty prompts included asking about mental health, internship sites and sharing information regarding community service and workshops. Additionally, two polls were created inviting students to share if they wanted to participate in an Alzheimer's walk or the Breast Cancer walk in October 2023. Student prompts included asking for clarifying information about assignments, internship requirements, and due dates. There were also engaging conversations centered around 'getting to know each other.'

STUDENT SATISFACTION

Students were sent a link to SurveyMonkey at the end of the semester. The survey aimed to assess their satisfaction with using GroupMe with the faculty 'in the group.' Twelve students responded to the study (48%). Overall, students were satisfied with GroupMe. For instance, 92% of students indicated they liked having access to the course professor, and 83% stated that they wanted to continue using GroupMe with access to the professor. Lastly, it is essential to note that 83% felt that there was more engagement using GroupMe vs Email. This could be because texting comes across as more personal than email.

	YES	NO
Do you like having access to your course professor in GroupMe?	92%	8%
Is there more engagement with GroupMe vs Email?	83%	17%
Do you want to continue using GroupMe with access to the professor?	83%	17%

The following questions used Likert scales to assess the students' feelings regarding GroupMe. Seventy-five percent of students felt a greater connection to the course professor. While 67% thought it led to greater accountability, 67% indicated that all their professors should use GroupMe. Half of the students felt it was not more work, while 16% indicated it was more work using GroupMe.

	Agree	Neither Agree /Disagree	Disagree
I felt a greater connection to my course professor	75%	25%	0%
All of myprofessors should use GroupMe	67%	8%	25%
…led to more accountability	67%	33%	0%
It felt like more work	16%	34%	50%

BENEFITS AND RISKS

There are always benefits and risks associated with technology. This is no different for GroupMe. The benefits of GroupMe are numerous; however, a few that students tend to like are the fact that telephone numbers are hidden. This allows faculty, students, and staff to communicate without sharing their numbers. GroupMe also allows for private messaging if students want private conversations with faculty and vice versa.
Additionally, it allows for group messages where the messages are seen by everyone who joins the group. GroupMe allowed for a more personal and engaging format with their faculty. It also allowed them to ask pressing questions when needed.

Contrary to the benefits, as with any texting or social media apps, there is the potential for cheating and bullying (Cosby, 2021). Students can quickly screenshot information and share messages quickly. This became a concern in 2017 when Ohio State University accused 83 students of cheating by using GroupMe. A year later, Louisiana State University found one student responsible for cheating during an exam (Daniel, 2019). Even though these universities have linked incidents to GroupMe, it is essential to note that cheating is not isolated to GroupMe, as students can cheat using email, text, and other methods.

CONCLUSION

Using GroupMe in an undergraduate course proved beneficial. Overall, the students and faculty were satisfied with its use. Using a group texting application can improve faculty-student engagement and increase students' feeling of belonging by adding a more personal means of communication.

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Increasing Course Engagement With ECHO360 In Undergraduate Management Classes

Amanda S. Hinojosa, Ph.D.

ABSTRACT

In this paper I describe several features of the Echo360 platform which I have implemented to address challenges faced in teaching undergraduate management classes at Howard University. I note three main challenges faced—attendance, baseline knowledge, and engagement with project presentations—and discuss Echo360 solutions I have implemented to address each challenge.

INCREASING COURSE ENGAGEMENT WITH ECHO360 IN UNDERGRADUATE MANAGEMENT CLASSES

Course engagement is a ubiquitous and ever-evolving challenge for post-secondary educators. In my undergraduate management classes, I have faced three primary challenges around course engagement, attendance, level of baseline knowledge, and low audience engagement with others' project presentations. In this paper, I discuss how I have incorporated the Echo360 platform into my undergraduate management classes to address these challenges.

The Center for Excellence in Teaching Learning and Assessment (CETLA) introduced the Echo360 platform to the Howard University community in recent years as a way to record and store courses (Echo360, n.d.). When the pandemic hit and Howard University shifted to online teaching, additional training on the platform was provided to allow professors to learn how to automatically record their zoom classes, archive those videos with the Echo360 platform, and how to explore the analytic data available to explain student engagement with the videos. After learning about the platform at that time, I began slowly integrating it into my classes. When the university returned to in person learning, I continued to use it, adjusting my usage based on lessons learned, things learned from additional CETLA trainings on the Echo360, and new features that were rolled out from Echo360 over time.

TEACHING CHALLENGES AND ECHO360 SOLUTIONS

Challenge: Attendance and Participation

In the academic year 2021-2022, Howard University reported an undergraduate student body of 9,809 students (Howard University, n.d.). This is certainly not a small number, however, it can be argued that Howard's prestige and brand recognition rivals and in some cases exceeds that of the universities with the highest number of undergraduates enrolled in the United States

(US news and World Report, 2023). Hence, Howard's reputation and image as a premier university and premier HBCU has made its footprint much larger than the size of the student body might suggest. This creates an interesting dilemma that is arguably unique to the Howard campus, the ratio of opportunities per student is likely to be much larger than other schools. The variety of opportunities offered is like many schools: student organizations, companies involved in recruiting, prominent guest speakers, and student-focused special events are all likely offered at many schools. Yet the number and frequency of these event offerings at Howard seems to be much greater.

Because of Howard's strong reputation externally, and high cohesion among students internally, the multitude of activities that students can engage in often conflict with the times courses are offered. The number of times a student misses a class due to a student enrichment activity offered seems to occur at a much higher rate at Howard than other universities. As such, in addition to universal challenges faced by instructors in managing attendance and its impact on student performance in a course, the opportunity-rich environment at Howard magnifies this issue, in that many high-performing students may also miss several classes due to their involvement in university affiliated opportunities.

As an instructor, I have found it challenging to balance the expectations of class attendance with support for students' engagement in the multitude of developmental opportunities available to them. In a typical week, I often receive several standard emails about missing classes due to sickness or death of loved ones, but I also receive several emails about student participation in a number of important opportunities available to them as Howard student. For example, I have had students let me know they will miss class due to a meeting with a United States senator, the Vice President of the United States, the CEO of Fortune500 company, and more. Students have also missed for their participation in athletics events, a key job interview, a university sponsored trip to business headquarters, a university sponsored trip to a different country, and to appear on national television representing Howard. These are all amazing opportunities that are important for students to engage with, however, as a professor it is challenging to determine how to address the classes and assignments that are missed due to these opportunities, particularly for the highly involved students that may miss multiple classes due to their engagement in these opportunities.

Even when attendance is not a graded portion of their class, the missed lectures and class discussion can make it more difficult to master course content and perform well on other course assessments. The general challenges around attendance and participation are likely universal across all colleges and universities, but the frequency of this is heightened at Howard in part due to the proportion of events and opportunities available to students on any given day. Faced with both the universal and specific challenges in attendance and participation, I have implemented Echo360 to balance support for student engagement in class and student engagement in developmental opportunities.

