BEFORE THE
STATE OF NEW YORK
PUBLIC SERVICE COMMISSION

In the Matter of

Niagara Mohawk Power Corporation d/b/a National Grid

Cases 24-E-0322 & 24-G-0323

September 26, 2024

Prepared Exhibits of:
Staff Consumer Services Panel (SCSP)

Chelsea Laquitara
Utility Consumer Program Specialist 4

Adam Polmateer
Utility Consumer Assistance
Specialist 4

Chrystie Stafford
Utility Analyst 1

Kyle LaBelle
Utility Analyst 1

Joshua Trichon
Excelsior Fellow

Office of Consumer Services
State of New York
Department of Public Service
Three Empire State Plaza
Albany, New York 12223-1350

90 Church Street
New York, New York 10007

List of Exhibits

Exhibit__(SCSP-1)

Relief Upon NMPC Responses to Information Requests

Table of Contents

Date of Request: June 5, 2024 Request No. DPS-274
Due Date: June 17, 2024 NG Request No. NG-291

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - John Castano

TO: National Grid

SUBJECT: Uncollectibles

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. On page 59 of its direct testimony of the Customer Panel, the Company states: "[it] is proposing a two-way uncollectible expense reconciliation mechanism that would reconcile the uncollectible expense recovered in base rates against actual net write-offs."

   a. Explain the difference between:

      i. bad debt expense;

      ii. uncollectible expense;

      iii. net write-offs;

      iv. arrears balances; and

      v. arrears accounts receivable.

   b. Does the Company agree that, for ratemaking purposes, the uncollectible expense reflected in revenue requirement is determined based on net-write offs? If not, provide an explanation of the Company's position.

   c. Explain how a reconciliation mechanism will neither hinder nor dis-incentivize the Company to enhance its collection strategies.

2. On pages 62-65 of its direct testimony of the Customer Panel, the Company uses a variety of collection activities and strategies to manage the collection process and minimize uncollectible expenses. More specifically, the Company employed five components: Accounting Initiation, Account Management, Field Collections, Residential Account Management, and Final Bill management.

a. For each collection activity mentioned above, identify the in-service date.

b. For each collection activity mentioned above, explain how the activity has reduced, or positively impacted the Company's net write-offs.

c. Is the Company seeking additional full time equivalent (FTEs), or contractors to assist with the Company's collection processes?

i. If yes, identify the number of requested FTEs, the position (e.g., field collection staff), and how the position would enhance the Company's collection process.
d. Outside of the COVID-19 pandemic, does the Company believe its collection strategies will generally become more efficient over time?

ii. If not, explain why the Company has not altered its collection strategies to become more efficient.

3. In the same format as Exhibit__(CP-5), Schedules 1-3, provide a schedule for Calendar Years 2017-2021.

4. In the same format as Exhibit__(CP-5), Schedules 1-3, provide a schedule from January 1, 2024-April 1, 2024.

a. Provide an updated response on a monthly basis.

Response:

1. a. "Bad debt expense" includes two components: (i) actual accounts that have been written-off as uncollectible, and (ii) changes to the bad debt reserve to account for "doubtful" accounts. "Bad debt expense" is not used in the calculation of the proposed uncollectible expense reconciliation.

The terms "uncollectible expense" and "write-offs" are used to describe the net amount of money that is written-off. A write-off typically occurs when an account is finaled as a result of the customer moving, or in cases when an account is terminated for non-payment and does not reconnect.

"Arrears" and "arrears accounts receivable" refer to the unpaid balance of the account or total amount due from the customer.

b. Yes, the Company agrees that for ratemaking purposes, the uncollectible expense reflected in revenue requirement is determined based on net-write offs.

c. The reconciliation mechanism proposed in this case will neither hinder nor disincentivize the Company from enhancing its collection strategies. The Company has an obligation to act prudently, which includes undertaking efforts to minimize uncollectible expense and assist customers with managing their arrears. Not doing so could result in customer dissatisfaction and higher call volumes and complaints, potentially triggering negative revenue adjustments under the Customer Performance Incentive Mechanism. To that end, the direct testimony of the Customer Panel, as well as the response below, describes the robust collection strategies the Company undertakes – and will continue to undertake – in the Rate Year and beyond to manage uncollectible expense.

The purpose of the proposed reconciliation mechanism is to address the uncertainty with forecasting uncollectible expense in the aftermath of the global COVID-19 pandemic. As explained by the Customer Panel, the prohibition of terminations of customers for non-payment during the pandemic resulted in anomalous uncollectible rates during the period thereafter. As a result, the Company developed its forecast using calendar years 2022-2023. While the Company believes these years serve as a reasonable basis upon which to forecast expense in the Rate Year and Data Years, it is difficult to accurately project the costs. In that regard, recent rate plans approved by the Commission have included similar reconciliations because of this uncertainty. It is the Company's understanding that Consolidated Edison Company of New York, Inc., Orange and Rockland, Central Hudson Gas & Electric Corporation, New York State Electric & Gas Corporation, and Rochester Gas and Electric Corporation have reconciliation mechanisms in place for all or part of their current rate plans. The mechanism proposed by the Company here aligns with recent precedent and is specifically intended to protect both customers and the Company given the variability, uncertainty, and difficulties associated with forecasting post-pandemic uncollectible expense. The proposal also aligns with the Company's compliance filing made on February 21, 2023 in Case 14-M-0565 to establish a two-way reconciliation mechanism associated with uncollectible expense under Niagara Mohawk's current rate plan, helping to enable the Company to offset any over-recovery of uncollectible expense against the Arrears Management Program, Phase 2 costs to be collected from customers.

For these reasons, the Company does not believe the proposed two-way uncollectible expense reconciliation mechanism provides a disincentive to enhance collection strategies.

2. a. Below are the in-service dates for each collection activity mentioned.

Account Initiation: Enhanced Account Initiation was implemented in the Customer Service System ("CSS") in June 2009.

Account Management: The Portfolio Management Package ("PMP") was implemented in CSS on June 20, 2008.

Field Collections: Niagara Mohawk has used CSS to manage its field collections strategy since its implementation in 1999.

Residential Account Management: The Residential Account Management collection strategy was implemented in 2016 and was expanded in September 2023.

Final Bill Management: The Company has managed final accounts for decades.

2. b. **Account Initiation**

The primary purpose of Account Initiation is to address the bad debt risk associated with the residential service application process by preventing fraudulent applications. Obtaining accurate and reliable information from an individual reduces the risk and benefits downstream functions such as Credit and Collections.

Account Initiation primarily consists of the following elements: positive identification and the resolution of uncollected balances. Each of these elements is discussed in additional detail below.

Positive Identification: National Grid attempts to verify the identity of all parties who apply for new or additional service. When the Company is unable to verify the individual's identity during initial contact with the Company, the individual may be required to provide written documentation that supplements their verbal service application. The written documentation is then reviewed and validated by the Company's Offline Work Group before the service application is approved. This process ensures that notifications and bills are issued to the rightful party and increases the likelihood of receiving payment for services rendered, which in turn decreases the Company's bad debt.

Uncollected Balance(s): National Grid uses the Experian PINpoint product to associate a service applicant with any uncollected balance(s) incurred for previous accounts, even when name variations exist. Individuals who have not had active service within the past 60 days are required to settle (*i.e.*, pay or make arrangements on, as applicable) uncollected balances before their service application would be approved. Holding individuals accountable for their uncollected balances decreases existing bad debt and mitigates the increase of additional bad debt.

Data Hygiene: The enhanced Account Initiation implemented in the CSS system includes the Data Hygiene process. As part of Data Hygiene, if a customer passes away, Experian will provide the Company the deceased customer's date of death. This, in turn, assists internal efforts to transition active accounts from a deceased individual's name to the current party responsible for the service. Additionally, as part of Data Hygiene, National Grid updates an account's mailing address under certain circumstances using information provided by Experian. As with Positive Identification, ensuring that notifications and bills are issued to and received by the rightful party increases the likelihood of receiving payment for services rendered and decreases the Company's bad debt.

Account Management

The Account Management process uses an Experian hosted scoring mechanism to determine the level of risk associated with an account. The risk score is developed using customer data internal to National Grid only and determines the collections path that an account will follow. A high-risk account will remain on the standard collections treatment path timeline, while a low-risk account that just entered collections may be provided more time to "self-cure" (*i.e.*, pay before collection action is initiated).

As part of the account management process, a champion/challenger strategy is used whereby half of the accounts within a given risk score go through the champion collection activities while the other half go through a different path (challenger). Periodically, the results of each path are compared to determine which path was more effective in resolving customer accounts. The more effective path becomes the new "champion" and a new "challenger" path is created. This allows for flexing strategies to determine the strategy that is most effective at reducing accounts receivable and future write-offs/uncollectible expense.

<u>Field Collections</u>

Field Collections in accordance with the Home Energy Fair Practices Act ("HEFPA") reduce and positively impact the Company's uncollectibles by collecting payments from customers or disconnecting service. Disconnecting the service prevents the account from accruing higher balances, which would result in higher uncollectibles. Many customers who have their service disconnected subsequently establish a payment agreement with the Company to have their service restored, which positively impacts uncollectibles.

<u>Residential Account Management</u>

Residential Account Management specializes in direct engagement via phone call and email with high-balance residential accounts who require extra assistance in reducing their balances. It focuses on building relationships with the customers to provide financial options and assistance, improve the customer experience, and help to avoid service terminations.

<u>Final Bill Management</u>

Final Bill Management is the process of collecting final or written-off accounts with the assistance of outside collection agencies. Only unpaid final bills are sent to outside collections. All recoveries from collection agencies are a direct reduction to uncollectible expense.

2. c. No, the Company is not seeking additional FTEs or contractors.

2. d. Yes, the Company continually reviews results from the strategies and adjusts the strategies accordingly. Some examples include the recently implemented text messaging to customers with mobile phone numbers who are behind on their bills. The Company is also planning to implement an enhanced email campaign to improve the customer experience and collect overdue balances more efficiently. While these strategies may improve efficiency, the Company is still collecting on historically larger arrears balances since the COVID-19 pandemic, which is offsetting efficiencies gained. The Company expects it to take at least four years to work these balances down.

3. Please see Attachment 1 for schedules covering calendar years 2017-2021.

4. Please see Attachment 2 for schedules covering January 1, 2024-April 1, 2024.

Name of Respondent:
Jeff Koenig

Date of Reply:
June 17, 2024

Niagara Mohawk Power Corporation d/b/a National Grid
Electric Business
Net Charge Off
For Periods January 2017 through December 2021
($000's)

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
				(B + C)		(D + E)	(A / F)
Period	Net Charge Off	Tariff Revenue	LPC Revenue	Non-ESCo Revenue	ESCo Revenue	Adjusted Revenue	Uncollectible Rate
Jan-17	$ 2,717.7	$ 203,014.3	$ 1,111.4	$ 204,125.7	$ 27,343.7	$ 231,469.4	
Feb-17	1,619.3	191,419.9	1,023.3	192,443.2	22,804.0	215,247.2	
Mar-17	1,290.8	176,419.2	1,201.5	177,620.8	23,492.8	201,113.5	
Apr-17	1,583.2	175,463.1	931.4	176,394.5	18,860.8	195,255.3	
May-17	2,243.8	172,142.8	860.4	173,003.2	20,618.1	193,621.3	
Jun-17	3,488.6	181,677.0	1,060.3	182,737.3	24,300.0	207,037.4	
Jul-17	3,398.3	206,496.2	986.6	207,482.7	26,228.9	233,711.6	
Aug-17	5,589.4	208,687.7	1,156.3	209,843.9	28,676.3	238,520.3	
Sep-17	4,669.3	190,125.2	1,053.1	191,178.3	23,937.3	215,115.5	
Oct-17	4,061.2	181,540.1	1,054.7	182,594.8	22,628.4	205,223.2	
Nov-17	3,402.0	173,699.8	1,196.6	174,896.4	20,488.1	195,384.6	
Dec-17	3,084.2	190,132.5	926.0	191,058.5	24,412.6	215,471.1	
12 Months Ending December 31, 2017	**$ 37,147.9**	**$ 2,250,817.8**	**$ 12,561.6**	**$ 2,263,379.4**	**$ 283,791.0**	**$ 2,547,170.4**	**1.4584%**
Jan-18	$ 2,941.52	$ 232,850.3	1,185.5	$ 234,035.9	$ 32,039.4	$ 266,075.2	
Feb-18	(12.2)	224,140.9	1,323.8	225,464.7	26,665.2	252,129.9	
Mar-18	996.6	188,630.0	986.0	189,616.0	24,295.0	213,911.0	
Apr-18	622.5	162,640.7	937.6	163,578.3	21,972.6	185,550.9	
May-18	1,826.1	155,726.6	1,090.0	156,816.6	20,011.8	176,828.3	
Jun-18	2,793.6	174,009.6	681.8	174,691.4	22,665.2	197,356.6	
Jul-18	3,405.2	212,495.8	864.0	213,359.8	27,818.6	241,178.4	
Aug-18	5,015.1	215,425.4	1,114.8	216,540.2	32,630.7	249,170.9	
Sep-18	3,859.9	214,030.9	1,214.4	215,245.3	25,908.6	241,153.9	
Oct-18	3,951.1	182,470.4	986.7	183,457.0	25,635.9	209,092.9	
Nov-18	3,307.6	162,094.3	1,277.0	163,371.3	20,094.4	183,465.7	
Dec-18	3,666.7	190,132.5	926.0	191,058.5	23,806.3	214,864.8	
12 Months Ending December 31, 2018	**$ 32,373.6**	**$ 2,314,647.2**	**$ 12,587.7**	**$ 2,327,234.9**	**$ 303,543.7**	**$ 2,630,778.6**	**1.2306%**
Jan-19	$ 2,965.9	$ 204,109.3	$ 1,215.0	$ 205,324.3	$ 28,833.3	$ 234,157.6	
Feb-19	1,187.3	196,263.6	1,151.4	197,415.0	25,367.1	222,782.2	
Mar-19	2,031.6	182,159.0	1,150.2	183,309.2	24,379.6	207,688.8	
Apr-19	492.5	160,591.1	1,084.3	161,675.4	20,595.6	182,271.0	
May-19	1,357.0	160,483.0	1,167.7	161,650.7	19,777.7	181,428.4	
Jun-19	2,472.7	157,373.5	693.5	158,067.0	20,037.7	178,104.8	

Jul-19	4,008.0	199,201.4	1,106.6	200,308.0	25,498.5	225,806.5	
Aug-19	5,032.2	221,546.6	925.9	222,472.6	27,324.2	249,796.8	
Sep-19	4,158.7	192,193.4	981.9	193,175.3	22,889.8	216,065.1	
Oct-19	3,495.6	157,590.1	965.9	158,556.1	20,860.3	179,416.4	
Nov-19	3,086.1	164,953.2	1,014.9	165,968.1	17,450.1	183,418.2	
Dec-19	2,581.9	195,729.9	740.0	196,469.9	23,777.6	220,247.5	
12 Months Ending December 31, 2019							
	$ 32,869.5	**$ 2,192,194.3**	**$ 12,197.3**	**$ 2,204,391.6**	**$ 276,791.6**	**$ 2,481,183.3**	**1.3248%**
Jan-20	$ 2,507.8	$ 208,728.0	$ 1,098.3	$ 209,826.3	$ 26,992.0	$ 236,818.3	
Feb-20	1,362.7	183,593.9	1,158.2	$ 184,752.1	21,263.2	$ 206,015.3	
Mar-20	1,118.0	174,169.1	542.7	$ 174,711.8	22,536.1	$ 197,247.9	
Apr-20	667.3	162,749.4	(11.2)	$ 162,738.2	19,499.9	$ 182,238.1	
May-20	(43.2)	166,051.0	(60.1)	$ 165,991.0	18,774.2	$ 184,765.2	
Jun-20	2,254.2	188,139.5	(106.5)	$ 188,033.0	21,931.7	$ 209,964.7	
Jul-20	333.9	241,986.9	3.7	$ 241,990.6	29,849.6	$ 271,840.2	
Aug-20	136.8	237,234.7	(2.1)	$ 237,232.7	27,064.7	$ 264,297.3	
Sep-20	1,017.0	212,757.3	(2.7)	$ 212,754.6	23,277.6	$ 236,032.2	
Oct-20	953.5	181,311.0	(0.7)	$ 181,310.4	19,130.2	$ 200,440.6	
Nov-20	648.1	185,979.1	(1.0)	$ 185,978.0	16,850.8	$ 202,828.8	
Dec-20	1,632.1	215,060.8	(1.0)	$ 215,059.7	23,749.8	$ 238,809.5	
12 Months Ending December 31, 2020							
	$ 12,588.2	**$ 2,357,760.7**	**$ 2,617.6**	**$ 2,360,378.3**	**$ 270,919.8**	**$ 2,631,298.2**	**0.4784%**
Jan-21	$ 1,465.3	$ 230,971.0	$ (2.0)	$ 230,968.97	$ 23,529.6	$ 254,498.6	
Feb-21	1,520.7	228,629.6	(0.6)	228,629.0	22,249.8	250,878.8	
Mar-21	992.9	208,920.8	(0.8)	208,920.0	22,287.3	231,207.3	
Apr-21	1,585.6	193,067.0	(0.1)	193,066.9	18,961.7	212,028.6	
May-21	1,885.2	171,300.1	(0.2)	171,299.9	16,631.3	187,931.2	
Jun-21	1,955.5	217,413.5	(0.7)	217,412.8	21,529.8	238,942.6	
Jul-21	1,967.6	263,494.9	(0.1)	263,494.8	26,238.6	289,733.3	
Aug-21	2,034.5	264,113.7	(5.3)	264,108.3	26,788.1	290,896.4	
Sep-21	1,914.9	268,269.2	(0.1)	268,269.1	28,686.6	296,955.7	
Oct-21	2,115.6	219,316.7	(0.0)	219,316.7	21,297.4	240,614.1	
Nov-21	2,922.1	196,147.7	(0.0)	196,147.7	19,757.2	215,904.9	
Dec-21	3,311.5	238,917.3	(0.1)	238,917.1	24,716.2	263,633.3	
12 Months Ending December 31, 2021							
	$ 23,671.3	**$ 2,700,561.5**	**$ (10.1)**	**$ 2,700,551.4**	**$ 272,673.5**	**$ 2,973,224.9**	**0.7961%**

Niagara Mohawk Power Corporation d/b/a National Grid
Gas Business
Net Charge Off
For Periods January 2017 through December 2021
($000's)

	(A)		(B)		(C)		(D) (B + C)		(E)		(F) (D + E)	(G) (A/F)
Period	Net Charge Off		Tariff Revenue		LPC Revenue		Non-ESCo Revenue		ESCo Revenue		Adjusted Revenue	Uncollectible Rate
Jan-17	$	858.2	$	73,620.8	$	234.8	$	73,855.6	$	12,437.9	$	86,293.5	
Feb-17		511.4		73,103.9		256.2		73,360.1		11,070.0		84,430.1	
Mar-17		407.6		72,032.9		358.7		72,391.6		12,111.9		84,503.4	
Apr-17		499.9		60,687.9		288.2		60,976.1		8,141.1		69,117.2	
May-17		708.6		38,659.4		251.1		38,910.6		4,450.2		43,360.8	
Jun-17		1,101.7		30,076.9		248.8		30,325.7		2,644.6		32,970.3	
Jul-17		1,073.2		23,327.1		174.0		23,501.1		1,543.6		25,044.7	
Aug-17		1,765.1		22,320.8		155.8		22,476.6		1,554.7		24,031.4	
Sep-17		1,474.5		23,080.2		120.1		23,200.3		1,651.9		24,852.1	
Oct-17		1,282.5		25,246.4		121.1		25,367.5		1,930.1		27,297.5	
Nov-17		1,074.3		39,753.7		149.4		39,903.1		5,004.5		44,907.6	
Dec-17		921.2		59,757.9		161.3		59,919.2		10,179.1		70,098.3	
12 Months Ending December 31, 2017	**$**	**11,678.2**	**$**	**541,667.7**	**$**	**2,519.6**	**$**	**544,187.3**	**$**	**72,719.7**	**$**	**616,907.0**	**1.8930%**
Jan-18	$	878.64	$	86,644.3	$	258.0	$	86,902.3	$	17,084.5	$	103,986.8	
Feb-18		(3.6)		84,450.6		377.5		84,828.1		12,886.5		97,714.6	
Mar-18		297.7		75,944.5		280.9		76,225.4		11,309.4		87,534.8	
Apr-18		185.9		71,043.5		283.9		71,327.4		10,366.0		81,693.4	
May-18		545.5		46,818.4		356.6		47,175.0		5,300.1		52,475.1	
Jun-18		834.4		28,648.7		164.0		28,812.7		2,133.7		30,946.5	
Jul-18		1,017.1		23,906.7		166.2		24,072.8		1,576.5		25,649.4	
Aug-18		1,498.0		22,243.0		152.5		22,395.5		1,484.0		23,879.5	
Sep-18		1,153.0		23,342.0		138.4		23,480.4		1,425.7		24,906.1	
Oct-18		1,180.2		28,713.1		102.7		28,815.8		2,854.3		31,670.1	
Nov-18		1,044.5		48,501.5		161.2		48,662.8		6,748.6		55,411.4	
Dec-18		1,157.9		77,006.9		197.2		77,204.1		11,127.7		88,331.9	
12 Months Ending December 31, 2018	**$**	**9,789.2**	**$**	**617,263.3**	**$**	**2,639.2**	**$**	**619,902.5**	**$**	**84,297.0**	**$**	**704,199.4**	**1.3901%**
Jan-19	$	936.6	$	94,284.6	$	328.5	$	94,613.1	$	14,741.8	$	109,354.9	
Feb-19		374.9		89,149.4		367.4		89,516.8		13,905.7		103,422.6	
Mar-19		641.6		75,996.5		389.5		76,386.0		12,741.8		89,127.8	

Apr-19	155.5	59,090.6	355.8	59,446.4	7,918.0	67,364.4	
May-19	428.5	41,157.2	355.7	41,512.9	4,314.6	45,827.6	
Jun-19	780.8	28,893.9	190.7	29,084.6	2,296.5	31,381.1	
Jul-19	1,265.7	22,744.3	215.7	22,960.0	1,293.9	24,253.9	
Aug-19	1,589.1	22,355.5	122.9	22,478.5	1,215.8	23,694.3	
Sep-19	1,313.3	23,056.3	111.2	23,167.5	1,286.1	24,453.6	
Oct-19	1,103.9	27,718.2	114.2	27,832.4	2,357.5	30,189.9	
Nov-19	1,084.3	43,556.0	142.4	43,698.4	4,871.9	48,570.3	
Dec-19	907.2	63,560.8	175.9	63,736.7	9,769.3	73,506.0	
12 Months Ending December 31, 2019	**$ 10,581.4**	**$ 591,563.3**	**$ 2,870.0**	**$ 594,433.3**	**$ 76,713.1**	**$ 671,146.4**	**1.577%**
Jan-20	$ 881.10	$ 75,014.3	$ 251.1	$ 75,265.4	$ 11,263.5	$ 86,528.9	
Feb-20	478.8	72,806.4	311.4	$ 73,117.8	10,455.6	$ 83,573.4	
Mar-20	392.8	64,626.2	161.0	$ 64,787.2	9,210.1	$ 73,997.3	
Apr-20	234.5	48,953.3	(0.6)	$ 48,952.7	6,241.5	$ 55,194.1	
May-20	(15.2)	39,168.6	(0.5)	$ 39,168.1	4,353.8	$ 43,521.9	
Jun-20	792.0	27,489.4	(0.6)	$ 27,488.8	1,810.2	$ 29,299.0	
Jul-20	117.3	23,337.2	(1.9)	$ 23,335.3	1,185.4	$ 24,520.7	
Aug-20	48.1	21,600.5	(0.1)	$ 21,600.4	925.5	$ 22,525.9	
Sep-20	357.3	23,464.7	(1.0)	$ 23,463.7	1,197.9	$ 24,661.6	
Oct-20	335.0	27,805.5	(0.1)	$ 27,805.4	1,958.2	$ 29,763.6	
Nov-20	204.7	43,945.1	(0.2)	$ 43,944.9	3,691.9	$ 47,636.8	
Dec-20	515.4	57,458.7	(0.1)	$ 57,458.5	7,446.9	$ 64,905.4	
12 Months Ending December 31, 2020	**$ 4,341.8**	**$ 525,669.9**	**$ 718.3**	**$ 526,388.3**	**$ 59,740.5**	**$ 586,128.7**	**0.7408%**
Jan-21	$ 462.7	$ 72,519.5	$ (0.3)	$ 72,519.19	$ 9,349.9	$ 81,869.1	
Feb-21	480.2	82,856.5	(0.1)	82,856.4	10,258.4	93,114.8	
Mar-21	313.5	79,067.6	(0.0)	79,067.6	9,889.3	88,956.9	
Apr-21	500.7	61,574.2	(0.0)	61,574.2	5,655.3	67,229.5	
May-21	595.3	41,979.0	(0.3)	41,978.7	3,306.1	45,284.8	
Jun-21	617.5	31,100.3	(0.0)	31,100.3	1,830.4	32,930.7	
Jul-21	621.3	25,918.3	(0.1)	25,918.2	1,261.4	27,179.6	
Aug-21	642.5	27,940.1	(0.0)	27,940.1	1,205.9	29,146.0	
Sep-21	604.7	27,055.1	(0.0)	27,055.0	1,305.2	28,360.2	
Oct-21	668.1	30,849.1	(0.0)	30,849.1	1,637.5	32,486.6	
Nov-21	776.8	55,408.5	-	55,408.5	4,140.6	59,549.1	
Dec-21	880.3	90,331.4	(0.0)	90,331.4	8,763.4	99,094.9	
12 Months Ending December 31, 2021	**$ 7,163.7**	**$ 626,599.6**	**$ (0.9)**	**$ 626,598.7**	**$ 58,603.5**	**$ 685,202.2**	**1.0455%**

Niagara Mohawk Power Corporation d/b/a National Grid
Residential Uncollectibles and Terminations
For Periods January 2017 through December 2021

Period	**Terminations**	**Uncollectibles**
Jan-17	898	$3,462,771.89
Feb-17	1,728	$2,009,341.00
Mar-17	1,560	$1,538,297.22
Apr-17	5,275	$1,850,928.40
May-17	8,695	$2,808,185.45
Jun-17	9,506	$4,409,836.09
Jul-17	8,003	$4,294,703.44
Aug-17	9,989	$7,165,150.30
Sep-17	9,141	$5,865,145.13
Oct-17	6,984	$5,740,593.68
Nov-17	518	$3,426,412.68
Dec-17	251	$3,881,202.94
Jan-18	483	$3,583,897.41
Feb-18	1,075	$30,582.01
Mar-18	530	$1,082,849.22
Apr-18	4,482	$471,100.62
May-18	10,054	$2,212,465.38
Jun-18	8,643	$3,242,589.33
Jul-18	6,265	$4,148,805.78
Aug-18	7,730	$6,215,032.63
Sep-18	6,892	$4,806,485.91
Oct-18	5,445	$4,638,507.82
Nov-18	5	$4,102,710.32
Dec-18	4	$4,434,837.62
Jan-19	58	$3,535,037.00
Feb-19	214	$1,265,830.70
Mar-19	180	$1,861,625.76
Apr-19	4,146	$482,133.27
May-19	8,444	$1,668,544.55
Jun-19	9,059	$3,005,301.55
Jul-19	10,377	$4,729,676.82
Aug-19	9,205	$6,472,376.21
Sep-19	7,647	$5,140,028.73
Oct-19	3,937	$4,493,092.88
Nov-19	50	$3,810,403.88
Dec-19	21	$3,269,758.01

Period	Terminations	Uncollectibles
Jan-20	2	$3,101,648.08
Feb-20	76	$1,607,033.98
Mar-20	258	$1,263,000.99
Apr-20	-	$685,136.38
May-20	-	-$97,979.22
Jun-20	-	$2,739,981.34
Jul-20	-	$304,425.80
Aug-20	-	$129,157.21
Sep-20	-	$783,472.09
Oct-20	-	$1,321,533.43
Nov-20	-	$816,248.90
Dec-20	-	$1,774,789.40
Jan-21	-	$2,364,802.32
Feb-21	-	$1,513,184.69
Mar-21	-	$951,095.22
Apr-21	-	$1,475,554.14
May-21	-	$2,184,372.26
Jun-21	-	$2,386,866.26
Jul-21	-	$2,193,251.01
Aug-21	-	$2,404,187.29
Sep-21	-	$2,378,517.25
Oct-21	-	$2,622,190.55
Nov-21	-	$3,545,452.04
Dec-21	-	$3,978,415.67

Niagara Mohawk Power Corporation d/b/a National Grid
Electric Business - Net Charge Off
For Periods January 2024 through April 2024
($000's)

	(A)	(B)	(C)	(D) (B + C)	(E)	(F) (D + E)	(G) (A / F)
Period	Net Charge Off	Tariff Revenue	LPC Revenue	Non-ESCo Revenue	ESCo Revenue	Adjusted Revenue	Uncollectible Rate
Jan-24	$ 5,650.6	$ 276,993.9	$ 1,489.5	$ 278,483.4	$ 31,392.4	$ 309,875.8	
Feb-24	3,430.7	274,429.7	1,828.0	276,257.7	28,183.9	304,441.5	
Mar-24	2,309.8	255,267.3	1,332.2	256,599.4	24,791.9	281,391.4	
Apr-24	2,859.6	236,615.8	1,464.5	238,080.3	25,880.4	263,960.6	
May-24							
Jun-24							
Jul-24							
Aug-24							
Sep-24							
Oct-24							
Nov-24							
Dec-24							
12 Months Ending December 31, 2024	$ 14,250.8	$ 1,043,306.6	$ 6,114.1	$ 1,049,420.8	$ 110,248.5	$ 1,159,669.3	1.2289%

Niagara Mohawk Power Corporation d/b/a National Grid
Gas Business - Net Charge Off
For Periods January 2024 through April 2024
($000's)

	(A)	(B)	(C)	(D) (B + C)	(E)	(F) (D + E)	(G) (A / F)
Period	Net Charge Off	Tariff Revenue	LPC Revenue	Non-ESCo Revenue	ESCo Revenue	Adjusted Revenue	Uncollectible Rate
Jan-24	$ 1,687.9	$ 94,505.7	$ 293.7	$ 94,799.5	$ 6,710.7	$ 101,510.2	
Feb-24	1,024.8	101,110.7	360.8	101,471.4	6,534.3	108,005.8	
Mar-24	690.0	88,250.8	388.0	88,638.7	5,547.3	94,186.0	
Apr-24	854.2	72,989.2	358.8	73,348.1	4,675.9	78,023.9	
May-24							
Jun-24							
Jul-24							
Aug-24							
Sep-24							
Oct-24							
Nov-24							
Dec-24							
12 Months Ending December 31, 2024	$ 4,256.7	$ 356,856.4	$ 1,401.3	$ 358,257.7	$ 23,468.2	$ 381,725.9	1.1151%

Niagara Mohawk Power Corporation d/b/a National Grid
Residential Uncollectibles and Terminations
For Periods January 2024 through April 2024

Period	**Terminations**	**Uncollectibles**
Jan-24	27	$6,342,330.92
Feb-24	179	$3,753,911.72
Mar-24	588	$2,487,509.52
Apr-24	6,626	$3,097,384.24
May-24	-	
Jun-24	-	
Jul-24	-	
Aug-24	-	
Sep-24	-	
Oct-24	-	
Nov-24	-	
Dec-24	-	

Date of Request: June 14, 2024 Request No. DPS-302
Due Date: June 24, 2024 NG Request No. NG-322

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Customer Service Performance Indicators (CSPI) - Call Center Staffing

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. For each month of the last 5 years (2019, 2020, 2021, 2022, and 2023), provide the following:

   a. The number of internal employees who were going through training for employment with the in-house call center(s);

   b. The number of trained, in-house, call center full-time equivalents (FTEs) who regularly take customer calls;

   c. The number of trained, in-house, customer service FTEs who answer Public Service Commission (PSC) complaints and/or regularly perform tasks other than taking calls;

   d. The number of internal customer service staff, including call-takers, who left the Company or changed their position within the Company;

   e. The average daily number of external call center employees utilized by the Company's third-party vendor(s);

   f. The number of customer service representative (CSR) positions the Company allocated for the call center(s);

   g. The number of vacant CSR positions in the call center(s).

2. For each month of the last 5 years (2019, 2020, 2021, 2022, 2023), provide the number of hours worked for the following positions:

a. Trained, in-house call center employees.

b. External call center employees through the Company's third-party vendor(s).

3. For each month of the last 5 years (2019, 2020, 2021, 2022, 2023), provide the following number of FTE positions:

a. Meter readers employed at the Company, both in-house and through the Company's third-party vendor(s) (separately state in-house and third-party).

b. In-house meter readers who left the Company or changed their position within the Company to a non-meter reader position.

4. As of December 31 of each of the past 5 calendar years (2019, 2020, 2021, 2022, 2023), provide the minimum, average, and maximum length of time that call center staff have been employed with the Company.

<u>Response</u>:

1. a. Please see the table below for the monthly breakdown of in-house, call center full-time equivalents ("FTEs") who were going through training for employment. Please note the Company has this data only for 2020 through to 2023.

	2020	**2021**	**2022**	**2023**
January	21	11	19	10
February	36	11	18	8
March	17	13	16	0
April	17	31	18	22
May	21	27	16	30
June	6	24	27	9
July	6	11	14	8
August	5	15	11	15
September	5	39	19	15
October	0	37	16	27
November	0	36	15	29
December	11	33	28	35

b. Please see the table below for the monthly breakdown of trained, in-house, call center FTEs who regularly take customer calls. Please note the Company has this data only for 2020 through to 2023.

	2020	2021	2022	2023
January	150	135	168	123
February	149	134	161	117
March	166	133	158	109
April	164	127	160	105
May	159	116	149	101
June	156	124	145	116
July	154	129	154	108
August	149	129	146	109
September	145	123	134	100
October	146	158	131	93
November	142	151	122	97
December	143	143	113	105

c. Please see the table below for the monthly breakdown of trained, in-house, customer service FTEs who answer Public Service Commission ("PSC") complaints and/or regularly perform tasks other than taking calls:

	2019	2020	2021	2022	2023
January	7	7	7	7	7
February	7	7	7	7	7
March	7	7	7	7	7
April	7	7	7	7	7
May	7	7	7	7	7
June	7	7	7	7	7
July	7	7	7	7	7
August	7	7	7	7	7
September	7	7	7	7	7
October	7	7	7	7	7
November	7	7	7	7	7
December	7	7	7	7	7

d. Please see the table below for the monthly breakdown of internal customer service staff, including call-takers, who left the Company or changed their position within the Company in the last four years. Please note, the Company has this data only from 2020 through to 2023.

	2020	2021	2022	2023
January	4	6	8	8
February	5	2	8	8
March	3	11	5	16
April	2	11	16	5
May	5	12	14	6

	2020	2021	2022	2023
June	3	7	6	7
July	2	9	5	10
August	4	10	11	7
September	5	6	14	10
October	5	5	6	9
November	5	8	8	4
December	6	8	10	1

e. Please see the table below for the monthly breakdown of average daily number of external call center employees utilized by the Company's third-party vendors.

	2019	2020	2021	2022	2023
January	51	186	126	186	154
February	58	186	141	143	130
March	50	174	151	158	145
April	49	147	175	199	182
May	72	129	163	187	197
June	68	133	148	203	213
July	76	125	190	230	236
August	81	115	232	186	217
September	69	128	228	196	224
October	94	121	263	203	223
November	67	120	254	197	223
December	65	127	238	167	217

f. Please see the table below for the monthly breakdown of customer service representative (“CSR”) positions allocated for the Niagara Mohawk call center. Please note, the Company has this data only from 2020 through to 2023.

	2020	2021	2022	2023
January	182	158	202	150
February	196	157	194	142
March	194	159	189	126
April	192	171	193	144
May	191	159	179	148
June	173	163	187	142
July	171	155	182	133
August	164	159	172	141
September	162	177	168	131
October	157	210	162	136
November	153	202	154	142
December	165	191	158	156

g. Please see the table below for the monthly breakdown of vacant call center CSR positions. Please note the Company has this data only from 2020 through to 2023.

	2020	2021	2022	2023
January	0	-14	0	-26
February	0	-3	0	-4
March	0	0	0	-13
April	0	0	0	-5
May	0	0	0	0
June	0	0	0	0
July	0	-7	-13	-9
August	0	-14	2	-12
September	0	-17	-3	-16
October	0	-7	-1	-10
November	-20	0	0	-8
December	-7	0	-11	-7

2. a. Please see the table below for the monthly breakdown of hours worked by trained, in-house call center employee representative. Please note the Company has provided the readily available data for April 2021 through the close of calendar year 2023.

	2021	2022	2023
January		19,540	12,121
February		17,595	11,663
March		21,229	15,902
April	14,501	20,025	11,496
May	14,420	22,361	13,962
June	16,604	21,305	13,329
July	16,208	18,692	15,924
August	17,711	21,093	16,493
September	17,307	20,698	17,484
October	22,253	21,377	17,823
November	22,416	23,816	21,925
December	24,804	30,944	18,969

b. Please see the table below for the monthly breakdown of hours worked by external call center employees through the Company's third-party vendors.

	2019	2020	2021	2022	2023
January	8,083	30,323	20,742	30,591	26,677
February	9,288	30,320	23,104	23,492	20,079
March	8,035	28,449	24,659	25,997	24,325

April	7,856	24,092	28,695	32,680	25,662
May	11,505	21,119	26,775	30,623	31,096
June	10,802	21,643	24,303	33,172	30,257
July	12,153	20,514	31,233	37,692	34,366
August	12,914	18,876	38,143	30,387	38,494
September	11,036	20,858	37,485	32,064	33,486
October	15,039	19,734	43,280	33,177	35,473
November	10,653	19,669	41,824	32,257	33,360
December	10,407	20,790	39,196	27,362	32,626

3. a. Please see the tables below for the monthly breakdown of in-house meter readers employed at the Company and those employed through the Company's third-party vendors.

In-House Meter Readers:

	2019	2020	2021	2022	2023
January	37	37	37	35	37
February	37	37	37	36	35
March	37	37	37	36	35
April	36	37	37	37	35
May	37	37	37	36	34
June	37	37	37	35	34
July	37	37	37	36	34
August	37	37	36	37	33
September	37	37	36	37	32
October	37	37	36	37	33
November	37	37	36	37	33
December	37	37	35	37	34

Third-Party Vendor Meter Readers:

	2019	2020	2021	2022	2023
January	0	0	0	0	0
February	0	0	0	0	0
March	0	0	0	0	0
April	0	0	0	0	0
May	0	0	0	0	0
June	0	0	0	0	0
July	0	0	0	0	0
August	0	0	0	0	0
September	0	0	0	0	0
October	0	0	0	0	0

	2019	2020	2021	2022	2023
November	0	0	0	0	0
December	0	0	0	0	0

b. Please see the tables below for the monthly breakdown of in-house meter readers who left the Company or changed their position within the Company to a non-meter reader position.