Echo360 Solutions to Attendance Challenges

I use Echo360's Echo Video (Echo360, n.d.) to record my class lectures in person while I am presenting my lecture in the classroom. When students inform me that they will miss a class or have already missed for whatever reason, I share with them how they can access the course recordings on Echo360. In classes where attendance counts toward their grade, I have offered the opportunity to make up missed attendance points if they watch the full recording on Echo360. This was particularly helpful early in our return to in person learning, when there were still quarantine protocols for students, so I could still emphasize the importance of the class but not penalize them for following the appropriate health and safety protocols. The analytics presented on Echo360 allows instructors to see which students watched each course recording, how many times they watched, as well as the percentage of each recording they watched. Thus, this can address some of the challenges around attendance; students can review what they missed, and instructors can use these analytics to provide points for watching the recording if they choose to do so.

Class	Weighted Engageme %	Attendanc %	Video View %	Video Views	Slide Deck Views	Polling Participati %	Polling Correct %	Note Events	Q&A Events
8-21-2023 Intro...	0	0	0	0	0	0	0	0	0
9-13-2023 Chap...	100	0	100	2	1	0	0	0	0
10-11-2023 Cha...	0	0	0	0	0	0	0	0	0
10-02-23 EXAM ...	0	0	0	0	0	0	0	0	0
9-20-2023 Chap...	0	0	0	0	0	0	0	0	0
9-27-2023 Chap...	0	0	0	0	0	0	0	0	0
8-30-2023 Mana...	78	0	78	1	0	0	0	0	2
9-6-2023 Team F...	100	0	100	1	0	0	0	0	0
9-11-2023 Chap...	100	0	100	1	0	0	0	0	1
10-18-2023 Cha...	0	0	0	0	0	0	0	0	0
9-18-2023 Chap...	0	0	0	0	0	0	0	0	0
10-16-2023 Cha...	0	0	0	0	0	0	0	0	0
10-23-2023 Cha...	0	0	0	0	0	0	0	0	0
9-25-2023 Chap...	0	0	0	0	0	0	0	0	0

Figure 1

Example Echo360 Summary Data Organized by Class Session

Challenge: Differing Levels of Baseline Knowledge

The next challenge I have encountered is likely universal to all instructors. In many of my classes, some students are well-versed in the baseline knowledge needed to perform well in the course, while others are still working to establish their baseline knowledge in the subject area. The dilemma for instructors in this situation is figuring out at what level and pace to teach the class: too fast or too high a level, the instructor risks losing the majority of students who do not have the baseline knowledge, yet too slow or lower level, the class learning objectives are unlikely to be met and the instructor risks alienating and inadvertently penalizing those who have the right level of baseline knowledge to proceed successfully in the course. In the courses I teach this is most often manifested as a difference between those who must take my class as a business major, versus those who take my class but are not a business major. Though the classes I teach are all in the School of Business, many of the classes I teach are taken by both business majors and non-business majors, which means not all of the students have taken the same core courses before my course.

Echo360 Solutions to Student variations in Baseline Knowledge

Discrepancies in baseline knowledge can also be addressed with access to course recordings on Echo360. By providing course recordings to all students, any student can go back and review recorded lectures. Students who would like to review content that they missed while absent are able to watch the video just as students who may have been present but want to review parts of the lecture again (for example to prepare for an upcoming exam or to see what was said about specific requirements for an assignment). If there is a particular area of content that is confusing, students can use the recording to review before following up with the professor and/or classmates for additional clarification.

Thus, this accessibility allows students a chance to bring themselves up to speed with the baseline knowledge required for the course. Additionally, as the instructor, I can suggest students review certain recordings that cover areas they did not perform well on in an assessment. For example, in a review of a poor exam grade, I can direct them to the course recording of the lecture which covered that topic and if desired I can even pinpoint specific sections of the video they should focus on reviewing.

What makes Echo360 unique compared to other recording options like Zoom or YouTube, is the explicit focus on educational review. In addition to watching the course recordings, students can also address their variations in understanding by using the additional discussion and question and answer features on the Echo360 platform. For example, when viewing the recording, students can post a question/comment on the video. I have found that most students did not use this feature unless otherwise prompted to do so. I suspect this is in part because many of these students are using Echo360 for the first time in my class. However, I have increased student usage of this tool by explicitly tying it to a graded activity to increase the engagement and usefulness of an exam review for the class.

I told students they could earn points by posting review questions within each video. This incentivized students to get onto the platform to review the video and post their own questions. Furthermore, I and/or their classmates were also able to respond to the question in a way that allowed people to have a record of the question and response and engage at times convenient to them even if outside of the traditionally scheduled class time. By incentivizing their use of the platform for review, we were able to model how to use the course recordings most effectively for studying. Figure 2 provides an example Q&A post from a class. In the actual instructor dashboard, the instructor can also see the name of the student who posed the question (hidden here to protect student privacy). In the question that appears on the right hand side of Figure 2, it shows how this question was tied to a specific section of the recording. I can then go back to see what was discussed at that point in the recording to get a better idea of the specific concepts that the students wish to review more. An additional feature not shown in this figure is the threaded response. In the snippet, the first question on the left side states "Describe each of the three individual characteristics." The speech bubble icon below that question has the number one next to it, indicating that one person has responded to that question. In this case, I responded to that question to provide additional clarification about the concept they were reviewing.