In-House Meter Readers who left the Company:

	2019	2020	2021	2022	2023
January	0	0	0	0	0
February	0	0	0	0	0
March	0	0	0	0	0
April	1	0	0	0	0
May	0	0	0	0	0
June	0	0	0	0	0
July	0	0	0	0	0
August	0	0	0	0	0
September	0	0	0	0	0
October	0	0	0	0	0
November	0	0	0	0	0
December	0	0	0	0	1

In-House Meter Readers who changed their position within the Company:

	2019	2020	2021	2022	2023
January	0	0	0	0	0
February	0	0	0	0	2
March	0	0	0	0	0
April	0	0	0	0	0
May	0	0	0	1	1
June	0	0	0	1	0
July	0	0	0	0	2
August	0	0	1	0	1
September	0	0	0	0	1
October	0	0	0	0	0
November	0	0	0	0	0
December	0	0	1	0	0

4. National Grid has the requested representative tenure data as of 2020, please see below.

<u>2020</u>
Min: 74 Days

Max:	49 Years, 1 Month, 24 Days
Avg:	6 Years, 1 Month, 27 Days

2021

Min:	1 Day
Max:	35 Years, 3 Months, 19 Days
Avg:	2 Years, 8 Months, 18 Days

2022

Min:	12 Days
Max:	40 Years, 3 Months
Avg:	1 Year, 11 Months, 6 Days

2023

Min:	1 Day
Max:	36 Years, 6 Months, 4 Days
Avg:	3 Years, 10 Months, 4 Days

Name of Respondent:
Jim MacVicar
Kadian Brown
Jeffrey Knighton
Julianne Pease

Date of Reply:
June 24, 2024

Date of Request: June 24, 2024 Request No. DPS-369
Due Date: July 5, 2024 NG Request No. NG-398

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Billing - Customer Payments

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. Specify each method of bill payment (e.g., walk-in offices, online portal, postal mail, Western Union/NYCE), and form of payment (e.g., electronic check, cash, credit card, and debit card and Electronic Benefits Transfer (EBT) card payments) that the Company makes available to residential customers.

2. Provide a breakout of the residential customer fee per transaction for each of the payment methods/forms identified in response to question (1).

3. Provide a breakout of the per-transaction cost to the Company for each residential customer payment method/form identified in response to question (1).

4. For each of the past five full calendar years (2019, 2020, 2021, 2022, and 2023), provide the total number of payments made through each payment method/form listed in response to question (1). Include in your response the percentage of total payments that each type represents per year.

Response:

1. Please see Attachment 1, column A for each payment method available to residential customers. Additional information on the ways customers can pay their bill is also available on the Company's website at https://www.nationalgridus.com/upstate-ny-home/billing-payments/ways-to-pay.aspx.

2. Please see Attachment 1, column B for a breakdown of the residential customer per-transaction fee for each of the payment methods identified in column A.

3. Please see Attachment 1, column C for a breakdown of the per-transaction cost to the Company for each of the residential customer payment options identified in column A.

4. Please see Attachment 1, columns D-M for the total number of payments made for each payment type listed in column A, and the percentage of total payments each type represents per year. Please note that the Company expanded digital pay options, such as Venmo, Apple Pay, PayPal, and Google Pay effective in January 2024. As such, there is no historical information regarding customer use of those digital payment options.

Name of Respondent:	Date of Reply:
Jeff Koenig	July 5, 2024

			2019		2020		2021		2022	
Customer Payment Methods	**Customer Cost Per Payment ($)**	**Company Cost Per Payment ($)**	**Payment Volumes**	**Percent to Total Payments**	**Payment Volumes**	**Percent to Total Payments**	**Payment Volumes**	**Percent to Total Payments**	**Payment Volumes**	**Percent to Total Payments**
Direct Pay (Auto Pay) - Customer can enroll in this auto payment method that allows the customer to setup their checking/savings account to have their monthly company bill automically paid.	$0.00	$0.04*	1,705,984	10%	1,736,359	11%	1,562,120	10%	1,844,338	12%
One-Time Web Payment/Recurring Web - Customers can use their checking/savings account to make one-time payment on the Company's website. NMPC customers can enroll in a simliar auto pay method at Direct Pay but this auto pay option gives more flexibility to customers to decide payment date and amount they want to pay.	$0.00	$0.04*	3,682,666	23%	4,014,043	26%	4,524,176	29%	4,903,479	31%
IVR/PaybyPhone - Customers can call into the Company's interactive voice recognition phone number system to make a payment using their checking/savings account. Customer can also call into a Call Center and with help from a CSR can make a payment using their checking/savings account.	$0.00	$0.04*	792,684	5%	633,815	4%	644,879	4%	641,803	4%
Home Banking/Third-Party Payment Consolidators (JP Morgan Chase Electronic Lockbox) - Customers can pay through their own personal bank. Customers can also pay via other third-party payment processors that accept taking the company payments.	Unknown - This would depend on the customers bank and/or if the customer is using a third-party payment processor that does not have a direct relationship with the Company.	$0.04	1,868,015	11%	2,122,252	14%	2,131,066	14%	2,059,385	13%
ACH/ Wire Payments Bank Statement - The Company can provide customers the Company's banking information so customers can send the an ACH/Wire payment to the company bank account directly.	Unknown - This would depend on what the customer's bank charges them to send the company an ACH/Wire.	$0.04*	701,027	4%	757,219	5%	748,126	5%	640,893	4%
Credit/Debit Card Payments - Customers can make a credit/debit card payment via the Speedpay (ACI) website, Speedpay IVR, and the Company's mobile app that connects to the Speedpay website. *Please note that the Company expanded digital pay options, such as Venmo, Apple Pay, PayPal, and Google Pay effective in January 2024. As such, there is no historical information regarding customer use of those digital payment options.	$1.75 for making a card payment up to $1,300.00 - Customer can make 5 payments in a 30 day period. This fee covers the cost to process the payment plus PCI compliance, support, and projects/enhancements made with Speedpay (ACI) services for customers.	$0.00	1,434,634	9%	980,479	6%	1,025,727	7%	1,215,553	8%
Checks - Lockbox Processor - Customers can mail a check to our Lockbox processor to make a payment.	$0.00	$0.07 per check	5,250,770	32%	4,779,324	31%	4,430,175	28%	4,070,832	25%
Western Union Walkin Locations - Customers can go to a Western Union Location and make a payment via Cash/Check**.**	$0.00	$1.25 per payment	847,131	5%	644,299	4%	598,186	4%	620,716	4%
Grand Total			**16,282,911**		**15,667,790**		**15,664,456**		**15,996,999**	

*This only covers the cost of processing the payment. This does not include maintaining systems (WEB/IVR, Kiosks) or manual labor costs (ACH/Wire payments bank statement/Customer Offices) to process some payments.

Date of Request: June 24, 2024 Request No. DPS-389
Due Date: July 5, 2024 NG Request No. NG-418

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Joshua Trichon

TO: National Grid

SUBJECT: Payment Method - Credit Card, Debit Card, Alternative Payment Methods

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. On page 66 of the Customer Panel testimony, the Company states that its customers use credit cards, debit cards, and alternative payment methods (Apple Pay, Google Pay, PayPal, and Venmo) to pay their bill. For the past three years (2021, 2022, and 2023), provide the following information, separately for each listed payment method.

    a. The percentage of customers who pay by credit card, debit card, or alternative payment method (Apple Pay, Google Pay, PayPal, and Venmo), separated by type of payment method;

    b. The total number of customers who pay by credit card, debit card, or alternative payment method (Apply Pay, Google Pay, PayPal, and Venmo), separated by type of payment method;

    c. The total number of Energy Affordability Program (EAP) customers utilizing each payment type for each calendar year, separated by type of payment method.

2. Page 3 of Exhibit__(CP-6) shows that the Company anticipates an 80 percent increase in payments made by credit card and debit card in the Rate Year under a no-fee model. Provide all studies and documentation that support the Company's forecast under the proposed no-fee model.

3. Confirm if the Company will continue to use Speedpay as its vendor for credit card, debit card, or alternative payment method transactions under the no-fee model.

    a. If so, provide Speedpay's fee per transaction and the annual cost the Company pays for its services.

b. If not, identify the vendor the Company uses, the vendor's fee per transaction, and the annual cost the Company pays for its services.

4. Provide the current fees charged to the customer that the Company applies for each of the following payment methods:

   a. credit cards;

   b. debit cards; and,

   c. alternative payment methods (Apply Pay, Google Pay, PayPal, and Venmo).

5. Provide the following information for customers who pay using credit cards, debit cards, and alternative payment methods, separately for each payment type.

   a. Percentage and total amount of customers who make multiple payments, and incur multiple fees, per statement balance in one billing period.

6. Provide any survey results the Company has performed regarding no fee payment options.

   a. Identify the number of surveys sent and the response rate. Specify whether the surveys were sent to Niagara Mohawk residential customers, or all Niagara Mohawk customers.

Response:

1. a. The Company does not track the percentage of customers who pay by credit card, debit card, or an alternative payment method; however, the Company does track the percentage of payments.

   Please refer to Attachment 1 to the response to DPS-369 for a history of payments from 2021-2023. The alternative payment methods were implemented in January 2024; therefore, there is no data for alternative payment methods for this period.

   b. The total number of customers who pay by credit card, debit card, or alternative payment method is not tracked by the Company; however, the Company does track the number of transactions.

   Please refer to Attachment 1 to the response to DPS-369 for a history of payments from 2021-2023. The alternative payments were implemented in January 2024; therefore, there is no data for alternative payment methods for this period.

   c. The Company does not track the total number of EAP customers utilizing each payment type for each calendar year.

2. The Company does not have any formal studies. The 80 percent projected increase is the Company’s best estimate based on feedback from other utilities who have adopted a no-

fee model. That feedback indicates they have experienced an increase to adoption rates of between 50% - 100% under a no-fee model. Because of the uncertainty associated with customer adoption, the Company is proposing a two-way reconciliation of these costs.

3. Currently, there are no plans on moving from Speedpay as a vendor.

   a. Speedpay's fee is currently $1.75 for residential customers but will increase to $1.85 in August of this year. If approved for this no fee proposal the Company will work with Speedpay to apply for the VISA utility rate that would lower that fee based on the merchant fees and fee agreement with Speedpay. There is no annual cost to the Company for the services that Speedpay provides.

   b. Not applicable

4. a. Speedpay's fee is currently $1.75 for residential customers but will increase to $1.85 in August of this year.

   b. Speedpay's fee is currently $1.75 for residential customers but will increase to $1.85 in August of this year.

   c. Speedpay's fee is currently $1.75 for residential customers but will increase to $1.85 in August of this year.

5. a. The Company was able to obtain this data for the past three months. Please see the table below for the percentage and total amount of customers who make multiple payments, and incur multiple fees, per statement balance in one billing period.

	Mar-24	**Apr-24**	**May-24**
Multiple CC Payments	4,001	4,683	3,367
Multiple DC Payments	1,674	1,787	2,024
Total CC/DC Payments	118,035	122,953	119,159
Percentage of Multiple Payments Resulting in Multiple Fees	4.81%	5.26%	4.52%

6. a. The Company has not conducted any surveys with customers specifically around the no fee payment option. It has received feedback through other surveys focused on the overall payment experience where customers have expressed frustration regarding having to pay a fee when using a credit/debit card.

Name of Respondent: Jeff Koenig

Date of Reply: July 5, 2024

Date of Request: July 3, 2024
Due Date: July 15, 2024

Request No. DPS-479
NG Request No. NG-509

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request
Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology (IT) – Customer Service System (CSS) Enhancements

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

Referring to the CSS Enhancements described on page 76-78 of the Customer Panel's direct testimony:

1. Provide a detailed breakdown of the capital expenditure costs that will be allocated to Niagara Mohawk, by category (e.g., hardware, software, equipment, etc.), projected for the Fiscal Years (FY) ending March 31, 2026 (FY26), March 31, 2027 (FY27), March 31, 2028 (FY28), and March 31, 2029 (FY29), separately for gas and electric.

2. Provide a detailed breakdown of the operations and maintenance costs that will be allocated to Niagara Mohawk, by category (e.g., internal labor, external labor, software updates, consulting contracts, support contracts, etc.), projected for the FY26, FY27, FY28, and FY29, separately for gas and electric.

3. Provide a detailed breakdown of the rent costs projected for Niagara Mohawk only for FY26, FY27, FY28, and FY29.

4. Provide a detailed timeline, with specific or estimated dates, to implement this program.

5. Describe in detail if the Company has identified any resourcing constraints for this program and explain how such identified constraints will be addressed.

    a. As part of your response, explain the Company's strategy for ensuring adequate resources are available to work on the program during the specified time-period.

6. Describe in detail any risks associated with this program that the Company identified and explain how these risks will be managed and mitigated.

a. As part of your response, provide the Company's risk management plan developed as part of the program.

7. Explain in detail if this program shares any interdependencies with other programs, processes, and/or systems.

   a. Include a description of the required sequence for implementing such programs, processes, and systems, and how the Company will address such sequencing.

8. Provide the Company's governance structure for implementing the program, including the names and titles of the people who will be implementing the program, as well as the identity of the executive sponsor.

9. Provide a specific description of the technology utilized for the program, including whether it is a custom build or a commercial off-the-shelf solution.

10. Provide the Company's benefit cost analysis for the proposed program.

11. Describe the Company's approach for developing cost estimates for this program, and provide supporting documentation (e.g., quotes, analyses, etc.) assumptions, and methodology used.

12. Explain whether the Company evaluated any alternatives to this program and include an explanation of why the Company ultimately chose this option versus an alternative.

13. Explain in detail how the Company's selected program solution compares with other utilities' solutions, and with industry standards.

14. Page 77 of the Customer Panel's direct testimony describes four enhancements. Regarding these enhancements, explain:

   a. whether there is a prioritization among the four enhancements;
   b. whether there is an optimal sequencing of deploying these enhancements; and
   c. the proportional cost of each of these enhancements?

15. Explain whether there are anticipated savings to result from these technology investments. If yes, describe:

   a. where in the Companies' cost structure will the savings manifest;
   b. whether they are one-time or ongoing savings;
   c. when the savings will occur;
   d. whether there are conditions that are required for the cost savings to be realized (milestones met, dates met, other systems work completed, etc.); and
   e. what form the cost savings will take (reduction in number & dollar amounts of support contracts for maintaining legacy systems, fewer FTEs, lower software costs, etc.).

16. What is the long-term plan for maintenance (costs as well as support strategy) and the Company's approach to mitigating technology obsolescence risk?

Response:

Please note that what was referred to as CSS Enhancements at pages 76-78 of the Customer Panel's direct testimony should have been referred to as CSS/Customer Information System ("CIS") enhancements. As described on page 76 of the Customer Panel's direct testimony, National Grid is implementing the CRIS to CSS consolidation project so that all of National Grid's U.S. customers will benefit from the efficiencies of a single customer system – CSS. As part of the project, the Company must make certain improvements to the existing CSS system. Information concerning the costs of those improvements is set forth on Exhibit __ (ITDP-4) at 1 (See reference to CSS Enhancements FY 25) and Exhibit __ (ITDP-8) at 47-53.

In addition, as also discussed by the Customer Panel at page 77, lines 9-21 of its direct testimony, the Company is also proposing a number of enhancements to its overall CIS platform that will both maintain the reliability of the existing CIS platform and provide the ability to continue to modify the system to support changes required by the clean energy transition. The costs of these investments are set forth on Exhibits __ (ITDP-4) at 6 (See reference to CIS Enhancements) and (ITDP-8) at 750-757. This clarification will be discussed in the Company's corrections and updates testimony.

1. Please see Exhibit__(ITDP-8), pages 750 through 757 of 1611, which provides the Company's Sanction Estimation Template ("SET"), SET-1099 for the CIS Enhancements. The SET is an updated investment analysis tool to better align early project development information with the overall Information Technology and Digital ("IT&D") sanctioning process. The SET captures key attributes of proposed future investments, including the investment description, supporting cost estimation calculations, scope, timing (Releases-Deliverables & Milestones), alternatives, and the expected benefitting company.

   The detailed breakdown of capital expenditures by fiscal years ending March 31, 2026, through March 31, 2029, is $48.98 million as shown at page 752 of SET-1099 and Exhibit__(ITDP-4) to the IT&D Panel's testimony. Please note that the SET is a point in time document that includes expected spend each year while Exhibit__(ITDP-4) reflects capital costs based on the anticipated in-service dates for purposes of calculating the revenue requirements. Thus, the total capital amounts are the same in SET-1099 and Exhibit__(ITDP-4), but the annual amounts may show slight differences.

   As shown in the SET, the Company followed a cost causal allocation methodology, using cost allocator C903, which allocates the costs of the CIS Enhancements investment across all National Grid's gas and electric U.S. operating companies. The C903 allocator distributes costs based on the meters installed to National Grid's retail companies. The allocator includes the following percentage allocations to the following operating companies:

Operating Companies	% Allocation
NMPC Electric	25.58%
NMPC Gas	9.66%
KEDNY	19.55%
KEDLI	9.39%
MECO-E	21.09%
NANTUCKET	0.22%
BOSTON Gas	11.24%
COLONIAL Gas	3.27%

2. The SET provides detailed project operations and maintenance ("O&M") expenditures and run-the-business ("RTB") costs on page 752. The total FY26 through FY29 project O&M expense and RTB costs for this investment is $5.78 million and $1.64 million, respectively, as shown in the SET and Exhibit__(ITDP-5) to the direct testimony of the IT&D Panel.

3. The detailed projected CIS Enhancements Service Company rent expense for Niagara Mohawk for electric and gas, respectively, are listed below:

Rent Costs	FY26	FY27	FY28	FY29
ELECTRIC	$0	$88,509	$821,469	$1,841,816
GAS	$0	$33,425	$310,218	$648,643

4. Please see page 751 of SET-1099 for the detailed timeline (Releases – Deliverables & Milestones) including deliverable description and plant-in-service dates.

5. Please see page 751 (Dependencies, Potential Risks & Assumptions) of SET-1099 for any potential resourcing constraints and how such potential constraints will be addressed. There are currently no resource constraints identified; however, should constraints arise during implementation, this will be managed through resource augmentation either using internal skilled resources who can support the effort without impacting other deliverables and/or via approved vendors with the proper skills sets and experience to deliver on this investment.

6. Please see page 751 (Dependencies, Potential Risks & Assumptions) of SET-1099 for any identified potential risks associated with this investment and how such potential risks will be mitigated and managed. The product/project teams use various tools to track a project's progress, risks, and challenges as they arise. Those tools include project Risks/Actions/Issues/Decisions ("RAID") logs, Microsoft Project Online, and RAID tooling capabilities within Jira, a project management software tool. As the project team works to mitigate or remediate risks, continuous status updates are provided to senior product directors who then assist in managing and escalating to the appropriate Chief Information Technology and Digital Officer ("CIDO"), as needed. All portfolios across

IT&D are required to hold recurring portfolio performance check in meetings, where portfolio leadership, IT&D Planning and Strategy, IT&D Finance, and IT&D Regulatory teams review updates on investments and outcomes delivered, risks and mitigating actions, and a financial summary. Following portfolio performance check-in meetings, quarterly portfolio performance reviews with IT&D leadership are conducted. In the quarterly review, each of the CIDOs builds on the feedback provided at the portfolio performance check-in and discuss portfolio performance. Typically, the National Grid US CIDO and New York CIDO attend and help determine if a project requires additional support or intervention to complete.

7. As identified in DPS-478 Attachment 1 (Mapping ITP-4 (July 3, 2024) Interdependencies), rows 585 through 589 of column E, the CIS Enhancements investment does not share any interdependencies with other investments.

8. The delivery of the CIS Enhancements will be managed by a project team within National Grid's US Customer function, led by the US CIDO identified on page 750 of SET-1099 with direction and oversight by the New York CIDO. In addition to IT&D leadership oversight, an executive in the US Customer Operations organization, also identified on page 750, will support this investment and both IT&D and the US Customer organization will be responsible for delivery and investment outcomes. The technical delivery of CIS Enhancements will be owned by Riziel Cruz-Bower, Director of CIS Platform Products.

9. Each of the Enhancement Concepts/Opportunities that have been described within SET-1099 will go through a formal technology evaluation and solution blueprinting process where vendor technologies offerings will be evaluated against the specific requirements and capability needs. The rate engine component is an off-the-shelf component that will be procured to deliver the required functionality and capabilities. A rate engine will allow the Company to leverage a best-in-breed solution to not only deliver existing rates, but also build, test, and implement modern rate structures needed to deliver the goals and aspirations of our clean energy future while decreasing the time and investment required to bring new rates to market. This technology will also allow the Company to take stress off the core CSS platform by moving all rates to a separate application.

10. SET-1099 provides a detailed benefit cost analysis ("BCA") on pages 752 and 756 including the different options explored for the project. Qualitative Type 2 benefits are listed on page 13 of Exhibit__(ITDP-7).

11. SET-1099 provides the cost estimate analysis for labor costs on page 754 and non-labor costs on page 755. Estimates are based on historical spends and assessments of future resource and service requirements to implement solutions for mandates, compliance, and enhancement initiatives. Cost estimates for the rate engine component were received from a third-party consultant that has supported numerous CIS projects and other utility industry software implementations. The estimate received was updated to include all software, labor, necessary consultancy support projections, and contingency.

12. Please see page 753 of SET-1099 for the alternatives the Company evaluated for this

investment and the respective reasons of choice and includes the estimated cost of the alternative solutions.

13. National Grid's CIS platform, including the CSS system, provides billing system capabilities for customers and is similar in nature to other utilities with comparable customer billing requirements. National Grid continues to evaluate the marketplace to add or complement capabilities to the overall CIS platform.

14. a. Upon completion of the technical assessments, a prioritization of the items will be determined.

    b. Please see the answer to question 14a.

    c. Please refer to SET-1099, which provides the cost breakdown for each item.

15. The Company performed a comprehensive review of all IT projects to identify and capture any potential savings in the revenue requirements. All SETs contain a benefits calculation. If the IT investment will deliver financial benefits, those benefits are captured in the revenue requirements either through a reduction to total RTB expenditures (if the benefit is specific to the IT function) or separately as part of National Grid's Efficiency Initiatives (if the project will deliver reductions across the business). This review and presentation of IT benefits is explained in more detail at pages 15-16 of 66 of the ITDP's direct testimony. As shown in the SET (at page 752 and 756 of 1611 of Exhibit ___ (ITDP-8)) and page 13 of Exhibit ___ (ITDP-7), while the CIS Enhancements investment will deliver qualitative Type 2 benefits such as enhancements to support AMI enabled programs such as bill alert notifications or better enable more complex billing arrangements, there are no Type 1 financial savings associated with this project.

16. All technology implementations, changes and enhancements are required to go through an architectural review and analysis to ensure technology obsolescence risk is mitigated. In addition, the Company's sanctioning process ensures appropriate review and approval which includes review by the IT&D Solution Design Authority to ensure proposals are aligned with IT&D obsolescence roadmaps and guidelines. The CIS Platform has a production support team in place to ensure continuity of service. The Company continuously works to ensure the platforms reliability, stability, and resiliency and this investment is a cornerstone for the future long-term plan in addressing technology obsolescence for the overall CIS Platform.

<u>Name of Respondent</u>:
Maria Lykos
Najat Coye

<u>Date of Reply</u>:
July 15, 2024

Date of Request: July 3, 2024 Request No. DPS-481
Due Date: July 15, 2024 NG Request No. NG-511

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology (IT) - Billing and Collections Mandates

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

Referring to the Billing and Collections Mandates program described on pages 34-35 of the Information Technology and Digital Panel's direct testimony:

1. Provide a detailed breakdown of the capital expenditure costs that will be allocated to Niagara Mohawk, by category (e.g., hardware, software, equipment, etc.), projected for the Fiscal Years (FY) ending March 31, 2026 (FY26), March 31, 2027 (FY27), March 31, 2028 (FY28), and March 31, 2029 (FY29), separately for gas and electric.

2. Provide a detailed breakdown of the operations and maintenance costs that will be allocated to Niagara Mohawk, by category (e.g., internal labor, external labor, software updates, consulting contracts, support contracts, etc.), projected for the FY26, FY27, FY28, and FY29, separately for gas and electric.

3. Provide a detailed breakdown of the rent costs projected for Niagara Mohawk only for FY26, FY27, FY28, and FY29.

4. Provide a detailed timeline, with specific or estimated dates, to implement this program.

5. Describe in detail if the Company has identified any resourcing constraints for this program and explain how such identified constraints will be addressed.

    a. As part of your response, explain the Company's strategy for ensuring adequate resources are available to work on the program during the specified time-period.

6. Describe in detail any risks associated with this program that the Company identified and

explain how these risks will be managed and mitigated.

a. As part of your response, provide the Company's risk management plan developed as part of the program.

7. Explain in detail if this program shares any interdependencies with other programs, processes, and/or systems.

a. Include a description of the required sequence for implementing such programs, processes, and systems, and how the Company will address such sequencing.

8. Provide the Company's governance structure for implementing the program, including the names and titles of the people who will be implementing the program, as well as the identity of the executive sponsor.

9. Provide a specific description of the technology utilized for the program, including whether it is a custom build or a commercial off-the-shelf solution.

10. Provide the Company's benefit cost analysis for the proposed program.

11. Describe the Company's approach for developing cost estimates for this program, and provide supporting documentation (e.g., quotes, analyses, etc.) assumptions, and methodology used.

12. Explain whether the Company evaluated any alternatives to this program and include an explanation of why the Company ultimately chose this option versus an alternative.

13. Explain in detail how the Company's selected program solution compares with other utilities' solutions, and with industry standards.

14. Explain whether there are anticipated savings to result from these technology investments. If yes, describe:

a. where in the Companies' cost structure will the savings manifest;

b. whether they are one-time or ongoing savings;

c. when the savings will occur;

d. whether there are conditions that are required for the cost savings to be realized (milestones met, dates met, other systems work completed, etc.); and

e. what form the cost savings will take (reduction in number & dollar amounts of support contracts for maintaining legacy systems, fewer FTEs, lower software costs, etc.).

15. What is the long-term plan for maintenance (costs as well as support strategy) and the Company's approach to mitigating technology obsolescence risk?

Response:

1. Please see Exhibit__(ITDP-8), pages 654 through 661 of 1611, which provides the Company's Sanction Estimation Template ("SET"), SET-1070 for the Billing and Collections Mandates. The SET is an updated investment analysis tool to better align early project development information with the overall Information Technology and Digital ("IT&D") sanctioning process. The SET captures key attributes of proposed future investments, including the investment description, supporting cost estimation calculations, scope, timing (Releases-Deliverables & Milestones), alternatives, and the expected benefitting company.

   The detailed breakdown of capital expenditures by fiscal years March 31, 2026, through March 31, 2029, is $89.25 million as shown at page 656 of SET-1070 and Exhibit__(ITDP-4) to the IT&D Panel's testimony. Please note that the SET is a point in time document that includes expected spend each year while Exhibit__(ITDP-4) reflects capital costs based on the anticipated in-service dates for purposes of calculating the revenue requirements. Thus, the total capital amounts are the same in SET-1070 and Exhibit__(ITDP-4), but the annual amounts may show slight differences.

   As shown in the SET, the Company followed a cost causal allocation methodology, using cost allocator C903, which allocates the costs of the Billing and Collections Mandates investment across all National Grid's gas and electric U.S. operating companies. The C903 allocator distributes costs based on the meters installed to National Grid's retail companies. The allocator includes the following percentage allocations to the following operating companies:

Operating Companies	% Allocation
NMPC Electric	25.58%
NMPC Gas	9.66%
KEDNY	19.55%
KEDLI	9.39%
MECO-E	21.09%
NANTUCKET	0.22%
BOSTON Gas	11.24%
COLONIAL Gas	3.27%

2. The SET provides detailed project operations and maintenance ("O&M") expenditures and run-the-business ("RTB") costs on page 656. The total FY26 through FY29 project O&M expense and RTB costs for this investment are $7.89 million and $11.302 million, respectively, as shown in the SET and Exhibit__(ITDP-5) to the direct testimony of the IT&D Panel.

3. The detailed projected Billing Collections Mandates Service Company rent expense for Niagara Mohawk for electric and gas respectively are listed below:

Rent Costs	FY26	FY27	FY28	FY29
ELECTRIC	$295,143	$1,736,724	$2,839,856	$3,825,633
GAS	$111,458	$655,854	$1,072,440	$1,444,707

4. Please see page 655 of SET-1070 for the detailed timeline (Releases – Deliverables & Milestones) including deliverable description and plant-in-service dates.

5. Please see page 655 (Dependencies, Potential Risks & Assumptions) of SET-1070 for any potential resourcing constraints and how such potential constraints will be addressed. There are currently no potential resource constraints identified; however, should constraints arise during implementation, this will be managed through resource augmentation either using internal skilled resources who can support the effort without impacting other deliverables and/or via approved vendors with the proper skills sets and experience to deliver on this investment.

6. Please see page 655 (Dependencies, Potential Risks & Assumptions) of SET-1070 for any identified potential risks associated with this investment and how such identified potential risks will be mitigated and managed.

The product/project teams use various tools to track a project's progress, risks, and challenges as they arise. Those tools include project Risks/Actions/Issues/Decisions ("RAID") logs, Microsoft Project Online, and RAID tooling capabilities within Jira, a project management software tool. As the project team works to mitigate or remediate risks, continuous status updates are provided to senior product directors who then assist in managing and escalating to the appropriate Chief Information Technology and Digital Officer ("CIDO"), as needed. All portfolios across IT&D are required to hold recurring portfolio performance check-in meetings, where portfolio leadership, IT&D Planning and Strategy, IT&D Finance, and IT&D Regulatory teams review updates on investments and outcomes delivered, risks and mitigating actions, and a financial summary. Following portfolio performance check-in meetings, quarterly portfolio performance reviews with IT&D leadership are conducted. In the quarterly review, each of the CIDOs builds on the feedback provided at the portfolio performance check-in and discuss portfolio performance. Typically, the US Customer CIDO and New York CIDO attend and help determine if a project requires additional support or intervention to complete.

7. As identified in DPS-478 Attachment 1 (Mapping ITP-4 (July 3, 2024) Interdependencies), rows 8 through 12 of column E, the Billing and Collections Mandates Enhancements investment does not share any interdependencies with other investments.

8. The delivery of the Customer Billing and Collections Mandates will be owned by Riziel Cruz-Bower, Director of CIS Platform Products. The governance structure is in place and administered by the US Customer function, led by the US Customer CIDO identified on page 654 of SET-1070 with direction and oversight by the New York CIDO. In addition to IT&D leadership oversight, an executive in the US Customer organization, also identified on page 654, will support this investment and both IT&D and the US Customer organization will be responsible for delivery and investment outcomes.

From a process perspective, the Product Team adheres to standard governance structures associated with the Scaled Agile (SAFe) and/or Waterfall delivery methodologies.

9. Most Customer related mandates require changes to be made to National Grid's core billing system application, Customer Service System ("CSS"). CSS is a custom-built legacy application that manages the meter-to-cash area of the customer billing system at National Grid. CSS, built by Accenture in the 90s as Customer/1, has a back-end system using Mainframe COBOL and a front-end object-oriented screen using C++.

   All changes required to satisfy the Billing and Collection mandates will align with the technology enhancements being planned for the CSS platform under CIS Enhancements (Phase 2 & 3) under SET-1099 page 750 of Exhibit__(ITDP-8).

10. SET-1070 provides a detailed benefit cost analysis ("BCA") on pages 656, 657 and 660 including the different options explored for the project. Qualitative Type 2 benefits are listed on pages 2 and 3 of Exhibit__(ITDP-7).

11. SET-1070 provides the cost estimate analysis for labor costs on page 658 and non-labor costs on page 659. CSS Billing and Collection estimates are based on historical spends and assessments of future resource requirements to implement solutions for mandates, compliance, and enhancement initiatives.

12. SET-1070 provides the alternatives on page 657 that the Company evaluated for this investment, the respective reasons of choices and the estimated cost of the alternative solutions.

13. CSS provides billing system capabilities that serve National Grid's customers and is similar in nature to other utilities with comparable customer billing requirements. National Grid continues to explore further enhancements to the technology solution as seen with SET-1099 CIS Enhancements Phase 2 and3.

14. The Company performed a comprehensive review of all IT projects to identify and capture any potential savings in the revenue requirements. All SETs contain a benefits calculation. If the IT investment will deliver financial benefits, those benefits are captured in the revenue requirements either through a reduction to total run-the-business expenditures (if the benefit is specific to the IT function) or separately as part of National Grid's Efficiency Initiatives (if the project will deliver reductions across the business). This review and presentation of IT benefits is explained in more detail at pages 15-16 of 66 of the ITDP's direct testimony. As shown in the SET (at pages 656 and 660 of 1611 of Exhibit ___ (ITDP-8)) and pages 2 and 3 of Exhibit ___ (ITDP-7), while the Customer Billing and Collections Mandates investment will deliver qualitative Type 2 benefits such as enhancements to help maintain regulatory compliance, reduce technical and security risks, and improve the overall customer experience, there are no Type 1 financial savings associated with this project.

15. All technology implementations, changes and enhancements are required to go through an

architectural review and the Company's sanctioning process before a project is started. National Grid's sanctioning process includes review by the IT&D Solution Design Authority to ensure proposals are aligned with IT&D obsolescence roadmaps and guidelines. CSS Platform has a production support team in place to ensure continuity of service. In addition, the Company continuously works to ensure the platform's reliability, stability, and resiliency. Please refer to CIS Enhancements (Phase 2 and 3) (SET-1099) for the future long-term plan in addressing technology obsolescence for the CSS Platform

Name of Respondent:	Date of Reply:
Najat Coye	July 15, 2024

Date of Request: July 12, 2024 Request No. DPS-564
Due Date: July 22, 2024 NG Request No. NG-609

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Energy Affordability Program

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

On page 30 of the Customer Panel's direct testimony, the Company states, "In December 2023, legislation was enacted in New York that requires OTDA to establish a statewide program for automated identification of eligible EAP participants. Once the program is implemented, Niagara Mohawk plans to participate and to incur an estimated $100,000 annually to reimburse program participants for their file matching costs."

1 Provide a detailed explanation of the annual costs that would be incurred through the estimated $100,000 for automated file-matching. Include any estimates and documentation to support this amount.

2. Provide a detailed description of the "program participants" who would be eligible for reimbursement.

3. Provide a detailed description of what costs would be reimbursable under the Company's proposal.

4. Provide the anticipated implementation date for this automated identification.

Response:

1. The Company estimated $100,000 based on the amount that was approved for HRA file matching for KEDNY ($50K) and KEDLI ($50K) in the 2019 Rate Cases. It has yet to be determined exactly what costs will be incurred as the information above is a placeholder while awaiting OTDA’s establishment of the statewide program.

2. The term “program participants” as mentioned in the testimony refers to the participating Niagara Mohawk territory counties or OTDA directly to disperse to the appropriate counties for their file matching costs.

3. The reimbursable costs included in the $100,000 comprise the cost of mailings and any associated costs for performing the file matches.

4. The original implementation date for OTDA to establish the statewide file matching was June 2024 but has since been extended to December 22, 2024 by the Governor and the two houses.

Name of Respondent:
Brittney Pietro

Date of Reply:
July 22, 2024

Date of Request: July 24, 2024 Request No. DPS-750
Due Date: August 5, 2024 NG Request No. NG-871

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology (IT) - Billing and Collections Mandates

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

Referring to the Billing and Collections Mandates on lines 8-12 of Exhibit_(ITDP-4):

1. For each of the last previous fiscal years (FY20, FY21, FY22, FY23, and FY24), provide a detailed breakdown of all budgeted amounts for Billing and Collections Mandates, for only NMPC, separately for electric and gas.

2. For each of the previous five fiscal years (FY20, FY21, FY22, FY23, and FY24), provide a detailed breakdown of all actual costs incurred for Billing and Collections Mandates, for only NMPC, separately for electric and gas.

Response:

1. As described in DPS-481, the Billing and Collections Mandates and Enhancements shown on lines 8 to 12 of Exhibit __ (ITDP-4) is a funding mechanism for anticipated new billing and collection mandates and enhancements not already identified under other established projects. Please see Attachment 1, which shows the budgets for these investments, which were initiated in FY23 and are for Niagara Mohawk only. Because these investments were initiated in FY23, the Company does not have budget information prior to that period.

2. The Billing and Collections Mandates and Enhancements is a funding mechanism that was established to support mandates and compliance and enhancement demands that were not previously accounted for in the budget year. Funding is transferred from this funding mechanism to individual projects via a formal Budget Exception Request ("BER") process, governed by the IT&D Finance and Investment Portfolio organization

to reallocate funding for identified Billing and Collections Mandates and Enhancements initiatives. Please see Attachment 1 for a summary of the BERs related to Billing and Collections Mandates and Enhancements.

<u>Name of Respondent</u>:
Ed Brodsky
Najat Coye

<u>Date of Reply</u>:
August 5, 2024

		NMPC - Electric	NMPC - Gas	NMPC - Total
FY23 Budget		**$1,060,410**	**$400,674**	**$1,461,084**
INV #	**Investment Name**			
5125	Customer Connection Program	$7,994	$3,021	$11,015
5160	NY Value Stack Billing (Mandated)	$1,184,817	$0	$1,184,817
5160	NY Value Stack Billing (Mandated)	$160,000	$0	$160,000
5778	Customer Ecosystem Stabilization	$132,244	$49,968	$182,211
6451	One Step Auto Cashiering Upgrade	$0	$0	$0
6492	NACHA Compliance- Security Encryption Effort	$260,433	$98,404	$358,837
6496	NY Gender Pronoun and Name Mandate	$41,509	$15,688	$57,198
6592	Transmission Services Agreement/Transmission Services Contract (TSA/TSC) Application Replacement	$175,000	$0	$175,000
FY23 -- Incremental Billing & Collections Mandates & Enhancements Demand		**$1,961,997**	**$167,080**	**$2,129,077**
Net		**($901,587)**	**$233,594**	**($667,993)**

		NMPC - Electric	NMPC - Gas	NMPC - Total
FY24 Budget		**$2,428,047**	**$917,167**	**$3,345,214**
INV #	**Investment Name**			
5125	Customer Connection Program	$145,017	$54,778	$199,795
5160	NY Value Stack Billing (Mandated)	$2,880,000	$0	$2,880,000
5778	Customer Ecosystem Stabilization	$21,398	$8,083	$29,480
6451	One Step Auto Cashiering Upgrade	$0	$0	$0
6492	NACHA Compliance- Security Encryption Effort	$324,272	$122,490	$446,762
6592	Transmission Services Agreement/Transmission Services Contract (TSA/TSC) Application Replacement	$219,000	$0	$219,000
6592	Transmission Services Agreement/Transmission Services Contract (TSA/TSC) Application Replacement	$53,177	$0	$53,177
6746	CXP Technical Debt Initiative	$735,216	$138,621	$873,838
6762	KEDLI Rate Case	$0	$0	$0
FY24 -- Incremental Billing & Collections Mandates & Enhancements Demand		**$4,378,080**	**$323,973**	**$4,702,053**
Net		**($1,950,033)**	**$593,194**	**($1,356,839)**

Note: BER allocations driven by receiving project's allocation

Date of Request: July 26, 2024 Request No. DPS-788
Due Date: August 5, 2024 NG Request No. NG-919

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology (IT) - CIS Enhancements

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

Referring to the CIS Enhancements in lines 589-593 of Exhibit__(ITDP-4CU):

1. Provide a detailed explanation of the bid process for this project.

2. Provide the list of developers and/or vendors that submitted a bid for this project. If no request for proposals was issued for this project, provide a detailed explanation of why not.