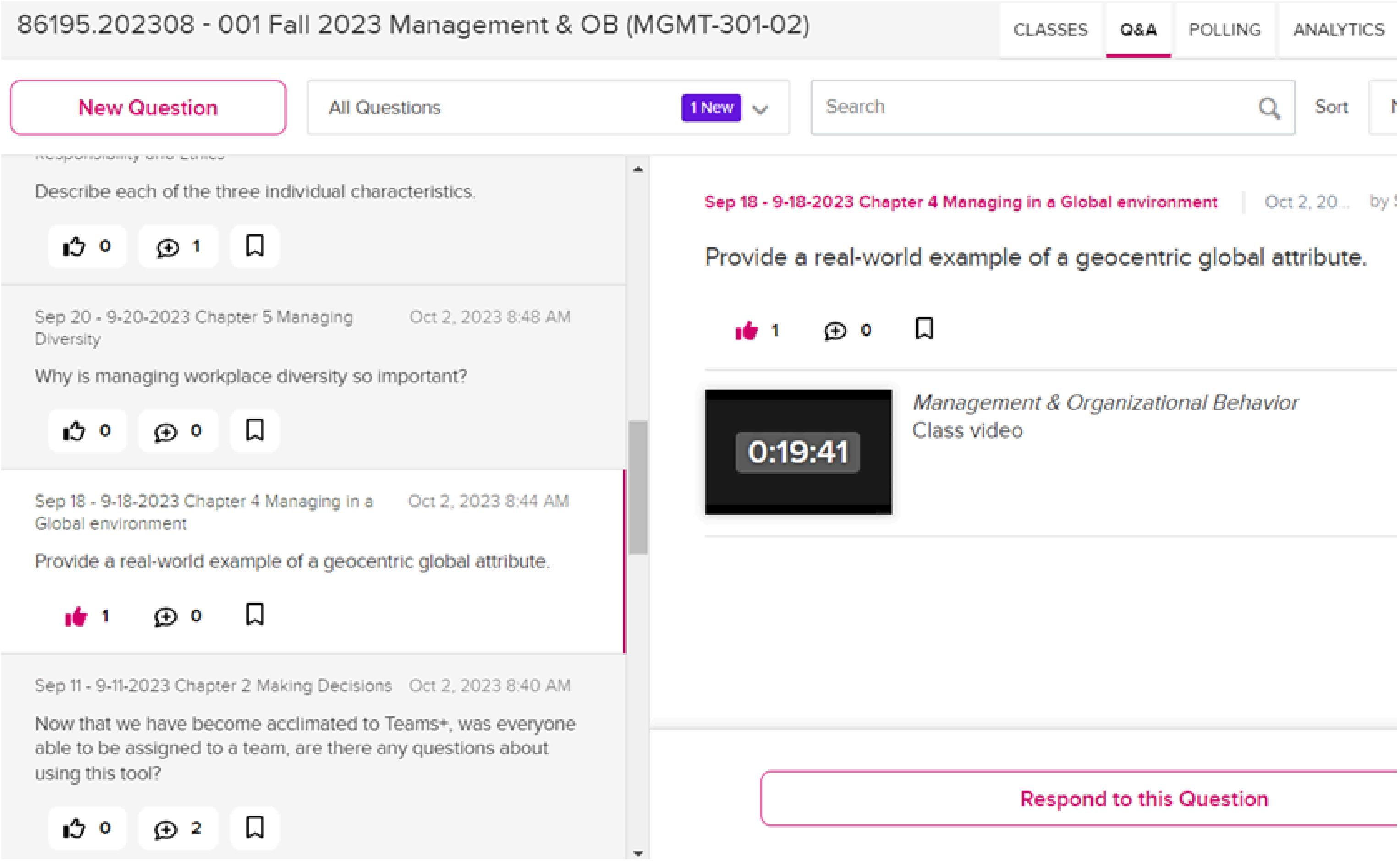


Figure 2

Example Echo360 Q&A

▶ Challenge: Student Engagement with Project Presentations

The final challenge I have faced in my classes is a lack of engagement with end of semester project presentations. In most of my classes, students are required to do a final project which often includes a project presentation. However, again, because of the aforementioned attendance challenges, this can create issues of people not being available during the day of presentations to present and/or to watch other presentations. Furthermore, students who do attend on the days of presentations are primarily concerned with their own presentations and 'tune out' when others are presenting, which can be demoralizing for presenters and professors alike. Additionally, given that these presentations typically occur at the end of the semester, students are also overwhelmed with final projects and exams in several classes, which also contributes to their likelihood to tune out when others present their final project. This has created a sort of anti-climactic end to the class where students present to check the box and then check out. In addition to the rather blasé end to the semester when everyone is 'checked out,' these issues also can mean that students don't make the connection between how engagement with their own and others' projects provides a different way to review course content which provides valuable feedback on their mastery of course learning objectives and can help prepare them for the final exam in the course as well.

▶ Echo360 Solution to Address Low Engagement with Project Presentations

To address the issue of low engagement and attendance issues with scheduled project presentations, I have used the platform to share student recordings of presentations. When students present during class time, I record their presentation live in the same way I would record my own lecture. However, I also allow them to submit a recorded presentation which I then upload to Echo360. This helps to reduce any issues of absenteeism affecting the presentation. I have used different variations of this depending on the nature of the class (for example, I have sometimes required that everyone submits a recording of their presentation, whereas other times I have allowed the choice to present in class or submit a recorded presentation).

This then allows me to require student engagement with others' presentations on the Echo360 platform without sacrificing class time on presentation days. As part of their grade, I direct students to interact with the recorded presentations on the platform. If they attended in person, they can post their question, and if they did not attend in person, they can watch the recording and then respond to each group's presentation.

The Echo360 analytics allow the instructor to view the questions/comments made, how many posts were made, and how much of the video was viewed. I have used this feature to assign some points for each question asked of other student presenters, and for follow-up responses that other students have made. This helps create a more active audience for the presentations and provides students with peer feedback. After implementing this Echo360 approach for final project presentations, student engagement with others' project presentations has increased in my classes. This has also helped me to manage the time constraints associated with presentations in larger classes and to address attendance issues that conflict with presentation days. Furthermore, by allowing for choice in their presentation modality (live in class, or pre-recorded submission) students can find something that works best for them and their group members without missing out on other points.

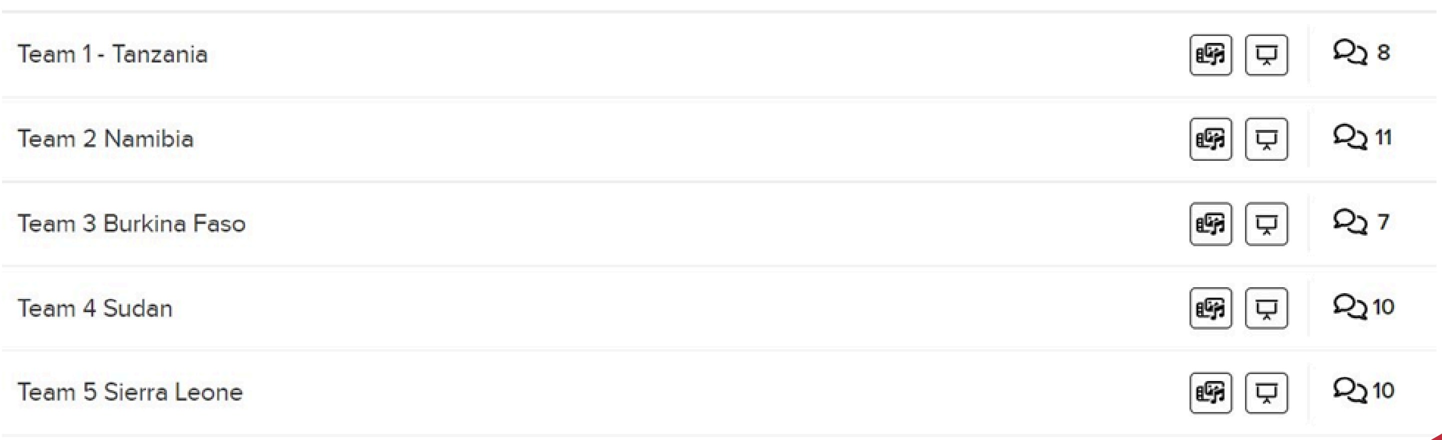
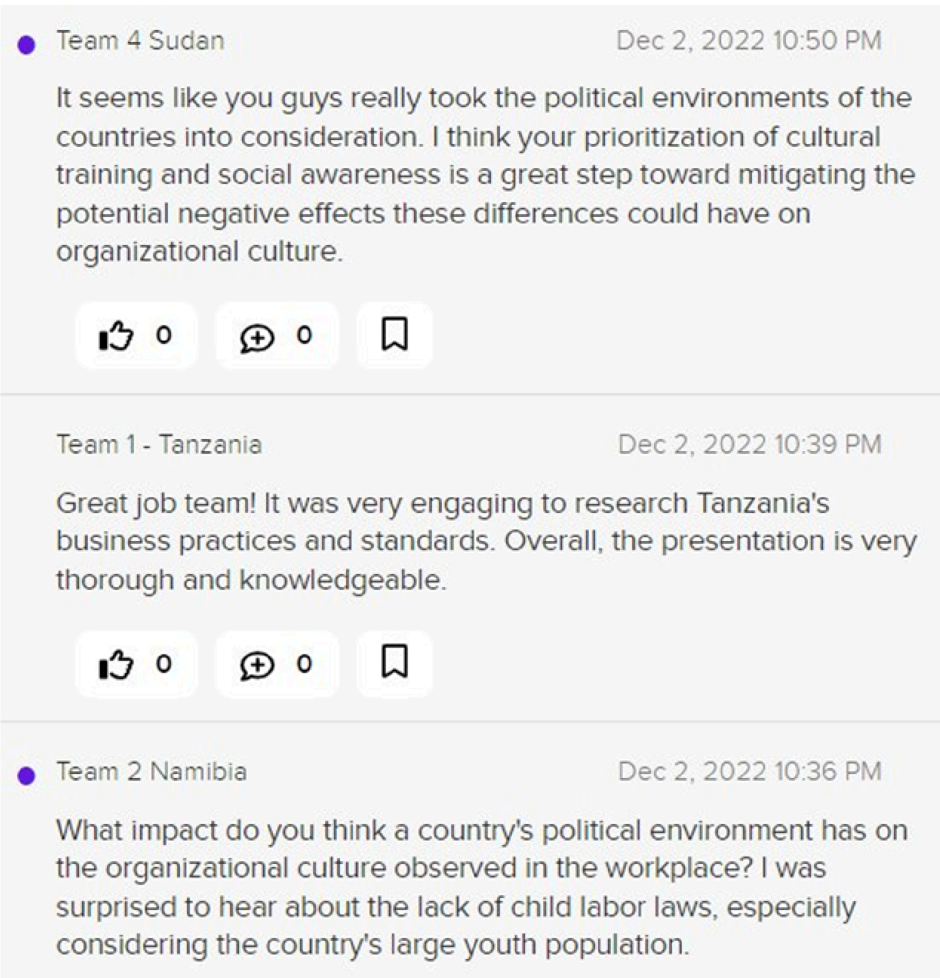