3. Provide the name of the vendor chosen by the Company for this project. Provide the quote(s) and invoice(s) received from the vendor.

4. Provide a detailed explanation of how the cost estimate was determined for this project.

Response:

1. Please see Exhibit __ (ITDP-8), pages 750 through 757 of 1611, which provides the Company's Sanction Estimation Template ("SET") for the CIS Enhancements (SET-1099). As there has been no final decision on the architecture of this solution, there has not yet been a bid process for this investment. As described in the Company's response to DPS-479, question 9, concepts/opportunities that have been described within SET-1099 will go through a formal technology evaluation and solution blueprinting process where vendor technology offerings will be evaluated against the specific requirements and capability needs. After the evaluation process, a formal bid process may ensue.

2. As described in the Company's response to DPS-479, question 5, the delivery of the CIS Enhancements investment will be managed by a project team within National Grid's US Customer function. If additional resources are required beyond internal labor to support

this initiative, resources are selected from one of National Grid's approved Application Development/Application Maintenance ("ADAM") and/or Digital partners. IT&D has third-party contracts with vendors for ADAM that are managed by the Company's procurement team. These competitively negotiated vendor agreements provide cost and operational efficiencies when delivering core IT programs and projects. Upon the final architecture decision discussed in response to question 1, vendor bids for the technology solution will be managed via National Grid's standard procurement process.

3. Please see the response to question two above.

4. As described in the Company's response to DPS-479, question 11, cost estimates for this investment were based on historical spends and assessments of future resource and service requirements to implement solutions for mandates, compliance, and enhancement initiatives based on competitively bid ADAM partner contracts.

<u>Name of Respondent</u>:	<u>Date of Reply</u>:
Ed Brodsky	August 5, 2024
Najat Coye	

Date of Request: July 26, 2024 Request No. DPS-792
Due Date: August 5, 2024 NG Request No. NG-923

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology (IT) - Customer Experience Initiatives

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

Referring to the seven Customer Experience Initiatives on pages 70-76 of the Customer Panel's initial direct testimony and the Customer Portfolio items listed on lines 2-78 and 586-601on Exhibit__(ITDP-4CU):

1. Provide a detailed explanation of how each Customer Portfolio item supports the seven Customer Experience Initiatives.

Response:

1. Please see the table below with the initiatives, associated line number on Exhibit __ (ITDP-4CU), and the rationales that support the seven Customer Experience Initiatives.

Investments Associated with the Customer Experience Initiatives	**ITDP-4CU Row(s)**	**Relationship(s) to the Customer Experience Initiatives**
AIMS Product Team – Annual Program AIMS Product Team FY25 AIMS Replatform INVP 6727 – AIMS FY24 Product Team INVP 6728 – AIMS Replatform	2-5 6 7 56 57	These investments will support Reducing Calls with Self-Service and Minimizing Call Average Handling Time initiatives. The investment will enable new and modified workflows within the Contact Center's Interactive Voice Response ("IVR") infrastructure, which will be one of the key drivers in reducing calls through self-service. Additionally, the re-platforming of Contact Center solutions such as Workforce Optimization will increase the Contact Center agent's capability to better manage customer calls, therefore improving the ability to complete first call resolutions.
Case Management	13	Improves management and efficiency of customer inquiries that are tracked via a case management tool.

Investments Associated with the Customer Experience Initiatives	ITDP-4CU Row(s)	Relationship(s) to the Customer Experience Initiatives
		The existing case management solutions do not provide the intelligence and analytics needed to provide the level of capability needed to improve the Contact Center's ability to address issues more efficiently and improve on first call resolution.
Customer Data Platform	28-32	This investment will support the Front Office optimizing project via improved data and analytics that will enable many of the self-service and Contact Center initiatives. The analytics and intelligence of the Customer Data Platform will provide solutions such as the Unified Web Portal and the AIMS Interactive Voice Response that will provide improved ways to understand the customer behaviors and drive towards improved customer self-service, therefore reducing calls, improving the first call response times, and supporting back-office optimization opportunities.
Customer Facing Mobile App – In House Solution (US) Customer Mobile Application INVP 6713 – Customer Facing Mobile App	33-37 38 54	These investments will support the Reducing Calls with Self-Service initiative by improving the customer experience through self-service by allowing for additional contact points and methods for customers to interact with the Company. As the improvement and expansion of the mobile application develops to include increased insight for addressing customers queries, there will be call reductions via self-service and additional opportunities to promote capabilities such as e-bill adoption
Digital Assistant	42-46	This investment supports the reducing calls with self-service initiative by providing additional options for customers to interact with National Grid to successfully resolve their inquiries. As the improvement and expansion of the Digital Assistant develops to include increased insight in addressing customers queries, it is expected to improve the self-service ratios. Additional opportunities to promote customer capabilities such as E-bill adoption will also be available through this interactive channel.
Documentum Application Modernization	47	This investment will support improved management and efficiency of documents utilized by Customer agents. The Company's current document management tools are outdated. An updated, more analytical document management solution will provide agents and Back-office support with improved access to information, which will improve first call resolution and optimize back-office processes.
GenAI	48	This investment will drive automation of various Front and Back-office tasks. Opportunities of GenAI, which are uses of Generative Artificial Intelligence technologies will optimize Back-office processes such

Investments Associated with the Customer Experience Initiatives	ITDP-4CU Row(s)	Relationship(s) to the Customer Experience Initiatives
		as taking several heavy manual intensive tasks and simplifying them via the use of this technology (an example being the effort taken in responding to common email queries from customers and converting that effort into a more automated process)
INVP 5673 – My Business Account My Business Account My Business Account (Nucleus) Enhancements	50 60 61-64	These investments will support the Reducing Calls with Self-Service initiative; impacting the customer experience by providing commercial and business customers a web portal targeted for their specific needs, thereby making it easier to conduct their business with National Grid. Expanding the capability to provide improved billing insight into the large commercial and industrial customers will reduce billing queries and create opportunities to reduce the incoming calls via self-service. This channel also will provide promotion of capabilities such as E-billing.
INVP 6706 – FY24 UWP Enhancements INVP 6715 – UWP 2.0 MyAccount Implementation UWP 2.0 MyAccount Implementation and Delivery UWP Product Team Annual Program UWP Product Team FY25	53 55 73 74-77 78	These investments will support the Reducing Calls with Self-Service initiative, improve customer experience through self-service, and allow for customers to self-serve on the web. As the most substantial online customer interfaces, an expanded suite of responses to certain calls to billing inquiries, Company offers, and other further actions required by customers will be handled through automated processes ultimately reducing calls via self-service into the Contact Center. Additionally, there will be promotion of capabilities such as e-billing and potential automation of manual work.
New Customer Digital Products	66-69	This investment supports the Optimize Front Office Service Delivery Model, Back office Automate Manual Work, and Optimize Back-office processes and capacity initiatives. As the Customer organization further analyzes new channels and/or data analytic solutions to better serve customers in a more efficient manner, new customer digital products will at a minimum, reduce calls with self-service, minimize call handling time and optimize back-office processes
Customer Experience Initiatives ZBR	601	This investment relates to the various initiatives used to drive self-service, automate Back-office functions, and improve the customer experience

<u>Name of Respondent</u>:
Ed Brodsky
MaryBeth Chliek
Najat Coye

<u>Date of Reply</u>:
August 5, 2024

Date of Request: August 2, 2024 Request No. DPS-832
Due Date: August 12, 2024 NG Request No. NG-1007

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Customer Contact Center FTEs

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference the proposed Small-to-Medium Commercial Customer Contact Center Group resources described in Exhibit__(CP-4) and pages 49-51 of the direct testimony of the Customer Panel:

1. For each month from January 2020 through June 2024, provide the following:

   a. The number of Contact Center Representatives employed by the Company. Specify whether they are full time or part time.

   b. The number of vacant Contact Center Representative positions.

   c. The number of Company employees from other departments supplementing the organization by performing Contact Center Representative functions.

   d. The number of contracted full-time equivalents supplementing the organization by performing Contact Center Representative functions.

2. Provide a detailed description of all duties that a Contact Center Representative may handle. Include in your response the roles in both blue-sky and storm conditions.

3. On pages 49-51 of the Customer Panel's direct testimony, the Company states that the addition of seven incremental representatives serving small-to-medium commercial customer contacts "will enable the company to effectively engage with the commercial customer class" and that the "specialized contact center group will enable the Company to provide a high quality customer experience." Provide a detailed explanation of the current effectiveness of the Company's engagement with commercial customers and the quality of the customers' experience. Include all studies and documentation that support the Company's response.

Response:

1. The below table contains the requested monthly break-down of the Company's Commercial Customer Service Representatives who are currently handling both residential and commercial customer calls and not solely dedicated to commercial customers (as proposed by the Company). The requested FTEs are driven by the need to create dedicated agents who will handle small to medium commercial and industrial ("C&I") customer calls. Among other things, the proposal will create capacity that allow these agents to spend more time on the phone with small to medium C&I customers, helping to provide tailored solutions to their issues.

	1.a		1.b	1.c	1.d
	Full Time	Part Time	Vacant Positions	Supplement Staff	Supplement Staff
Jan-20	25	0	0	0	0
Feb-20	25	0	1	0	0
Mar-20	24	0	2	0	0
Apr-20	24	0	6	0	0
May-20	24	0	0	0	0
Jun-20	24	0	0	0	0
Jul-20	24	0	0	0	0
Aug-20	24	0	0	0	0
Sep-20	30	0	0	0	0
Oct-20	30	0	0	0	0
Nov-20	30	0	0	0	0
Dec-20	28	0	0	0	0
Jan-21	28	0	0	0	0
Feb-21	27	0	0	0	0
Mar-21	25	0	1	0	0
Apr-21	24	0	0	0	0
May-21	20	0	0	0	0
Jun-21	20	0	0	0	0
Jul-21	19	0	0	0	0
Aug-21	17	0	0	0	0
Sep-21	13	0	5	0	0
Oct-21	16	0	6	0	0
Nov-21	15	0	2	0	0
Dec-21	15	0	1	0	0
Jan-22	39	0	0	0	0
Feb-22	38	0	0	0	0
Mar-22	37	0	0	0	0
Apr-22	36	0	0	0	0
May-22	31	0	0	0	0
Jun-22	30	0	0	0	0
Jul-22	30	0	0	0	0
Aug-22	32	0	0	0	0

Sep-22	35	0	0	0	0
Oct-22	31	0	0	0	0
Nov-22	27	0	0	0	0
Dec-22	26	0	0	0	0
Jan-23	34	0	0	0	0
Feb-23	34	0	0	0	0
Mar-23	29	0	0	0	0
Apr-23	28	0	0	0	0
May-23	24	0	0	0	0
Jun-23	23	0	0	0	0
Jul-23	21	0	0	0	0
Aug-23	30	0	0	0	0
Sep-23	26	0	0	0	0
Oct-23	25	0	0	0	0
Nov-23	29	0	0	0	0
Dec-23	31	0	0	0	0
Jan-24	22	0	0	0	0
Feb-24	22	0	0	0	0
Mar-24	22	0	0	0	0
Apr-24	22	0	0	0	0
May-24	22	0	0	0	0
Jun-24	18	0	3	0	0

2. The Company's current C&I customer service representatives under general supervision can perform the following duties during blue sky and storm conditions:

    1. Commercial and Industrial Customers inquiries
    2. Commercial Customer Deposits
    3. Commercial Applications
    4. Connect/Disconnect- Residential
    5. Payments (including Balance Billing)
    6. Issue Turn Off None Payment (cut in after payment satisfied)
    7. Financial Statements
    8. Electric Outages
    9. Life Support
    10. Field Orders/Emergency Orders
    11. Trouble Reporting
    12. All residential billing inquiries (including Net Metering & Solar)
    13. Issuing orders for high usage investigations
    14. Mic Metering Calls
    15. Off-line work-general customer correspondence (including web/email)
    16. Transfer excess credit/refunds (including Payment Transfers)
    17. High Bill investigations

3. As shown in the response to DPS-310 (on pages 2-3), the Company performed below target on the small to medium C&I customer satisfaction survey in Calendar Year 2023 and so far

in Calendar Year 2024. The survey results analysis revealed low First Call Resolution as a key contributor to lower customer satisfaction. As part of the Company's effort to improve customer experience, the Company is focusing on customer issue escalation and First Call Resolution improvement.

Furthermore, through the small to medium C&I customer satisfaction survey, customers have expressed a wish for a dedicated account management team and a more proactive engagements from the Company as shown in the example comments below:

"*I think they could have more direct consumer contact aside from their bills and offer a few more green energy credits from them*"

"either have a rep, or account manager reach out periodically to see if they can improve the service"

"give big clients a dedicated rep to call to resolve issues"

"Having a dedicated line for government accounts and have them understand that its harder to work with a government account due to fiscal years being different and that we have to justify the cost and can't just give a Credit Card to pay"

"Work with me more on my business account"

The comments above come from the Calendar Year 2024 small to medium C&I customer satisfaction survey; Question *"Thinking about National Grid's Overall Performance, what more could National Grid have done to better serve you?"*

The request for seven incremental Contact Center representatives, as stated in the Customer Panel Testimony, will allow for more time spent with individual small to medium C&I customers to directly address the concerns expressed above.

Name of Respondent:	Date of Reply:
Jim MacVicar	August 12, 2024

Date of Request: August 2, 2024 Request No. DPS-834
Due Date: August 12, 2024 NG Request No. NG-1009

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology - Regulatory Requirements

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

Referring to the Customer Portfolio items listed on lines 2-78 and 586-601 on Exhibit__(ITDP-4CU):

1. For each line item listed above, provide a detailed explanation of the existing regulatory requirement (i.e., case number and page of applicable Commission Order and/or Public Service Law) mandating the proposed item. Include whether the Company currently has the capability to perform the required work and if the proposed items are upgrades or new projects intended to meet existing regulations.

Response:

1. Public Service Law Section 65 provides that "[e]very gas corporation, every electric corporation and every municipality shall furnish and provide such service, instrumentalities and facilities as shall be safe and adequate and, in all respects, just and reasonable." PSL § 65(1). As the Information Technology and Digital ("IT&D") Panel explains in its direct testimony, the IT&D investments being proposed in these cases will "enabl[e] the Company to continue providing safe, reliable, and affordable service, support New York's energy transition, and provide high-quality customer service." IT&D Panel direct testimony, p. 7. Detailed information about the IT&D investments proposed in these cases is included in the Sanction Estimate Templates ("SETs") in Exhibit __ (ITDP-8) for the respective initiatives.

   Investments listed on lines 2 – 78 and 586 – 601 in Exhibit __ (ITDP-4CU) support functionality to enable the Company to deliver on its responsibility to provide safe and adequate service, support State energy policy, and otherwise meet the service and performance requirements established by the Commission and expected by customers. Please see Attachment 1 column F.

Name of Respondent:
Najat Coye
Ed Brodsky

Date of Reply:
August 12, 2024

Niagara Mohawk Power Corporation
d/b/a National Grid
Cases 24-E-0322 & 24-G-0323
DPS-834 Attachment 1
1 of 2

Investment Name	PRJ #	INVP #	Category	Portfolio	Company's capability	Inflight/Future	Allocation Code	Forecasted In Service Date	Amortization Period	CWIP - Inception to date	Forecast - CAPEX - FY24	FY25 CAPEX	FY26 Beginning Balance	FY26 CAPEX	FY27 CAPEX	FY28 CAPEX	FY29 CAPEX	Total
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer	As detailed in SET-1071 (pages 646 - 653 of Exhibit__(ITDP-8)), this investment is to procure product level funding for the existing AIMS (Agent Interaction Management System) dedicated product team to deliver on small- to mid-sized upgrades and enhancements, including regulatory mandates, that are not otherwise funded through other initiatives.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 3,574,584	$ -	$ -	$ -	$ 3,574,584
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 3,454,015	$ -	$ -	$ 3,454,015
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 3,443,008	$ -	$ 3,443,008
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 3,448,587	$ 3,448,587
AIMS Product Team FY25	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 1,000,000	$ 1,000,000	$ -	$ -	$ -	$ -	$ 1,000,000
AIMS Replatform	PRJ-5802	6728	Core	Customer	High Performing Customer Contact Center. This investment addresses contact center technology, which is approaching end of life. The investment is needed for the Company to perform required work, and implementation of this initiative is necessary to maintain current Customer-facing operations.	Future	C903	3/31/2025	84	$ -	$ -	$ 7,800,000	$ 7,800,000	$ -	$ -	$ -	$ -	$ 7,800,000
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer	Implement Billing Changes Required by PSC. This funding mechanism supports investments including system modifications, changes and enhancements to comply with emergent mandates and directives from the PSC or other authorities that require changes to billing and other critical customer systems to meet regulatory requirements.	Future	C903	3/31/2025	84	$ -	$ -	$ 1,640,000	$ 1,640,000	$ -	$ -	$ -	$ -	$ 1,640,000
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 26,355,299	$ -	$ -	$ -	$ 26,355,299
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 21,811,282	$ -	$ -	$ 21,811,282
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 20,902,478	$ -	$ 20,902,478
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 21,811,282	$ 21,811,282
Case Management	PRJ-5909	6775	Core	Customer	As detailed in the Case Management Sanction, the Customer Business manages inquiries, requests and complaints from external parties via different methods depending on the organization and solution that was originally selected to manage the case intake process. These existing solutions are outdated and on technology stacks that are no longer supported or require significant investment to keep them supported. The Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 2,600,000	$ 2,600,000	$ -	$ -	$ -	$ -	$ 2,600,000
Community Solar Bill Portal	PRJ-7764	N/A	Core	Customer	As detailed in SET-1082 (pages 662 - 669 of Exhibit__(ITDP-8), this investment is requesting to fund a Self-Serve Billing and Credit Allocation Portal to improve the Community Distributed Generation (CDG) customer experience and further support the implementation of CDG. This would be new functionality. If approved, the Company currently has the ability to perform the required work.	Future	C902	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 512,006	$ -	$ -	$ 512,006
Community Solar Bill Portal	PRJ-7764	N/A	Core	Customer		Future	C902	8/1/2026	84	$ -	$ -	$ -	$ -	$ -	$ 7,680,097	$ -	$ -	$ 7,680,097
Community Solar Bill Portal	PRJ-7764	N/A	Core	Customer		Future	C902	4/30/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 341,338	$ -	$ 341,338
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer	As detailed in SET-7770 (pages 670- 677 of Exhibit__(ITDP-8), this investment will provide new functionality for a single "select all that apply" application form and process for all Distributed Energy Resources (DERs) and electric loads, leveraging existing platform, interfaces, and functionality. If approved, the Company currently has the ability to perform the required work.	Future	C902	3/31/2026	84	$ -	$ -	$ -	$ -	$ 5,986,751	$ -	$ -	$ -	$ 5,986,751
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 7,531,719	$ -	$ -	$ 7,531,719
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,510,573	$ -	$ 2,510,573
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	4/1/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,510,573	$ -	$ 2,510,573
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	4/1/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 772,484	$ 772,484
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer	As detailed in SET-1079 (pages 678 - 685 of Exhibit__(ITDP-8), ConnectNow is a continuation, modernization and expansion of the existing Customer Connections program powered by Gridforce platform and applications portal. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 3,700,000	$ 3,700,000	$ -	$ -	$ -	$ -	$ 3,700,000
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 9,747,594	$ -	$ -	$ -	$ 9,747,594
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 10,633,739	$ -	$ -	$ 10,633,739
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 11,519,884	$ -	$ 11,519,884
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 12,406,029	$ 12,406,029
CSS Enhancements FY25	PRJ-7175	6773	Core	Customer	As detailed in the CSS Enhancements FY25 sanction paper, this project provides a funding base and governance structure that allows the IT organization to effectively deliver small system changes to the entire Customer portfolio, in response to any regulatory mandates, operational requirements and value-added enhancements that will occur during the course of the year. These could be new or existing products, depending on the mandate/enhancement. If approved, the Company has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 350,000	$ 350,000	$ -	$ -	$ -	$ -	$ 350,000
Customer Data Platform	PRJ-5955	6740	Core	Customer	As detailed in SET-1072 (pages 686 - 693 of Exhibit__(ITDP-8), this investment will fund the existing Customer Data Platform which provides a centralized platform for Customer data to improve and optimize access to customer data and will provide a full 360 degree of a customer which is inline with the Company's direction of being customer centric. If approved, the Company currently has the ability to perform the required work.	Future	G911	3/31/2025	84	$ -	$ -	$ 5,500,000	$ 5,500,000	$ -	$ -	$ -	$ -	$ 5,500,000
Customer Data Platform	PRJ-5955	6740	Core	Customer		Future	G911	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 4,147,381	$ -	$ -	$ 4,147,381
Customer Data Platform	PRJ-5955	6740	Core	Customer		Future	G911	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 4,147,381	$ -	$ 4,147,381
Customer Data Platform	PRJ-5955	6740	Core	Customer		Future	G911	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 4,665,804	$ 4,665,804
Customer Data Platform	6740	6740	Core	Customer		Inflight	G911	3/31/2024	84	$ 4,173,915	$ 519,326	$ -	$ 4,693,241	$ -	$ -	$ -	$ -	$ 4,693,241
Customer Facing Mobile App – In House Solution (US)	PRJ-7777	6786	Core	Customer	As detailed in SET-1074 (pages 694 - 701 of Exhibit__(ITDP-8), this project's focus is to build, deliver and support a new in-house customer facing mobile app that provides new customer experience capabilities including: unlocking a new channel for customers to sign in using their existing National Grid credentials to view account, billing and payment information and submit payments to National Grid. If approved, the Company currently has the ability to perform the required work.	Future	C175	3/31/2026	84	$ -	$ -	$ -	$ -	$ 929,491	$ -	$ -	$ -	$ 929,491
Customer Facing Mobile App – In House Solution (US)	PRJ-7777	6786	Core	Customer		Future	C175	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 1,956,579	$ -	$ -	$ 1,956,579
Customer Facing Mobile App – In House Solution (US)	PRJ-7777	6786	Core	Customer		Future	C175	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,956,579	$ -	$ 1,956,579
Customer Facing Mobile App – In House Solution (US)	PRJ-7777	6786	Core	Customer		Future	C175	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,956,579	$ 1,956,579
Customer Facing Mobile App – In House Solution (US)	PRJ-7777	6786	Core	Customer		Future	C175	6/1/2025	84	$ -	$ -	$ -	$ -	$ 2,494,755	$ -	$ -	$ -	$ 2,494,755
Customer Mobile Application	PRJ-7777	6786	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 3,600,000	$ 3,600,000	$ -	$ -	$ -	$ -	$ 3,600,000
Customer Tech Debt Remediation	PRJ-7178	6791	Core	Customer	As detailed in SET-1080 (pages 702 - 709 of Exhibit__(ITDP-8), this investment seeks to replace/update network equipment, servers and operating systems etc. that are end of life and no longer supported by the vendors. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,858,632	$ -	$ -	$ -	$ 1,858,632
Customer Tech Debt Remediation FY25	PRJ-7178	6791	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 2,287,000	$ 2,287,000	$ -	$ -	$ -	$ -	$ 2,287,000
CXP Technical Debt	PRJ-7592	6776	Core	Customer	As detailed in the CXP Technical Debt Sanction paper, Customer Experience Products (CXP) has accumulated significant technical debt over the past decade, which requires migration and/or re-writing of applications that are currently being used by the Customer Business and our external customers. If approved, the Company currently has the ability to perform the required work.	Future	C175	3/31/2025	84	$ -	$ -	$ 2,999,000	$ 2,999,000	$ -	$ -	$ -	$ -	$ 2,999,000
Digital Assistant	PRJ-4584	6777	Core	Customer	As detailed in SET-1077 (pages 710 - 717 of Exhibit__(ITDP-8), this project will focus on continuing to improve and deliver personalized experiences and customer self-service opportunities by leveraging National Grid's (NG) innovative Digital Assistant Chatbot (DA), to deflect customers to digital channels and contain them digitally within NG's Unified Web Portal (UWP) and Mobile Web. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 2,000,000	$ 2,000,000	$ -	$ -	$ -	$ -	$ 2,000,000
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,919,844	$ -	$ -	$ -	$ 1,919,844
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 1,919,844	$ -	$ -	$ 1,919,844
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,079,831	$ -	$ 2,079,831
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,079,831	$ 2,079,831
Documentum Application Modernization	PRJ-5263	6686	Core	Customer	As detailed in the Documentum Sanction paper (page 125 - 134 Exhibit__(ITDP-8), Documentum is an existing content management application that is used by both back- and front-office employees. The current legacy application is operating on out of support software and has supporting assets which are considered end of life. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 750,000	$ 750,000	$ -	$ -	$ -	$ -	$ 750,000
GenAI	6769	6769	Core	Customer	This investment will transform the existing Account Maintenance & Operations' (AMO) mailbox management by augmenting it with generative artificial intelligence and other advanced technologies. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 970,000	$ 970,000	$ -	$ -	$ -	$ -	$ 970,000
INVP 5125 Customer Connection	5125	5125	Core	Customer	As detailed in the Customer Connection Sanction paper (pages 36 - 46 Exhibit__(ITDP-8), this investment is a continuation, modernization and expansion of the existing Customer Connections program powered by Gridforce platform and applications portal. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/29/2024	84	$ 913,654	$ 384,536	$ -	$ 1,298,189	$ -	$ -	$ -	$ -	$ 1,298,189
INVP 5673 My Business Account	5673	5673	Core	Customer	My Business Account (MBA) is focused re-engineering the National Grid commercial and industrial (C&I) customers' digital interactions to create a streamlined and seamless customer experience throughout the customer's journey. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/29/2024	84	$ 788,569	$ 233,494	$ -	$ 1,022,063	$ -	$ -	$ -	$ -	$ 1,022,063
INVP 6492 NACHA Compliance Sec	6492	6492	Core	Customer	As detailed in the project Sanction paper (pages 173 - 178 of Exhibit__(ITDP-8), the National Automated Clearinghouse Association (NACHA) requires that National Grid protect deposit account information by rendering it unreadable when it is stored electronically. This is an ongoing investment to complete the required functionality. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/31/2024	84	$ 245,642	$ 139,076	$ -	$ 384,718	$ -	$ -	$ -	$ -	$ 384,718

Niagara Mohawk Power Corporation
d/b/a National Grid
Cases 24-E-0322 & 24-G-0323
DPS-834 Attachment 1
2 of 2

Investment Name	PRJ #	INVP #	Category	Portfolio	Company's capability	Inflight/Future	Allocation Code	Forecasted In Service Date	Amortization Period	CWIP - Inception to date	Forecast - CAPEX - FY24	FY25 CAPEX	FY26 Beginning Balance	FY26 CAPEX	FY27 CAPEX	FY28 CAPEX	FY29 CAPEX	Total
INVP 6687 FY24 Cust Minor Works	6687	6687	Core	Customer	This project provides a funding base and governance structure that allows the IT&D organization to effectively deliver small system changes to the entire Customer portfolio, in response to any regulatory mandates, operational requirements and value-added enhancements that occur during the course of the year. These could be new or existing products, depending on the mandate/enhancement. If approved, the Company has the ability to perform the required work.	Inflight	C903	3/31/2024	84	$ 357,665	$ 44,479	$ -	$ 402,144	$ -	$ -	$ -	$ -	$ 402,144
INVP 6706 FY24 UWP Enhancements	6706	6706	Core	Customer	This investment is to continue to maintain the existing UWP platform as customer and regulatory needs change and to exploit new technologies that benefit customers. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/29/2024	84	$ 982,579	$ 546,642	$ -	$ 1,529,221	$ -	$ -	$ -	$ -	$ 1,529,221
INVP 6713 Customer Facing Mobile Ap	6713	6713	Core	Customer	This project's focus is to build, deliver and support a new in-house customer facing mobile app that unlocks a new channel for customers to sign in using their existing National Grid credentials to view account, billing and payment information and submit payments to National Grid. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/29/2024	84	$ 4,127,620	$ 530,913	$ -	$ 4,658,533	$ -	$ -	$ -	$ -	$ 4,658,533
INVP 6715 UWP 2.0 MyAccount Impleme	6715	6715	Core	Customer	As detailed in the UWP 2.0 Sanction paper (pages 189 - 205 of Exhibit__(ITDP-8), this investment focuses on transitioning the existing Unified Web Portal (UWP) to a new, more robust, higher performing and adaptable platform. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/31/2024	84	$ 5,049,743	$ 1,804,628	$ -	$ 6,854,371	$ -	$ -	$ -	$ -	$ 6,854,371
INVP 6727 AIMS FY24 Product Team	6727	6727	Core	Customer	This investment is to procure product level funding for the existing AIMS (Agent Interaction Management System) dedicated product team to deliver on small to mid-sized upgrades and enhancements, including regulatory mandates, that are not otherwise funded through other initiatives. If approved, the Company currently has the ability to perform the required work.	Inflight	C903	3/29/2024	84	$ 613,973	$ 259,383	$ -	$ 873,356	$ -	$ -	$ -	$ -	$ 873,356
INVP 6728 AIMS RePlatform Sanction	6728	6728	Core	Customer	The current AIMS (Agent Interaction Management System) contact center technology is approaching end of life; thus, the implementation of this new technology is necessary to maintain current Customer-facing operations. If approved, the Company has the ability to perform the required work	Inflight	C903	3/31/2024	84	$ 780,129	$ 902,237	$ -	$ 1,682,365	$ -	$ -	$ -	$ -	$ 1,682,365
INVP 6746 CXP Tech Debt Initiative	6746	6746	Core	Customer	Customer Experience Products (CXP) has accumulated significant technical debt over the past decade, which requires migration and/or re-writing of applications that are currently being used by the Customer business and our external customers. If approved, the Company currently has the ability to perform the required work.	Inflight	C175	3/29/2024	84	$ 2,150,178	$ 191,021	$ -	$ 2,341,199	$ -	$ -	$ -	$ -	$ 2,341,199
Mainframe Security Realignment	PRJ-7162	6778	Core	Customer	As detailed in the Sanction paper (pages 159 -165 of Exhibit__(ITDP-8), this investment seeks to streamline access to the existing mainframe. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 450,000	$ 450,000	$ -	$ -	$ -	$ -	$ 450,000
My Business Account	PRJ-7180	6785	Core	Customer	My Business Account (MBA) is focused on re-engineering the National Grid commercial and industrial (C&I) customers' digital interactions to create a streamlined and seamless customer experience throughout the customer's journey. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 1,800,000	$ 1,800,000	$ -	$ -	$ -	$ -	$ 1,800,000
My Business Account (Nucleas) Enhancements	PRJ-7778	6785	Core	Customer	As detailed in SET-1076 pages 718 - 7725 of Exhibit__(ITDP-8), My Business Account (MBA) is focused on re-engineering the National Grid commercial and industrial (C&I) customers' digital interactions to create a streamlined and seamless customer experience throughout the customer's journey. If approved, the Company currently has the ability to perform the required work.	Future	C175	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,999,113	$ -	$ -	$ -	$ 1,999,113
My Business Account (Nucleas) Enhancements	PRJ-7778	6785	Core	Customer		Future	C175	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 1,919,149	$ -	$ -	$ 1,919,149
My Business Account (Nucleas) Enhancements	PRJ-7778	6785	Core	Customer		Future	C175	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,999,113	$ -	$ 1,999,113
My Business Account (Nucleas) Enhancements	PRJ-7778	6785	Core	Customer		Future	C175	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,079,078	$ 2,079,078
NACHA	PRJ-3636	6492	Core	Customer	As detailed in the project Sanction paper (pages 173 - 178 of Exhibit__(ITDP-8), the National Automated Clearinghouse Association (NACHA) requires that National Grid protect deposit account information by rendering it unreadable when it is stored electronically. This is an ongoing investment to complete the required functionality. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 588,000	$ 588,000	$ -	$ -	$ -	$ -	$ 588,000
New Customer Digital Products	PRJ-7369	N/A	Core	Customer	As detailed in SET-1073 (pages 726 - 733 of Exhibit__(ITDP-8), the New Customer Digital Products investment will be used to continue National Grid's customer-centric digital transformation. These could be new or existing products. If approved, the Company has the ability to perform the required work.	Future	C903	3/30/2026	84	$ -	$ -	$ -	$ -	$ 2,262,203	$ -	$ -	$ -	$ 2,262,203
New Customer Digital Products	PRJ-7369	N/A	Core	Customer		Future	C903	3/30/2027	84	$ -	$ -	$ -	$ -	$ -	$ 3,800,500	$ -	$ -	$ 3,800,500
New Customer Digital Products	PRJ-7369	N/A	Core	Customer		Future	C903	3/30/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,266,833	$ -	$ 1,266,833
New Customer Digital Products	PRJ-7369	N/A	Core	Customer		Future	C903	3/30/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,719,275	$ 1,719,275
NY Green Button Connect	PRJ-2095	N/A	Core	Customer	As detailed in SET- 1089 (pages 734 - 741 fo Exhibit__(ITDP-8), Green Button Connect (GBC) is an existing application whereby utilities can enable customers to share their energy consumption data with 3rd Party energy solution providers and companies (such as Retail Energy, Solar, EE, etc.). If approved, the Company currently has the ability to perform the required work.	Future	C914	4/1/2025	84	$ -	$ -	$ 190,421	$ 190,421	$ -	$ -	$ -	$ -	$ 190,421
STS Clean-up (backlog from C2C)	PRJ-7168	6780	Core	Customer	As detailed in the STS Clean-up Sanction Paper (pages 179 - 188 of Exhibit__(ITDP-8), this investment seeks to address tickets and requests inputted by the Business to fix issues such as account errors, missed compliance targets, etc.. within the Customer Service System (CSS). If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 1,800,000	$ 1,800,000	$ -	$ -	$ -	$ -	$ 1,800,000
STS Clean-up (backlog from C2C)	PRJ-7168	6780	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,000,000	$ -	$ -	$ -	$ 1,000,000
UWP 2.0 MyAccount Implementation and Delivery	PRJ-5323	6715	Core	Customer	As detailed in the UWP 2.0 Sanction paper (pages 189 - 205 of Exhibit__(ITDP-8), this investment focuses on transitioning the existing Unified Web Portal (UWP) to a new, more robust, higher performing and adaptable platform. If approved, the Company currently has the ability to perform the required work.	Future	C903	8/30/2024	84	$ -	$ -	$ 6,696,000	$ 6,696,000	$ -	$ -	$ -	$ -	$ 6,696,000
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer	As detailed in SET-1075 (pages 742 - 749 of Exhibit__(ITDP-8), this investment is to continue maintaining the existing UWP platform as customer and regulatory needs change and to exploit new technologies and capabilities that benefit customers. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 4,704,454	$ -	$ -	$ -	$ 4,704,454
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 5,345,971	$ -	$ -	$ 5,345,971
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 5,559,810	$ -	$ 5,559,810
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer		Future	C903	3/30/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 5,773,649	$ 5,773,649
UWP Product Team FY25	PRJ-7179	6784	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 1,500,000	$ 1,500,000	$ -	$ -	$ -	$ -	$ 1,500,000
AMI NY	PRJ-279	4704	Strategic	Customer	As detailed in the AMI Sanction paper (pages 216 - 231 of Exhibit__(ITDP-8), this investment seeks to deploy Advanced Metering Infrastructure (AMI) across National Grid's Niagara Mohawk Power Company (NMPC) service territory to modernize its electric meters, gas modules and supporting infrastructure and systems, offering new capabilities to customers. If approved, the Company currently has the ability to perform the required work.	Future	C113	3/31/2025	84	$ -	$ -	$ 6,931,000	$ 6,931,000	$ -	$ -	$ -	$ -	$ 6,931,000
AMI NY	PRJ-279	4704	Strategic	Customer		Future	C113	3/31/2026	84	$ -	$ -	$ -	$ -	$ 3,379,000	$ -	$ -	$ -	$ 3,379,000
AMI NY	PRJ-279	4704	Strategic	Customer		Future	C113	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 2,421,000	$ -	$ -	$ 2,421,000
CIS Enhancements	PRJ-8343	6434	Strategic	Customer	As detailed in SET-1099 (pages 750 - 757 of Exhibit__(ITDP-8), CSS Enhancements will begin with a discovery phase that will further refine and validate all potential new concepts/opportunities related to the CIS Platform, define the supporting architecture blueprints and develop business cases with implementation plans for all prioritized enhancements under this program. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 2,761,324	$ 2,761,324	$ -	$ -	$ -	$ -	$ 2,761,324
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	12/31/2026	84	$ -	$ -	$ -	$ -	$ -	$ 4,418,118	$ -	$ -	$ 4,418,118
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	9/30/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 19,881,533	$ -	$ 19,881,533
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	6/30/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,761,324	$ 2,761,324
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 25,404,181	$ 25,404,181
Clean Energy	PRJ-2082	5100	Strategic	Customer	As detailed in SET-1078 (pages758 - 765 of EXHIBIT__(ITDP-8), Clean Energy 2.0, is a new cloud based digital platform designed to deliver enterprise technology solutions to address current business management needs and future digital capabilities for expanding Energy Efficiency, Electric Vehicle charging infrastructure and programs, Demand Response and Distributed Energy programs offered to National Grid's customers directly or via clean energy trade partners while progressing on New York State's and the Company's strategic carbon reduction goals. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 12,500,000	$ 12,500,000	$ -	$ -	$ -	$ -	$ 12,500,000
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	6/15/2025	84	$ -	$ -	$ -	$ -	$ 5,319,773	$ -	$ -	$ -	$ 5,319,773
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	11/30/2025	84	$ -	$ -	$ -	$ -	$ 5,359,473	$ -	$ -	$ -	$ 5,359,473
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	4/1/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 11,512,942	$ -	$ 11,512,942
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	4/1/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 6,748,966	$ 6,748,966
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	4/15/2026	84	$ -	$ -	$ -	$ -	$ -	$ 5,399,173	$ -	$ -	$ 5,399,173
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	11/15/2026	84	$ -	$ -	$ -	$ -	$ -	$ 5,359,473	$ -	$ -	$ 5,359,473
Customer Experience Initiatives (ZBR)	PRJ-1718	6606	Strategic	Customer	As detailed in the Sanction paper (pages 240 - 255 of Exhibit__(ITDP-8), the existing Customer Experience Initiatives (ZBR) program is proposing to undertake additional programs to modernize and enhance the customer experience. If approved, the Company currently has the ability to perform the required work.	Future	C903	3/31/2025	84	$ -	$ -	$ 5,827,000	$ 5,827,000	$ -	$ -	$ -	$ -	$ 5,827,000

Date of Request: August 2, 2024 Request No. DPS-848
Due Date: August 12, 2024 NG Request No. NG-1023

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Strategic Account Managers

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. For each of the last five calendar years (2019, 2020, 2021, 2022, and 2023), provide the total number of employees who are considered Strategic Account Managers. Identify how many of these employees are full-time and part-time at NMPC.