Figure 3
Example of Interface for Group Presentation Recordings on Echo360

Figure 3 provides an example of the course recordings I uploaded for a group project in which each student group presented research related to doing business in a country they were assigned. In the right-hand side of this figure, the speech bubble icons note how many questions were asked for each presentation. On Echo360, the questions can be viewed overall or by recording. Figure 4 shows a snippet of some of the questions posed, in this layout, it shows which presentation the question/comment is associated with. To protect student privacy, I have removed the names from the figures, but in the full Echo360 dashboard, the instructor can see the names of the students who have asked and answered questions on the platform.

Figure 4

Example Student Feedback to Group Presentations on Echo360



Conclusion

Issues of attendance and participation, variations in student readiness to cover course learning objectives, and engagement with other learners are three challenges I have faced in my undergraduate management classes at Howard University. CETLA at Howard University has provided support through software and training to address teaching challenges, and I have used much of this to make improvements to my classes each semester. In this paper I discussed how I integrated solutions from the Echo360 platform to counter these challenges. Though these solutions do not completely solve the issues presented, I have found that these solutions have facilitated improvement in course participation, engagement, and student performance.

What AI Says About The Education Of Black Children And Their Future Development

Hakim M. Rashid, Ph.D.

As Artificial Intelligence (AI) becomes an increasingly important component of modern society in terms of policy analysis and policymaking, it is essential that those concerned with the education of children of African descent be mindful of the perspectives of various AI systems as they relate to analyses, predictions and recommendations. Depending upon how questions are asked, AI systems can provide responses that range from the most optimistic to those that paint a dire picture for the future of Black children. It is essential that those who make decisions based upon knowledge generated by AI systems be fully aware of the divergent perspectives that can be offered, and how those perspectives came to be divergent in the first place.

When asked to assess the future educational prospects for Black children, for example, Bard (now known as Gemini) noted the following, “Overall, the future of Black children and their education is bright. There are a number of initiatives underway to address the educational disparities faced by Black children, and there is a growing awareness of the need to improve the educational outcomes of Black children.” However, when Bard was asked specifically about how long it might take to close the “achievement gap” between Black and white students based on data from the National Assessment of Education Progress (NAEP), the following was the result: “The NAEP data shows that the achievement gap between Black and white students has narrowed over time. However, the progress has been slow. In reading, for example, the gap has narrowed by about 2 points per decade. If this trend continues, it would take about 125 years to close the gap completely.”

It is here that the phenomenon of the AI hallucination becomes critical as it relates to discussions of the education of Black children. “An AI hallucination is when a large language model (LLM) generates false information.... Hallucinations can be deviations from external facts, contextual logic or both... They occur because LLMs have no understanding of the underlying reality that language describes.” (https://www.techtarget.com/whatis/definition/AI-hallucination) When Bard says that “Overall, the future of Black children and their education is bright”, this is a statement that is detached from reality, and shows no understanding of the underlying historical, political, and cultural realities that have shaped the development and education of Black children in the United States for four centuries. When asked why Black children fail in school, Bard offered the following reasons:

" 1. Systemic racism: Black children are more likely to attend underfunded schools with inexperienced teachers. They are also more likely to be suspended or expelled from school for minor infractions.

2. Poverty: Black children are more likely to live in low-income communities where there is a lack of access to quality educational resources.

3. Lack of access to early childhood education: Black children are less likely to be enrolled in early childhood education programs, which can put them at a disadvantage when they start kindergarten.

4. Cultural mismatch: Black children may experience a cultural mismatch between their home life and school, which can make it difficult for them to succeed.

5. Lack of role models: Black children may have fewer role models who have succeeded in school, which can make it difficult for them to see themselves as successful students."

However, when the question was rephrased, and Bard was asked "Why do schools fail Black children?" In addition to systemic racism, poverty, lack of access to early childhood education, cultural mismatch and lack of role models, Bard also added:

" 1. Teacher expectations: Teachers may have lower expectations for Black students, which can lead to lower student achievement.

2. Discipline practices: Black students are more likely to be disciplined than white students, even for the same infractions. This can lead to Black students feeling disengaged from school and less likely to succeed.

3. Tracking: Black students are more likely to be placed in lower-level academic tracks, which can limit their opportunities to succeed.

4. Lack of representation in the curriculum: Black students may not see themselves reflected in the curriculum, which can make them feel less connected to school and less motivated to learn.

5. School climate: Black students may experience a hostile school climate, which can make it difficult for them to feel safe and supported."

Each of these explanations is rooted in the Eurocentrism and racism that has permeated both American culture and the American educational system. In terms of teacher expectations and discipline practices, Black children have been victimized by the white supremacy inherent in many teacher education programs. Teachers bring their own cultural biases to the classroom, and their assessments of Black children too often reflect the broader society's dehumanization of Black people. The result is an educational system that has tracked Black children into less demanding academic programs, provided a curriculum that has often marginalized and minimized Black contributions to the cultural fabric of American society, and school climates that have in too many cases been compared to correctional institutions.