2. For calendar year 2024, provide the total number of employees who are considered Strategic Account Managers. Identify how many of these employees are full-time and part-time at NMPC.

3. Regarding the Strategic Account Managers:

   a. Provide a detailed explanation of the Strategic Account Manager's current job duties and functions.

   b. Provide all changes made to these duties over the last five years.

Response:

1.-2. The following table summarizes the total number of full-time equivalents ("FTEs") from 2019 to present who performed some of the activities associated with large customer managed accounts that will now be handled by the Strategic Account Managers. All of these FTE are full-time.

	2019	2020	2021	2022	2023	2024
1. Corporate Affairs - Program Managers	17	17	16	17	17	10
% allocation to Large Customer Account Management activities	40%	40%	40%	40%	25%	10%
Corporate Affairs - Large Customer Account Management FTE	7	7	7	7	4	1
2. Energy Efficiency - Strategic Account Partnerships Program Managers	1	2	3	3	3	0
3. Customer Account Management UNY (starting June 2024)	0	0	0	0	0	9
4. Commercial Services - Large-Scale Renewables Developers / Wholesale Transmission Customers	4	4	4	5	5	5
5. National Accounts - EE / Account Management	1	1	1	1	1	1
TOTAL FTE - Strategic Account Management	**13**	**14**	**15**	**16**	**13**	**16**

From 2019 through mid-2024, Program Managers on the Company's Corporate Affairs performed large-customer account management in addition to their corporate affairs duties. The primary responsibility of the Corporate Affairs Program Managers during this time period, however, was to lead stakeholder engagement activities such as building and maintaining relationships with local chambers of commerce, business associations, environmental groups, and community leaders.

In addition, from 2019 to 2024, Strategic Account Partnerships Program Managers on the Energy Efficiency team worked on developing Strategic Energy Management Partnerships with large customers. These activities were mapped to the new Customer Account Management Upstate New York team in 2024, which will include the Strategic Account Managers.

Five Account Managers in the Commercial Services team are responsible for the relationships with Large Scale Renewables ("LSR") developers and wholesale transmission customers. The work associated with LSR development has increased and requires incremental resources beyond 2024.

One Account Manager from the Energy Efficiency team was responsible for energy efficiency sales and account management with national accounts customers in upstate New York. The work associated with national accounts requires incremental resources beyond 2024.

As shown above, while some of the activities associated with large customer managed accounts were performed by different functions across the Company, the purpose of the

Strategic Account Managers is to centralize management of large customer accounts into a dedicated group. This will enable the Company to provide more proactive assistance to its large commercial and industrial customers and address the planned increase of managed accounts from approximately 509 to 805 accounts. Additionally, the proposal will allow the Company's other functions that previously performed some of these activities to better focus on their core work while avoiding the need for incremental resources in those areas,

3a. The following is a description of the Strategic Account Manager's current job duties and functions:

Key Accountabilities

- Develop proactive account planning for assigned customers.
- Key activities of the Customer Account Management team may include, but are not limited to:
  - **Account Plans**: Develop and manage account plans with the customer that document shared objectives related to the customers' strategic business plans and daily operations related to energy. Manage associated action plans among internal and external stakeholders.
  - **Infrastructure Planning**: Assist customers with electric and gas infrastructure master planning. Engage Customer Connections and Engineering teams as needed for technical and financial analysis and problem solving.
  - **New Connections**: Engage Customer Connections teams on specific projects and monitor interactions with the customer on their portfolio of electric connections work, gas connections work and DG interconnections. Coordinate with the Electric and Gas functions as needed.
  - **SEMPs**: Partner with Customer Solutions sales teams to develop multi-year Strategic Energy Management Partnerships (SEMPs) with largest accounts focused on achieving clean energy objectives (*i.e.*, EE, EV, electrification, GHG reduction).
  - **Clean Energy**: Explore opportunities to increase customer implementation of clean energy projects (including EE, EV, electrification). Engage with Customer Solutions sales and program management teams on specific projects and monitor interactions with the customer.
  - **Executive Engagement:** Engage National Grid senior leadership in direct discussions with key customers on a periodic basis to ensure the voice of the customer is heard.
- Engage customers with curiosity and intent to learn.
- Share knowledge and develop technical understanding for economic development, energy efficiency and the future of heat to determine and shape the customer experience.
- Provide technical guidance, support and coaching to establish National Grid as a leader in energy solutions.
- Build multithreaded relationships within customer account to ensure balanced feedback and account strategy development.
- Distill customer requirements and create a succinct action plan for internal National Grid stakeholders.
- Document action plans and track progress to key metrics, leveraging Salesforce.com.
- Take initiative to understand business functions within National Grid and supporting organizations, building relationships across teams.

Additional Responsibilities

- Provide support during electric and/or natural gas service quality issues or interruptions – managing the communication of resolutions to the customer executive management.
- Liaise with other groups within the Customer Organization team (*e.g.*, Managed Account Services, Account Maintenance & Operations, etc.) and Electric/Gas Operations to address metering, billing, and/or payment disputes, performing initial triage on issues at an appropriate level of detail necessary to handoff for issue resolution.
- Support operations and customer service, including, but not limited to, on-call duties, storm restoration efforts, outage coordination and support for customer service on a 24/7 basis.
- Participate in major storm events as the information liaison for assigned region, stakeholders, and/or customers during outages and other emergencies.

3b. In 2023 and 2024, the Corporate Affairs Program Managers increased external engagement with stakeholders and community leaders because of the Phase 2 CLCPA work in Upstate New York. As such, they spent less time on large-customer account management. The Customer Account Management UNY team was formed in June 2024. The Strategic Account Manager roles are in the process of combining the large-customer account management activities of the Corporate Affairs Program Managers together with the Strategic Account Partnerships activities of the Energy Efficiency Program Managers as discussed above.

Name of Respondent: Date of Reply:
Matthew Foran August 12, 2024

Date of Request: August 2, 2024 Request No. DPS-855
Due Date: August 12, 2024 NG Request No. NG-1030

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Strategic Account Managers 3

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference page 37 of the Customer Panel's initial testimony, which states, "The Company plans to expand the number of Managed Account customers to 805, with the goal of providing a dedicated account manager to accounts that exceed 750 kW of electric demand or annual gas consumption of 25,000 dekatherms."

1. For each of the last five calendar years (2019, 2020, 2021, 2022, and 2023), provide the total number of Managed Account customers. Include a breakdown of electric and gas accounts.

2. For calendar year 2024 to date, provide the total number of Managed Account customers. Include a breakdown of electric and gas accounts.

3. Provide a detailed explanation for the Company's increased forecast from 509 managed Accounts to 805 accounts and the anticipated timeline for this increase. Include workpapers, studies, or other documentation to support the Company's forecast.

Response:

1.-2. The Company does not have historic account lists dating back to 2019 but the total number of managed accounts did not materially change from the current count of 509. These are enterprise level customer entities. The Company provides electricity distribution to all 509 managed accounts and also provides gas distribution service to 298 of these accounts.

3. Beginning with the list of 509 currently managed accounts, the Company believes it is

important that customers that met or exceeded either 750 kW in yearly average demand or 25,000 Dth in annual gas consumption have a Strategic Account Manager assigned to their account. Customers of this size typically spend at least $500,000 on energy and would benefit from an account manager who could provide proactive guidance on infrastructure planning, new connections, clean energy programs, and assistance on operational concerns. The expanded target list of 805 managed accounts includes additional enterprises that met or exceeded either 750 kW in yearly average demand or 25,000 Dth in annual gas consumption. The timing for active management of this expanded list is dependent on the timing of additional Strategic Account Manager hiring into the Customer Account Management Upstate New York team, which is expected to continue through mid-2025.

Name of Respondent:	Date of Reply:
Matthew Foran	August 12, 2024

Date of Request: August 9, 2024 Request No. DPS-908
Due Date: August 19, 2024 NG Request No. NG-1118

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Call Center Staffing

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. For each of the last five calendar years (2019, 2020, 2021, 2022, 2023), provide the number of customer contacts from residential customers that were handled in the internal call center. Include a breakdown of contact type, such as incoming calls, emails, web contacts, etc.

2. For each of the last five calendar years (2019, 2020, 2021, 2022, 2023), provide the number of customer contacts from residential customers that were handled in the vendors' call center. Include a breakdown of contact type, such as incoming calls, emails, web contacts, etc.

3. For each of the last five calendar years (2019, 2020, 2021, 2022, 2023), provide the number of customer contacts from commercial customers that were handled in the internal call center. Include a breakdown of contact type, such as incoming calls, emails, web contacts, etc.

4. For each of the last five calendar years (2019, 2020, 2021, 2022, 2023), provide the number of customer contacts from commercial customers that were handled in the vendors' call center. Include a breakdown of contact type, such as incoming calls, emails, web contacts, etc.

Response:

1. For the last five calendar years the number of residential customer contacts handled internally by the call center can be found below by contact type.

Year	Total
2019	30,166
2020	27,636
2021	28,995
2022	19,554
2023	758

Note: With respect to residential emails, in September 2022, the Company disabled the email functionality for customers on the website, as it found that communication via chat or phone were more preferred options. The 2023 volume represents interactions with customers sending messages directly to the email address they received on a prior interaction and bypassing the web site.

Residential web contacts:

Year	Total
2019	5,725,121
2020	6,161,800
2021	5,350,520
2022	7,602,392
2023	5,791,021

Note that all calls are included for residential inbound calls handled within the call center. As such, the numbers here will not align to any of the Company's monthly or annual calls answered filings.

Year	Calls Handled
2019	854,019
2020	1,173,271
2021	1,092,430
2022	1,169,536
2023	1,216,693

2. For the last five calendar years the number of residential customer contacts handled in the vendor call center can be found below.

Note that all calls are included for residential inbound calls answered within the call center. As such, the numbers here will not align to any of the Company's monthly or annual calls answered filings. In addition, one of the Company's vendor, iQor, are not included in these numbers because they do not have the ability to report on handled calls.

Year	Calls Answered
2019	2,105,329
2020	987,304
2021	1,650,664
2022	1,985,469
2023	1,980,774

3. For the last five calendar years the number of commercial customer contacts handled internally by the call center can be found below by contact type.

Year	**Total**
2019	144
2020	134
2021	140
2022	168
2023	58

Note: With respect to commercial emails, in September 2022, the Company disabled the email functionality for customers on the website, as it found that communication via chat or phone were more preferred options. The 2023 volume represents interactions with customers sending messages directly to the email address they received on a prior interaction and bypassing the web site.

Commercial web contacts:

Year	Total
2019	555,888
2020	458,035
2021	566,277
2022	676,268
2023	428,674

Note that all calls are included for commercial inbound calls handled within the call center. As such, the numbers here will not align to any of the Company's monthly or annual calls answered filings:

Year	Calls Handled
2019	108,023
2020	106,971
2021	70,845
2022	82,280
2023	79,751

4. The Company's commercial customer contacts are not handled within any of the vendor call centers.

Name of Respondent:
Jim MacVicar

Date of Reply:
August 19, 2024

Date of Request: August 9, 2024 Request No. DPS-910
Due Date: August 19, 2024 NG Request No. NG-1120

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Information Technology - Customer Portfolio

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

For each line item in the Customer Portfolio listed on rows 2-78 and 586-601 in Exhibit__(ITDP-4CU):

1. Provide a detailed description of the specific operational efficiencies that the Company has achieved or expects to achieve (e.g., reduced full-time equivalents or contracted resources) and how the efficiencies affect the workload of the Company's customer service employees.

Response:

1. Please see Attachment 1, column F, for the descriptions of operational efficiencies that the Company has achieved or expects to achieve.

   As explained in testimony and prior discovery responses, the Company performed a comprehensive review of all IT projects to identify and capture any potential savings in the revenue requirements. If the IT investment will deliver financial benefits, those benefits are captured in the revenue requirements either through a reduction to total run the business expenditures (if the benefit is specific to the IT function) or separately as part of National Grid's Efficiency Initiatives (if the project will deliver reductions across the business). This review and presentation of IT benefits is explained in more detail at pages 15-16 of 66 of the ITDP's direct testimony.

   IT Enabled Efficiency Savings

   Exhibit__(RRP-3CU), Schedule 27, Workpaper 1 presents the IT projects that are projected to deliver savings as part of National Grid's Efficiency Initiatives. As shown in that exhibit, the total IT enabled efficiency savings delivered by the Customer Portfolio of IT investments is $10.231 million for Electric and $3.435 million for Gas in the Historic Test Year with additional savings of $2.901 million for Electric and $1.071 million for Gas forecast in the Rate Year. The total cumulative savings from the Customer Portfolio of IT investments for Electric and Gas is $13.092 million and $4.496 million, respectively. As discussed in the direct testimony of the Revenue Requirement Panel, the Company carried the Rate Year level of savings forward for the Data Years and applied inflation in a manner that increased the level of savings.

Name of Respondent:	Date of Reply:
Ed Brodsky	August 19, 2024
Najat Coye	

Investment Name	PRJ #	INVP #	Category	Portfolio	Operational Efficiencies Achieved/Expected To Achieve	Inflight/Future	Allocation Code	Forecasted In Service Date	Amortization Period	CWIP - Inception to date	Forecast - CAPEX - FY24	FY25 CAPEX	FY26 Beginning Balance	FY26 CAPEX	FY27 CAPEX	FY28 CAPEX	FY29 CAPEX	Total
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer	The Agent Interaction Management System (AIMS) product team delivers Interactive Voice Response (IVR) tactical initiatives that have increased transaction processing within the IVR, allowing customers more self-service options that reduce the need for human/agent assistance from the Company's Customer Service employees. Self service initiatives will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 3,574,584	$ -	$ -	$ -	$ 3,574,584
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 3,454,015	$ -	$ -	$ 3,454,015
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 3,443,008	$ -	$ 3,443,008
AIMS Product Team - Annual Program	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 3,448,587	$ 3,448,587
AIMS Product Team FY25	PRJ-7779	6787	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 1,000,000	$ 1,000,000	$ -	$ -	$ -	$ -	$ 1,000,000
AIMS Replatform	PRJ-5802	6728	Core	Customer	This investment will provide a new platform to support continued IVR (for self-service interactions) and Workforce Optimization (WFO) to improve the Company's ability to address customer calls, thereby reducing the need for human/agent assistance from the Company's Customer Service employees. WFO and increases in self-service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2025	84	$ -	$ -	$ 7,800,000	$ 7,800,000	$ -	$ -	$ -	$ -	$ 7,800,000
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer	This funding mechanism supports investments including system modifications, changes and enhancements to comply with emergent mandates and directives from the PSC or other authorities that require changes to billing and other critical customer systems to meet regulatory requirements. These could be new or existing products, depending on the mandate/enhancement, and contribute to various operational efficiencies across the Customer portfolio. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the Customer Billing Collections Mandates Enhancements investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Future	C903	3/31/2025	84	$ -	$ -	$ 1,640,000	$ 1,640,000	$ -	$ -	$ -	$ -	$ 1,640,000
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 26,355,299	$ -	$ -	$ -	$ 26,355,299
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 21,811,282	$ -	$ -	$ 21,811,282
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 20,902,478	$ -	$ 20,902,478
Billing Collections Mandates Enhancements	PRJ-3756	6538	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 21,811,282	$ 21,811,282
Case Management	PRJ-5909	6775	Core	Customer	The Customer function manages inquiries, requests and complaints from external parties via different methods depending on the organization and solution that was originally selected to manage the case intake process. Once the proper solution is implemented, immediate business benefits such as enhanced reporting capabilities enabling end to end root cause analysis will lead to continued customer service experience improvements and reduced intervention from the Company's Customer Service employees.	Future	C903	3/31/2025	84	$ -	$ -	$ 2,600,000	$ 2,600,000	$ -	$ -	$ -	$ -	$ 2,600,000
Community Solar Bill Portal	PRJ-7764	N/A	Core	Customer	This investment is requesting to fund a Self-Serve Billing and Credit Allocation Portal to improve the Community Distributed Generation (CDG) customer experience and further support the implementation of CDG. This new functionality would allow Customers to self-manage their allocations with less human intervention and processing time, thereby reducing the burden on the Company's Customer Service employees.	Future	C902	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 512,006	$ -	$ -	$ 512,006
Community Solar Bill Portal	PRJ-7764	N/A	Core	Customer		Future	C902	8/1/2026	84	$ -	$ -	$ -	$ -	$ -	$ 7,680,097	$ -	$ -	$ 7,680,097
Community Solar Bill Portal	PRJ-7764	N/A	Core	Customer		Future	C902	4/30/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 341,338	$ -	$ 341,338
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer	A single self-service platform for all Distributed Energy Resources (DER) and Electric Connections request. This investment will enable full queue management of DER (Solar, ESS, EV) and Load (EV, Heat Electrification, etc.) from engineering and planning perspective. It will provide enhanced functionality such as pre-application research assistant, connection schedule, connection finance for better visibility externally to trade allies, customers and installers.The self service portal will help customer to receive information faster that will result in improvement to interconnection timelines/ customer hold time, less cancellations and increase in customer satisfaction. The self service is allowing Customer Service Employees to focus on more complex customers and issues.	Future	C902	3/31/2026	84	$ -	$ -	$ -	$ -	$ 5,986,751	$ -	$ -	$ -	$ 5,986,751
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 7,531,719	$ -	$ -	$ 7,531,719
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,510,573	$ -	$ 2,510,573
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	4/1/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,510,573	$ -	$ 2,510,573
ConnectNow (incremental functionality)	PRJ-7770	N/A	Core	Customer		Future	C902	4/1/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 772,484	$ 772,484
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer	The legacy Customer Connections project is a mandate to offer interconnection online application portal to DG customers. This investment will help keep up with regulatory changes, bug fixes, and ongoing minor enhancements to DG interconnnection process. The portal helps with tracking tariff timeliness, online status and e-payments of Distributed Generation (DG) interconnections. This investment will continue to improve customer experience and ease of doing business with the Company. The self service is allowing Customer Service Employees to focus on more complex customers and issues.	Future	C903	3/31/2025	84	$ -	$ -	$ 3,700,000	$ 3,700,000	$ -	$ -	$ -	$ -	$ 3,700,000
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 9,747,594	$ -	$ -	$ -	$ 9,747,594
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 10,633,739	$ -	$ -	$ 10,633,739
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 11,519,884	$ -	$ 11,519,884
ConnectNow (legacy Customer Connections)	PRJ-3633	5125	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 12,406,029	$ 12,406,029
CSS Enhancements FY25	PRJ-7175	6773	Core	Customer	This project provides a funding base and governance structure that allows the IT&D organization to effectively deliver small system changes to the entire Customer portfolio, in response to any regulatory mandates, operational requirements and value-added enhancements that will occur during the course of the year. These could be new or existing products, depending on the mandate/enhancement, and contribute to various operational efficiencies across the Customer portfolio. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the CSS Enhancements investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Future	C903	3/31/2025	84	$ -	$ -	$ 350,000	$ 350,000	$ -	$ -	$ -	$ -	$ 350,000
Customer Data Platform	PRJ-5955	6740	Core	Customer	This investment will fund the existing Customer Data Platform which provides a centralized platform for Customer data. By providing access to clean, accessible Customer data insights, 360-degree view of Customer data, and advanced analytics to improve customer service and decision making, the Customer Data Platform contributes to various operational efficiencies across the Customer portfolio, including indirectly reducing the need for manual intervention from the Company's Customer Service employees by operating from a single source of data instead of siloed sources of data. With the increased quality and analytics to make decisions, the customer service employees will be able focus in and provide better and more effective decisions and information to customers.	Future	G911	3/31/2025	84	$ -	$ -	$ 5,500,000	$ 5,500,000	$ -	$ -	$ -	$ -	$ 5,500,000
Customer Data Platform	PRJ-5955	6740	Core	Customer		Future	G911	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 4,147,381	$ -	$ -	$ 4,147,381
Customer Data Platform	PRJ-5955	6740	Core	Customer		Future	G911	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 4,147,381	$ -	$ 4,147,381
Customer Data Platform	PRJ-5955	6740	Core	Customer		Future	G911	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 4,665,804	$ 4,665,804
Customer Data Platform	6740	6740	Core	Customer		Inflight	G911	3/31/2024	84	$ 4,173,915	$ 519,326	$ -	$ 4,693,241	$ -	$ -	$ -	$ -	$ 4,693,241
Customer Facing Mobile App – In House Solu	PRJ-7777	6786	Core	Customer	This project's focus is to build, deliver and support a new in-house customer facing mobile app that provides new customer experience capabilities including: unlocking a new channel for customers to sign in using their existing National Grid credentials to view account, billing and payment information and submit payments to National Grid. By driving self-service transactions, this investment will reduce the burden on the Company's Customer Service employees. Self service initiatives will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C175	3/31/2026	84	$ -	$ -	$ -	$ -	$ 929,491	$ -	$ -	$ -	$ 929,491
Customer Facing Mobile App – In House Solu	PRJ-7777	6786	Core	Customer		Future	C175	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 1,956,579	$ -	$ -	$ 1,956,579
Customer Facing Mobile App – In House Solu	PRJ-7777	6786	Core	Customer		Future	C175	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,956,579	$ -	$ 1,956,579
Customer Facing Mobile App – In House Solu	PRJ-7777	6786	Core	Customer		Future	C175	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,956,579	$ 1,956,579
Customer Facing Mobile App – In House Solu	PRJ-7777	6786	Core	Customer		Future	C175	6/1/2025	84	$ -	$ -	$ -	$ -	$ 2,494,755	$ -	$ -	$ -	$ 2,494,755
Customer Mobile Application	PRJ-7777	6786	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 3,600,000	$ 3,600,000	$ -	$ -	$ -	$ -	$ 3,600,000
Customer Tech Debt Remediation	PRJ-7178	6791	Core	Customer	This investment seeks to replace/update network equipment, servers and operating systems etc. that are end of life and no longer supported by the vendors. These updates will reduce and prevent system outages impacting National Grid customers and improve operational efficiencies by providing a more productive and reliable solution for the Company's Customer Service employees.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,858,632	$ -	$ -	$ -	$ 1,858,632
Customer Tech Debt Remediation FY25	PRJ-7178	6791	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 2,287,000	$ 2,287,000	$ -	$ -	$ -	$ -	$ 2,287,000
CXP Technical Debt	PRJ-7592	6776	Core	Customer	Customer Experience Products (CXP) has accumulated significant technical debt over the past decade, which requires migration and/or re-writing of applications that are currently being used by the Customer function and our external customers. These updates will reduce and prevent system outages impacting National Grid customers and improve operational efficiencies by reducing manual intervention from the Company's Customer Service employees.	Future	C175	3/31/2025	84	$ -	$ -	$ 2,999,000	$ 2,999,000	$ -	$ -	$ -	$ -	$ 2,999,000
Digital Assistant	PRJ-4584	6777	Core	Customer	This project will focus on continuing to improve and deliver personalized experiences and customer self-service opportunities by leveraging National Grid's Digital Assistant Chatbot (DA) to direct customers	Future	C903	3/31/2025	84	$ -	$ -	$ 2,000,000	$ 2,000,000	$ -	$ -	$ -	$ -	$ 2,000,000