In an article entitled "When AI Gets It Wrong: Addressing AI Hallucinations And Bias" MIT Management provides a comprehensive analysis of bias issues faced by large language models:

"1. Training Data Sources: Generative AI models are trained on vast amounts of internet data. This data, while rich in information, contains both accurate and inaccurate content, as well as societal and cultural biases. Since these models mimic patterns in their training data without discerning truth, they can reproduce any falsehoods or biases present in that data (Weise & Metz, 2023).

2. Limitations of Generative Models: Generative AI models function like advanced autocomplete tools: They're designed to predict the next word or sequence based on observed patterns. Their goal is to generate plausible content, not to verify its truth. That means any accuracy in their outputs is often coincidental. As a result, they might produce content that sounds plausible but is inaccurate (O'Brien, 2023).

3. Inherent Challenges in AI Design: The technology behind generative AI tools isn't designed to differentiate between what's true and what's not true. Even if generative AI models were trained solely on accurate data, their generative nature would mean they could still produce new, potentially inaccurate content by combining patterns in unexpected ways (Weise & Metz, 2023)."

It is not difficult to see a future where AI based software is used to plan, organize, and implement strategies whose stated goal is the improvement of educational outcomes for Black children. In spite of the biases in programming and the misinformation that can be generated by AI hallucinations, Bard offers useful suggestions for reducing the effects of AI bias.

"It is important to be aware of the potential biases and pitfalls of AI systems in education, particularly for Black children. Educators should carefully evaluate AI systems before using them in their classrooms, and they should take steps to mitigate any potential biases.

Here are some recommendations for mitigating bias in AI systems used for grading, tracking, and recommendations:

- Use datasets that are as diverse as possible, and avoid using datasets that are biased against Black students.
- Train AI systems to be aware of different writing styles, including AAVE.
- Use multiple measures of student performance to make decisions about grading, tracking, and recommendations.
- Monitor AI systems for bias and make adjustments as needed.
- Engage with Black students and their families to get their feedback on AI systems and how to use them in a way that is fair and equitable."

Conclusion

The integration of Artificial Intelligence (AI) into policymaking and the analysis of educational issues is rapidly evolving. This evolution necessitates a nuanced understanding of AI's perspectives and potential biases, especially concerning the education of children of African descent. AI systems can offer divergent perspectives based on how questions are framed, ranging from optimistic to bleak outlooks. These perspectives, often influenced by underlying historical contexts and societal biases, can significantly affect decision making processes. The phenomenon of AI hallucinations where AI systems generate false information due to their lack of understanding of underlying realities, underscores the importance of critically evaluating AI generated insights and perspectives. Statements like "the future of Black children and their education is bright" are clearly not consistent with the harsh realities of systemic racism, poverty, and cultural mismatches that suppress Black children's educational opportunities. In conclusion, navigating AI's role in education policymaking requires a deep understanding of its biases and limitations, especially concerning marginalized communities such as those out of which children of African descent emerge. It is essential that the educational community be vigilant, engage in critical evaluation, and adopt inclusive practices that are essential to harnessing the potential of AI, while mitigating its harmful effects on educational equity.

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Generative AI and the Essay; or, Understanding ChatGPT in the Writing Classroom through Genre Study

Travis Sharp, Ph.D., MFA

Text-generation has long played a part in computing. We can find examples as early as the 1950s and 60s, such as Joseph Weizenbaum's 1966 ELIZA, an early example of a chatbot that operated on basic algorithms utilizing language datasets to create vaguely human personae. Before that, British computer scientist Christopher Strachey composed what is considered to be the first example of digital literature in 1952, an untitled project informally known as the Strachey love letter algorithm, on the Manchester Mark I, which composed texts according to a simple algorithm (one reminiscent of a Mad Libs structure):

> Apart from position commands like carriage return ("CR"), line forward ("LF"), and spaces ("spaces" or "sp"), the algorithm prints two salutations ("Add." = address). Then it enters a loop, which is carried out "5 times" and, depending on a random variable ("Rand"), follows one of two alternative paths. One generates a sentence following the syntactic skeleton "You are my—Adjective (adj)—Substantive (noun)"; the other path gives "My—[Adjective]—Substantive—[Adverb (adv)]—Verb (verb)—Your—[Adjective]—Substantive" ... Each phrase ends with a "Full stop". After the programme leaves the loop, it closes with the ending "Yours—Adverb (in the schematic this is given erroneously as 'Adj')—MUC." (Link, 2016, p. 19)

Strachey's generator has not found significant attention in literary critical circles, however, which Noah Wardrip-Fruin attests in part to the perception that "the output simply isn't very compelling," as in these two examples Wardrip-Fruin presents:

> Darling Sweetheart
>
> You are my avid fellow feeling. My affection curiously clings to your passionate wish. My liking yearns for your heart. You are my wistful sympathy: my tender liking.
>
> Yours beautifully
> M. U. C.

Honey Dear

My sympathetic affection beautifully attracts your affectionate enthusiasm. You are my loving adoration: my breathless adoration. My fellow feeling breathlessly hopes for your dear eagerness. My lovesick adoration cherishes your avid ardour.

Yours wistfully
M. U. C. (Wardrip-Fruin, 2011)

Many readers will find some familiarity in these examples given the proliferation of chatbots over the past decades as well as generative textual technologies such as text recommendations and auto-correct: technology has long been invested in textual interventions and inventions, which have improved and become backgrounded into our everyday lives. The shock of ChatGPT that many in academia have felt, however, comes from the way that this already-familiar invention of text via technology has become all the more swift, efficient, and disturbingly near-human.

What makes ChatGPT (and its numerous counterparts) stand out from this long history of textual technology is its sheer scale. ChatGPT is made possible by a Large Language Model (LLM), or a text-based generative AI model that can generate enormous amounts of text in a short amount of time—text that typically reads as, if not human-made, then at least human enough. A key feature of this new wave of text-based AI is that they operate probabilistically: they generate text in response to prompts based on the most probable output, which is in turn determined via algorithmic analysis of massive troves of source texts. Generative AI platforms are “trained” (to use a metaphor) on source data which, in ChatGPT’s case, is a large portion of the Internet, as well as many thousands of news and magazine articles and printed books (typically undertaken without appropriate copyright permissions). ChatGPT is designed to analyze these source texts, identifying patterns, tendencies, and commonalities. A sort of deeply complex sorting machine, generative AI classifies, categorizes, and identifies. It is then able to replicate a text of a similar type, creating a believable document of the type the user requests. We might analogize this process architecturally: on the levels of the word, the sentence, the paragraph or stanza, the section, and the whole, generative AI determines, probabilistically and through algorithmic analysis, the various textual selections that 1) make sense on that individual level and 2) make sense in coordination with selections at all other levels.

We can, I argue, best understand how to approach LLMs such as ChatGPT within the writing classroom by understanding how LLM functionality fits within preexisting writing studies paradigms. The rhetorician Carolyn Miller’s seminal essay “Genre as Social Action” is particularly revelatory here. Miller (1984) defines a “genre” as “a convention of discourse that society establishes as ways of ‘acting together’” (p. 163). Members of a society “act together” through discourse communities and through established patterns of discourse common to those communities, and these patterns are—to metaphorize from evolutionary biology—non-agentially and non-deterministically evolved over time based on the best needs and to suit the perpetuation of the discourse community. In other words, a genre is a pattern of communication established over centuries of accumulated discourse that can be analyzed and replicated.

This is how writing classes have long operated: through the intensive study, via close reading and textual analysis, of the historical and contemporary patterns of discourse that result in the texts we read, and which we then task our students with replicating. The source of so much anxiety in writing studies is that this is the very thing that LLMs do. In effect, an LLM is simply a genre detector and replicator, capable of identifying patterns in human writing, general tendencies, and likely outcomes. When we task our students with analyzing a text and creating their own iteration of it—when we task them with learning from and then participating in a discourse community—we are giving them a task that ChatGPT can quite easily do, too.

This anxiety has been shared in department and committee meetings, emails, hallway discussions, and conferences such as MLA, but it has also burst into the public sphere. Stephen Marche (2022) argued rather infamously in The Atlantic that LLMs have irrevocably shifted the ground under the feet of writing studies, declaring that "the college essay is dead," and writing programs as we know them dead along with it (Marche, 2022). Conversely, Ted Chiang (2023) in the New Yorker argues that the discourse of anxiety has been overplayed: if, Chiang argues, LLMs could perfectly replicate human thought and generate novel concepts, then we would be in deep trouble indeed. But, he says, that's not actually what LLMs do, analogizing their output to blurry photocopies rather than ideation and execution. This distinction is captured when he writes:

> Having students write essays isn't merely a way to test their grasp of the material; it gives them experience in articulating their thoughts... There's nothing magical or mystical about writing, but it involves more than placing an existing document on an unreliable photocopier and pressing the Print button. It's possible that, in the future, we will build an A.I. that is capable of writing good prose based on nothing but its own experience of the world. The day we achieve that will be momentous indeed—but that day lies far beyond our prediction horizon. In the meantime, it's reasonable to ask, What use is there in having something that rephrases the Web? (Chiang, 2023)

Marche and Chiang's competing arguments diverge on two fronts. First: what does GenAI accomplish? And second: can what GenAI accomplish fully replicate the work of a student essay? Marche and Chiang's arguments are both predicated on a technological claim: Marche assumes that GenAI is either already or inevitably going to be good enough to write human essays.

Conversely, Chiang assumes that GenAI is not there yet, and perhaps they might not ever be—we might note that he calls this point of GenAI perfection a "horizon," or that which we can see but never quite reach. But they're both stuck on what GenAI can do—something that we can't entirely predict—we're reduced to guesswork.

This is where writing studies and Miller's understanding of genre come in: the focus on the possibilities of the technology—potentially overstated, impossible to predict or determine in advance—leaves us in a space of uncertainty as to how to proceed. Do we approach GenAI as a powerful threat to the writing classroom? Is it a benefit? Can we use it? If so, how do we use it? Should we use it? These questions are not easy or even possible to answer if we just consider the technology itself. However, we can learn much by turning to Miller and her conception of genre. Since GenAI constructs a text based on recognized patterns within its many thousands or millions of similar sample texts in its training database, it can categorize and replicate a text in a given genre. Drawing on the many cover letters or book reviews accessible in its training database, ChatGPT can produce a serviceable-enough version of these—with sufficiently skillful prompting, that is. But what it cannot do is advance a genre. Its analysis and replication model allows ChatGPT and other similar platforms to replicate a genre, creating a copy of a text that fits into the discursive tendencies and patterns that have historically accumulated into the thing we call a genre. But it cannot innovate; it doesn't make advances on what the genre is or can be. It doesn't blend genres together to create a new genre. It doesn't move the genre forward in any sort of textual or cultural evolutionary step. Language gets stuck in time at the moment of its cultural and historical progress, approaching the moment of the end point of its data set. Furthermore, it generates a mirror of the most mainstream iterations of genres—in other words, not only can it not innovate, but it reduces to the most common denominator of genre, mainstream, dominant discourse—that is, standardized English and the dictates of white-centric linguistic and cultural production.

This understanding of the fundamental limit of an LLM is vital to in turn understanding what we as writing instructors should do in response to their proliferation. If a professor is concerned about the more fundamental question of "is the essay even valuable anymore?" then the answer is: yes, because while ChatGPT can curate an image of an essay reflective of analyzable patterns, it cannot write an essay in the sense of an original act of creation that is both the creation of a product and a heuristic honing thought itself. We might also turn to the etymological roots of essay to see what I mean: deriving from Michel de Montaigne's early examples of the form, the essay is titled by the French essai, meaning to try. An essay, at its most elementary, is an attempt at something: an attempt at answering a question, coming to conclusions, tracing one's thought, entering into discourse. In the most human way imaginable, an essay won't ever be perfect—something writing professors are telling their students all the time, sometimes to no avail—but instead is one piece of the immensely massive and historical project that is called knowledge.

Discourse within writing studies has been attentive to the limitations of GenAI and the impact this has on the writing classroom. Scholars and teachers of writing such as S. Scott Graham (2023) approach this question by turning to pedagogy itself. In a recent article in Composition Studies, Graham (2023) argues that contemporary writing pedagogy—what he refers to as "post-process pedagogy"—is not in danger from GenAI at all. "Post-process pedagogy" is built on the rejection of a linear "writing process," or a process that moves unproblematically from ideation to outlining to drafting to revising to completion—a tidy structure that, for post-process thinking, is a fiction (Graham, 2023). Post-process thinking is not new; Lisa Ede (1994) argued against a linear conception of the writing process, noting that the teaching of writing had been "...co-opted and commodified by textbooks that oversimplified and rigidified a complex phenomenon, by overzealous language arts coordinators and writing program administrators who assumed that the process approach to teaching could be 'taught' in one or two in-service sessions." Similarly, Lee-Ann Kastman Breuch has argued that writing is not a linear process but a "reciprocal hermeneutical process" with multiple non-linear engagements with imagined audiences, teachers, mentors, gatekeepers, institutions, reviewers, sources, and ideas (Graham, 2023). Post-process is the idea that writing is not a linear straight shot from ideation to product, but an admission that, along the way, we loop back around, we return to and revise ideas mid-stream, we sometimes start over, we have our assumptions checked by research, we have our ideas honed by the thought process that writing instigates, we wrangle not only with ideas but with readers, mentors, scholars, peers, all of whom have an influence on the eventual text. In effect, it's the same idea presented above, but presented differently: it's the difference between writing an essay as an easily replicable act of mimesis versus writing an essay as a complicated, stumbling move toward knowledge. Graham argues that, yes, a linear writing process is in great danger from GenAI, since ChatGPT can easily take over many of those steps—brainstorming, drafting, revising are all possible within ChatGPT. But writing isn't just a checklist of stages. Writing requires analysis and replication of writing conventions—genres—but it is also, and more importantly, about the reinvigoration, the changing, and the adaptation of those conventions, and of applying these conventions to analysis, close reading, critical thinking. Annette Vee (2023) offers a quick summary of this thinking when she writes: "Shrink the vision of what writing is for and then it can be automated."

In a way, this discourse around GenAI has simply underscored an already-present debate about what role writing and essays actually play in student learning versus how students encounter or contemplate these things for themselves. It's one thing to say that writing an essay isn't meant to be about the masterful creation of a perfect product but instead the messy process of learning along the way—that it's the journey, not the destination, that we have our sights on. But is this the case for students, for all professors, for administrators, for accreditors, and so on? GenAI can't completely take over a non-linear writing practice—but we have to then ensure that the practice is upheld and done well in the way that we envision it working. This means integrating our expectations around GenAI into our assignments rather than running from it. A framework for how to navigate this fine line is offered by Marc Watkins. In a book chapter "AI in First Year Writing Courses" in TextGenEd, he makes a distinction between "AI-assisted writing" and "AI-generated writing." The distinction is between using GenAI as an assistant or a tool versus letting it do the heavy lifting:

> With the rise of AI writing assistants, students must take special care to ensure that they use this new technology ethically and honestly. In our class, we will distinguish between 'AI-assisted writing' versus 'AI-generated writing'. AI-assisted writing is only permitted in this course provided a student uses an AI writing assistant as a collaborative tool to help the student with the development and advancement of their own writing process. Collaborating with an AI writing assistant can include brainstorming, outlining, and drafting, so long as there is substantial writing, research, and composing by the student which is not generated solely by the AI. 'AI-generated writing' means there has been little or no involvement from the student as an author, with the majority of the writing being generated by an AI. The goal of using AI-assisted writing in this class is to help students develop their writing process and critical thinking, not to replace or substitute for either. Therefore, using an AI to generate writing or compositions without substantial original contribution from a student is neither acceptable nor allowed. (Watkins, 2023)

As professors of writing, we have to help students understand that distinction between assisted and generated. We have to talk about what it can and can't do, and this means applying the textual and rhetorical analysis skills we've had our students hone so well to studying generated texts. We have to not be shy about what it can do, even if it steps on our toes a bit. If, as I argue, GenAI platforms are genre detectors and replicators, then they could have great utility, not as outright essay generators producing blurry photocopies, but as genre sample producers for in-class analysis of conventions and tendencies. As generators of probable articulations, we can study why y follows x in a given sentence—and where those assumptions might come from, either from grammatical necessity or cultural imposition. We have to level with our students about the ethics of using GenAI, just like we study the ethics and politics of citation and of who we choose to be in conversation with. We also have to slow down in our classes. Students will only be able to walk that fine line between AI-assisted and AI-generated if they're guided through it. This means more one-on-one instruction, more check-ins with students, more in-progress review and feedback, and more reflection by students on their work as they go, and, most likely, fewer but more processual writing assignments.

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Breaking News or Making News?: Artificial Intelligence's Impact on Journalism

Ingrid Sturgis, M.A.

When ChatGPT launched in November 2022, it set off a frenzy of news coverage, office chatter, and hyperbole pegged to artificial intelligence's impact on the survival of journalism (Heaven, 2023). Considered the best artificial intelligence chatbot ever, ChatGPT -- the GPT stands for generative pretrained transformer -- was developed by Open AI, and when released more than 1 million people signed up to use it in just five days (Milmo, 2023).

Even Microsoft founder Bill Gates said artificial intelligence, the power behind ChatGPT, was as revolutionary as the microprocessor at the heart of the computer that he helped popularize that started the modern computer age. He called AI as "fundamental as the personal computer, Internet and mobile phone... that would change the way people will learn, work, travel and get health care and communicate" (Gates, 2023).

ChatGPT reached 100 million users two months after launch (Hu, 2023; Milmo, 2023). Two years later, it has more than 180 million users, and news industry leaders are experimenting and watching AI developments with excitement and some dread (Hu, 2023). The technology has blossomed since Apple's Siri was founded in 2011, and Amazon's Alexa was founded in 2014. Back then both were the most widely used manifestation of artificial intelligence (Chen, et al., 2023).

Other AI competitors have since launched, such as Bing Chat, which is based on Open AI technology and the Edge browser (Microsoft is an investor in ChatGPT), the Pi chatbot, created by Inflection AI, Google's Gemini chatbot; Claude AI, which is owned by California-based startup Anthropic and founded by former Open AI employees, and Perplexity, also founded by Open AI alumni. Other chatbots that focus on image generation include Open AI's Dall-e, and Midjourney (Chen, 2024).

Use of artificial intelligence tools in the news business is not new. But past experience, when journalism failed to act on the new technology that has devastated the industry, has spurred news organizations to learn how best to harness its beneficial attributes and mitigate its harms (Caswell, 2023; Sturgis, 2013). Publishers are taking off their kid gloves as it becomes clear that news organizations figure heavily in the success of artificial intelligence tools. According to Radsch (2024), journalism provides a fresh source of human-generated data, which can be used to train AI systems.

For example, the Associated Press was one of the first news organizations to use artificial intelligence in 2014 (Rinehart & Kung, 2022). AI, popularly defined as "a collection of ideas, technologies, and techniques that relate to a computer system's capacity to perform tasks that normally require human intelligence" (Peretti, 2022).

The Associated Press uses it to automate writing story briefs and quarterly earnings reports from financial data feeds. It also has helped reporters discover stories hidden on the internet or buried in vast document repositories. The Associated Press also uses AI technologies to get alerts of breaking news events, to generate summaries from longer articles, to categorize and tag digital metadata to news content, and to transcribe audio from video— among many other use cases (Rinehart & Kung, 2022). At the New York Times algorithms are used to determine how many free articles to show a reader before hitting the paywall. Another journalistic use is to assess the newsworthiness of research papers (Supekar, 2022).

Despite such innovations, there has been a steady 20-year decline of the news industry, during which the United States lost a third of its newspapers and two-thirds of its newspaper journalists, with an average of 2.5 newspapers closing each week (Abernathy, 2023; Becker, 2024; Pew, 2023). Now 86% of Americans say they use digital devices -- a smartphone, computer or tablet – to get news from news websites, apps, search engines as well as social media, and podcasts (Pew 2023). Conversely, tech companies like Apple, Amazon, Alphabet (Google), Meta (Facebook), and Microsoft have grown to become some of the most valuable companies in the world. These privately owned, Silicon Valley-based tech corporations, also known as the Big Five, hold significant influence in digital advertising, publishing, audience engagement, data management, cloud computing, and search functionality. Combined they have had a devastating impact on business models of journalism worldwide. And now, some industry experts said AI may be doing it again (Radsch, 2023).

Already battered by technological changes, scholars said the journalism profession may experience further erosion of jobs, credibility and revenue once artificial intelligence takes hold. Radsch (2024) questioned the survival of journalism given the current business models. Even stalwarts are feeling the pressure. Recently, for example, media outlets like The Washington Post cut 240 jobs through buyouts, NPR laid off employees, and the Associated Press began seeking donations from readers, and a number of other newsrooms closed or consolidated (Bauder, 2023; Becker, 2024).

Literature Review

This issue has prompted much research into the survival of the press and the presence of artificial intelligence, but little of it focuses on the impact of artificial intelligence on lesser resourced news outlets, such as the Black press. For instance, Rasch (2023) investigated how lenient government regulations overlooked the mechanisms enabling tech giants to dominate the distribution channels via the internet, social media, and now artificial intelligence, influencing much of the news and information consumed by the public. Rasch (2023) questioned whether regulatory measures proposed by policymakers would suffice to rebalance the dynamic between journalism and online platforms. These measures include taxation and subsidies, copyright and licensing, as well as competition and anti-trust initiatives.

Similarly, Hanley (2019) demonstrated how the dominance of Google, Apple, Facebook, Amazon, and Microsoft, each with billions of users – has eroded the financial position of journalism. The so-called Big Five have a combined total of 33% market share in 15 separate markets but also replaces the middleman for the buyers and sellers. Hanley (2019) argued this anti-competitive behavior has locked out journalism, preventing it from maint.ning a solid financial footing, a behavior which, demands scrutiny.

But AI is not invulnerable, according to Shumailov et al. (2023). The self-generating feature of these data systems eventually degrades into a “model collapse,” which spotlights its demand for ever more data. The insatiable appetite for new data has led to unethical behavior according to Metz et al. (2024). The authors detailed how Open AI, Google and Meta bent the rules and ignored corporate polices to hoover up news stories, fictional works, message board posts, Wikipedia articles, scraping YouTube videos to harvest text, computer programs, photos, podcasts and movie clips from creators to train their artificial intelligence systems in a quest for content as companies are using data faster than it can be produced (Metz et al., 2024). The New York Times is just one company suing Open AI and Microsoft for copyright infringement as the AI models seek to change copyright rules in order to gain access to published work to train artificial intelligence technologies (Metz et al., 2024).

Workers

In the past year, 2,700 journalists have lost jobs, despite increasing traffic for news. Revenues at news organizations declined by 56% as a handful of tech corporations control the tools of production. The use of artificial intelligence tools threatens to exacerbate this further (Radsch, 2024). In addition, artificial intelligence products rely on a global labor force of outsourced and contract workers. These anonymous workers perform the invisible labor generating and labeling the masses of data that AI systems thrive on, often for extremely low wages and with few worker protections. This underclass of task-drive workers is also responsible for vetting content for reliability and bias (Deck, 2023; Dzieza, 2023; Perrigo, 2023).

These activities demand a significant workforce to label data for training and to clarify data when it becomes unclear. Companies with the vast resources to employ such a workforce can effectively compete and opt to keep their processes secret. Consequently, users know very little about how this information is being compiled and nothing about the people who are shaping it (Dzieza, 2023). However, the effects of this technology are already evident in job displacement, with a significant number of journalists facing layoffs and newsrooms experiencing closures or downsizing. Automated content generation and data analysis could further exacerbate the decline in demand for human-written articles, potentially widening job losses in the industry. While digital outlets have emerged to fill some voids, they're closing almost as fast as others open, according to Medill (2023). There have been discussions about public funding and increased philanthropic support for the industry but none of that has changed the trajectory (Medill, 2023).

The result is that more than 200 counties in the country are "news deserts," defined as an area that lacks access to local news and information that can inform the public (Ferrier, 2014; Medill, 2023). They are also places where the practices of local businesses and large corporations receive scant attention from the media, and little public scrutiny. Even large metropolitan areas are no longer exempt from becoming news deserts. Media watchdogs have lamented the widespread layoffs at the Los Angeles Times, buyouts at The Washington Post, and the continuing collapse of major local papers nationally. The papers that have managed to survive have significantly cut back on their coverage of local and national politics. The decline in news coverage has severe implications for civic participation and ultimately democracy, according to Medill (2023). In a longitudinal study that tracked falling congressional news coverage, the result is less political knowledge and less election participation (Hayes & Lawless, 2018).

Credibility

The use of AI tools, already has resulted in lower-quality or misleading articles, impacting the credibility of news organizations. For example, CNET and Sports Illustrated recently experienced scandals caused by the dubious use of artificial intelligence tools in their reporting. Last year, tech publisher CNET, used automated technology to produce stories were found to contain plagiarism and mistakes (Harrington, 2023). Similarly, Sports Illustrated laid off most of its 100 remaining journalists after announcing a pivot to AI content and was later forced to delete articles published under fake author names and fake profile images that were produced by a marketing firm it had hired to produce content. It subsequently ended a contract with the company that produced the content (Landymore, 2023).

Reduced Diversity

Because Black journalists make up a small number in mainstream newsrooms, such downsizing will eliminate their unique perspectives and the lived experiences that they bring to newsrooms. Prioritizing AI-generated content will help perpetuate biases that is present in the data it is trained on, leading to biased reporting. For examples, tweets written by African Americans are more often flagged as "offensive" as compared to other tweets (Ahmed, et al, 2022). In addition, the demise of legacy news organizations will exacerbate the digital divide and increase news deserts as the flow of resources goes to more affluent communities. These communities have access to alternative news sources that are growing to fill the void left by legacy news organization. Economically struggling and underserved communities do not.

Although a number of articles have highlighted the loss of Black and other minoritized groups in mainstream newsroom declines, few have focused specifically on the legacy Black press. In addition, the resources required to fund innovative artificial intelligence projects may be beyond the capabilities of most black news organizations. For example, the legacy Black press has been slow to prioritize the use of technology in their newsrooms. Many of the members of the National Newspaper Publishers Association still lack websites. Further, they lack the specialized newsroom technology talent to develop build AI-driven reporting initiative, news features and services (Waldman, 2024).

As journalism grapples with the spread of artificial intelligence, how it handles these three critical challenges — workers' rights, diversity, and ethics — will shape its ability to maintain its vital role as a watchdog of democracy in an evolving media landscape.

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CONCLUSION

As we conclude the CETLA 20th Anniversary Conference: The Next Frontier, AI and Beyond, we reflect on the profound insights and innovative discussions that have unfolded throughout this event. Over the past two decades, the Center for Excellence in Teaching, Learning, and Assessment (CETLA) has consistently championed the integration of cutting-edge technologies into the academic sphere, and this year's focus on AI underscores its critical role in reshaping education and research.

The conversations sparked here have illuminated not only the immense potential of AI to revolutionize teaching and learning, but also the ethical, social, and practical considerations we must navigate in this brave new world. As we venture into this next frontier, we are reminded of the importance of collaboration, interdisciplinary engagement, and a commitment to inclusivity in the technological landscape.

We leave this conference with a shared sense of responsibility—one that encourages us to explore new educational paradigms, empower students and educators alike, and leverage AI's capabilities to foster a more equitable and accessible learning environment. The future is unfolding before us, and as a community, we are equipped to lead, adapt, and innovate.
Thank you to all the speakers, panelists, and attendees for contributing to a thought-provoking and forward-thinking dialogue. We look forward to the continued collaboration and progress as we embrace the transformative power of AI and beyond at Howard University and beyond.

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