Investment Name	PRJ #	INVP #	Category	Portfolio	Operational Efficiencies Achieved/Expected To Achieve	Inflight/Future	Allocation Code	Forecasted In Service Date	Amortization Period	CWIP - Inception to date	Forecast - CAPEX - FY24	FY25 CAPEX	FY26 Beginning Balance	FY26 CAPEX	FY27 CAPEX	FY28 CAPEX	FY29 CAPEX	Total
Digital Assistant	PRJ-4584	6777	Core	Customer	service opportunities by leveraging National Grid's Digital Assistant Chatbot (DA) to direct customers to digital channels within NG's Unified Web Portal (UWP) and Mobile Web. Key operational efficiencies include managing call center costs to serve customers by promoting digital adoption and transaction processing on the Web and reducing dependence on traditional Customer Service employee interactions (telephone and mail) which have higher costs and may not be aligned to customer expectations. DA will enable the Company to respond swiftly to customer needs and market demands. As Customers increasingly use web and self service options, employees will focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,919,844	$ -	$ -	$ -	$ 1,919,844
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 1,919,844	$ -	$ -	$ 1,919,844
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,079,831	$ -	$ 2,079,831
Digital Assistant	PRJ-4584	6777	Core	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,079,831	$ 2,079,831
Documentum Application Modernization	PRJ-5263	6686	Core	Customer	Documentum is an existing content management application used by both back- and front-office employees. The current legacy application is operating on out of support software and has supporting assets that are considered end of life. Future operational efficiencies include automating manual back office processes and reducing outage incidents, leading to a reduced need for manual intervention from the Company's Customer Service employees. This will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2025	84	$ -	$ -	$ 750,000	$ 750,000	$ -	$ -	$ -	$ -	$ 750,000
GenAI	6769	6769	Core	Customer	This investment will transform the existing Account Maintenance & Operations' (AMO) mailbox management by augmenting it with generative artificial intelligence and other advanced technologies. Upon completion, this investment will improve productivity, work quality, and satisfaction for both employees and customers, thereby leading to a reduced need for manual intervention from the Company's Customer Service eymployees. By harnessing the power of automation and artificial intelligence (AI), we will automate repetitive tasks, enabling our teams to focus on higher-value and more complex activities and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2025	84	$ -	$ -	$ 970,000	$ 970,000	$ -	$ -	$ -	$ -	$ 970,000
INVP 5125 Customer Connection	5125	5125	Core	Customer	The legacy Customer Connections project is a mandate to offer interconnection online application portal to DG customers. This investment will help keep up with regulaotry changes, bug fixes, and ongoing minor enhancements to DG interconnnection process. The portal helps with tracking tariff timeliness, online status and e-payments of DG interconnections. This investment will continue to improve customer experience and ease of doing business with the Company. The self service is allowing Customer Service Employees to focus on more complex customers and issues.	Inflight	C175	3/29/2024	84	$ 913,654	$ 384,536	$ -	$ 1,298,189	$ -	$ -	$ -	$ -	$ 1,298,189
INVP 5673 My Business Account	5673	5673	Core	Customer	My Business Account (MBA) is focused on re-engineering the National Grid commercial and industrial (C&I) customers' digital interactions to create a streamlined and seamless customer experience throughout the customer's journey. This project will continue to deliver operational efficiencies through providing digital tools to customers to self manage their accounts which will reduce the number of inquiries that the customer service employees address in this segment of the business. This will enable the Company to focus on higher-value and more complex activities and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Inflight	C175	3/29/2024	84	$ 788,569	$ 233,494	$ -	$ 1,022,063	$ -	$ -	$ -	$ -	$ 1,022,063
INVP 6492 NACHA Compliance Sec	6492	6492	Core	Customer	The National Automated Clearinghouse Association (NACHA) requires that National Grid protect deposit account information by rendering it unreadable when it is stored electronically. If we do not acheive compliance, National Grid is subject to revocation or suspension of processing ACH processing capabilities, penalties up to $500K per transaction and reputational damage. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the NACHA Compliance investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Inflight	C175	3/31/2024	84	$ 245,642	$ 139,076	$ -	$ 384,718	$ -	$ -	$ -	$ -	$ 384,718
INVP 6687 FY24 Cust Minor Works	6687	6687	Core	Customer	This project provides a funding base and governance structure that allows the IT&D organization to effectively deliver small system changes to the entire Customer portfolio, in response to any regulatory mandates, operational requirements and value-added enhancements that will occur during the course of the year. These could be new or existing products, depending on the mandate/enhancement, and contribute to various operational efficiencies across the Customer portfolio. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the Minor Works investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Inflight	C903	3/31/2024	84	$ 357,665	$ 44,479	$ -	$ 402,144	$ -	$ -	$ -	$ -	$ 402,144
INVP 6706 FY24 UWP Enhancements	6706	6706	Core	Customer	This investment is to continue to maintain the existing UWP platform Product Team as customer and regulatory needs change, allowing our customers more self-service options that reduce the need for human/agent assistance from the Company's Customer Service employees. Increase in self service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Inflight	C175	3/29/2024	84	$ 982,579	$ 546,642	$ -	$ 1,529,221	$ -	$ -	$ -	$ -	$ 1,529,221
INVP 6713 Customer Facing Mobile Ap	6713	6713	Core	Customer	This project's focus is to build, deliver and support a new in-house customer facing mobile app that provides new customer experience capabilities including: unlocking a new channel for customers to sign in using their existing National Grid credentials to view account, billing and payment information and submit payments to National Grid. By driving self-service transactions, this investment will reduce the burden on the Company's Customer Service employees.	Inflight	C175	3/29/2024	84	$ 4,127,620	$ 530,913	$ -	$ 4,658,533	$ -	$ -	$ -	$ -	$ 4,658,533
INVP 6715 UWP 2.0 MyAccount Impleme	6715	6715	Core	Customer	This investment focuses on transitioning the existing Unified Web Portal (UWP) to a new, more robust, higher performing and adaptable platform, allowing for continued self-service opportunities that reduce the need for human/agent assistance from the Company's Customer Service employees. Increase in self service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Inflight	C175	3/31/2024	84	$ 5,049,743	$ 1,804,628	$ -	$ 6,854,371	$ -	$ -	$ -	$ -	$ 6,854,371
INVP 6727 AIMS FY24 Product Team	6727	6727	Core	Customer	The Agent Interaction Management System (AIMs) product team delivers Interactive Voice Response (IVR) tactical initiatives that have increased transaction processing within the IVR, allowing our customers more self-service options that reduce the need for human/agent assistance from the Company's Customer Service employees. Increase in self service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Inflight	C903	3/29/2024	84	$ 613,973	$ 259,383	$ -	$ 873,356	$ -	$ -	$ -	$ -	$ 873,356
INVP 6728 AIMS RePlatform Sanction	6728	6728	Core	Customer	This investment will provide a new platform to support continued IVR (for self-service interactions) and Workforce Optimization (WFO) to improve the Company's ability to address Customer's calls, thereby reducing the need for human/agent assistance from the Company's Customer Service employees. WFO and increases in self service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Inflight	C903	3/31/2024	84	$ 780,129	$ 902,237	$ -	$ 1,682,365	$ -	$ -	$ -	$ -	$ 1,682,365

Niagara Mohawk Power Corporation
d/b/a National Grid
Cases 24-E-0322 & 24-G-0323
DPS-910 Attachment 1
Page 3 of 4

Investment Name	PRJ #	INVP #	Category	Portfolio	Operational Efficiencies Achieved/Expected To Achieve	Inflight/Future	Allocation Code	Forecasted In Service Date	Amortization Period	CWIP - Inception to date	Forecast - CAPEX - FY24	FY25 CAPEX	FY26 Beginning Balance	FY26 CAPEX	FY27 CAPEX	FY28 CAPEX	FY29 CAPEX	Total
INVP 6746 CXP Tech Debt Initiative	6746	6746	Core	Customer	Customer Experience Products (CXP) has accumulated significant technical debt over the past decade, which requires migration and/or re-writing of applications that are currently being used by the Customer Business and our external customers. These updates will reduce and prevent system outages impacting National Grid customers and improve operational efficiencies by reducing manual intervention from the Company's Customer Service employees.	Inflight	C175	3/29/2024	84	$ 2,150,178	$ 191,021	$ -	$ 2,341,199	$ -	$ -	$ -	$ -	$ 2,341,199
Mainframe Security Realignment	PRJ-7162	6778	Core	Customer	This investment seeks to streamline access to the existing mainframe leading to enhanced operational efficiencies, particularly in regards to security and monitoring. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the Mainframe Security Realignment investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Future	C903	3/31/2025	84	$ -	$ -	$ 450,000	$ 450,000	$ -	$ -	$ -	$ -	$ 450,000
My Business Account	PRJ-7180	6785	Core	Customer	My Business Account (MBA) is focused on re-engineering the National Grid commercial and industrial (C&I) customers' digital interactions to create a streamlined and seamless customer experience throughout the customer's journey. This project will continue to deliver operational efficiencies through providing digital tools to customers to self manage their accounts which will reduce the number of inquiries that the customer service employees address in this segment of the business. Increase in self service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2025	84	$ -	$ -	$ 1,800,000	$ 1,800,000	$ -	$ -	$ -	$ -	$ 1,800,000
My Business Account (Nucleas) Enhancement	PRJ-7778	6785	Core	Customer	My Business Account (MBA) is focused on re-engineering the National Grid commercial and industrial (C&I) customers' digital interactions to create a streamlined and seamless customer experience throughout the customer's journey. This project will continue to deliver operational efficiencies through providing digital tools to customers to self manage their accounts which will reduce the number of inquiries that the customer service employees address in this segment of the business.Increase in self service will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C175	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,999,113	$ -	$ -	$ -	$ 1,999,113
My Business Account (Nucleas) Enhancement	PRJ-7778	6785	Core	Customer		Future	C175	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 1,919,149	$ -	$ -	$ 1,919,149
My Business Account (Nucleas) Enhancement	PRJ-7778	6785	Core	Customer		Future	C175	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,999,113	$ -	$ 1,999,113
My Business Account (Nucleas) Enhancement	PRJ-7778	6785	Core	Customer		Future	C175	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,079,078	$ 2,079,078
NACHA	PRJ-3636	6492	Core	Customer	The National Automated Clearinghouse Association (NACHA) requires that National Grid protect deposit account information by rendering it unreadable when it is stored electronically. If we do not acheive compliance, National Grid is subject to revocation or suspension of processing ACH processing capabilities, penalties up to $500K per transaction and reputational damage. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the NACHA Compliance investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Future	C903	3/31/2025	84	$ -	$ -	$ 588,000	$ 588,000	$ -	$ -	$ -	$ -	$ 588,000
New Customer Digital Products	PRJ-7369	N/A	Core	Customer	The New Customer Digital Products investment will be used to continue National Grid's customer-centric digital transformation to promote self-service transactions, improve overall customer experience, and reduce manual/inefficient operational processes, leading to reduced invervention from the Company's Customer Service employees. Improved digital offereings and increases in self service initiatives will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/30/2026	84	$ -	$ -	$ -	$ -	$ 2,262,203	$ -	$ -	$ -	$ 2,262,203
New Customer Digital Products	PRJ-7369	N/A	Core	Customer		Future	C903	3/30/2027	84	$ -	$ -	$ -	$ -	$ -	$ 3,800,500	$ -	$ -	$ 3,800,500
New Customer Digital Products	PRJ-7369	N/A	Core	Customer		Future	C903	3/30/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,266,833	$ -	$ 1,266,833
New Customer Digital Products	PRJ-7369	N/A	Core	Customer		Future	C903	3/30/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,719,275	$ 1,719,275
NY Green Button Connect	PRJ-2095	N/A	Core	Customer	Green Button Connect (GBC) is an existing application whereby utilities can enable customers to share their energy consumption data with 3rd Party energy solution providers and companies (such as Retail Energy, Solar, EE, etc.). Upon completion of the proposed enhancements, the Company will be compliant with GBC standards and regulatory requirements. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the GBC investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Future	C914	4/1/2025	84	$ -	$ -	$ 190,421	$ 190,421	$ -	$ -	$ -	$ -	$ 190,421
STS Clean-up (backlog from C2C)	PRJ-7168	6780	Core	Customer	This investment seeks to address tickets and requests inputted by the Business to fix issues such as account errors, missed compliance targets, etc. within the Customer Service System (CSS), which will contribute to various operational efficiencies across the Customer portfolio. The Company has not made an adjustment for these Type 2 benefits/efficiencies because they do not result in a direct cost reduction. The cost forecast included in the case assumes the Service Tracking System (STS) Clean-up investment is approved and implemented. Therefore, the higher costs that would otherwise result absent this investment are not included in the Rate Year and Data Years' forecast.	Future	C903	3/31/2025	84	$ -	$ -	$ 1,800,000	$ 1,800,000	$ -	$ -	$ -	$ -	$ 1,800,000
STS Clean-up (backlog from C2C)	PRJ-7168	6780	Core	Customer		Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 1,000,000	$ -	$ -	$ -	$ 1,000,000
UWP 2.0 MyAccount Implementation and De	PRJ-5323	6715	Core	Customer	This investment focuses on transitioning the existing Unified Web Portal (UWP) to a new, more robust, higher performing, and adaptable platform, allowing for continued self-service opportunities that reduce the need for human/agent assistance from the Company's Customer Service employees. As the Company moves to this new solution which is a lower cost technology the overall operating costs and environment will be less complex, simpler to utilize and less expensive. Self-service initiatives will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	8/30/2024	84	$ -	$ -	$ 6,696,000	$ 6,696,000	$ -	$ -	$ -	$ -	$ 6,696,000
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer	This investment is to continue to maintain the existing UWP platform Product Team as customer and regulatory needs change, allowing customers more self-service options that reduce the need for human/agent assistance from the Company's Customer Service employees. Self service increases will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2026	84	$ -	$ -	$ -	$ -	$ 4,704,454	$ -	$ -	$ -	$ 4,704,454
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer		Future	C903	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 5,345,971	$ -	$ -	$ 5,345,971
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer		Future	C903	3/31/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 5,559,810	$ -	$ 5,559,810
UWP Product Team Annual Program	PRJ-7179	6784	Core	Customer		Future	C903	3/30/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 5,773,649	$ 5,773,649
UWP Product Team FY25	PRJ-7179	6784	Core	Customer		Future	C903	3/31/2025	84	$ -	$ -	$ 1,500,000	$ 1,500,000	$ -	$ -	$ -	$ -	$ 1,500,000
AMI NY	PRJ-279	4704	Strategic	Customer	This investment seeks to deploy Advanced Metering Infrastructure (AMI) across the Company's service territory to modernize its electric meters, gas modules and supporting infrastructure and systems, offering operational efficiencies, improving customer experience/insights, and providing a foundational platform supporting grid modernization efforts.	Future	C113	3/31/2025	84	$ -	$ -	$ 6,931,000	$ 6,931,000	$ -	$ -	$ -	$ -	$ 6,931,000
AMI NY	PRJ-279	4704	Strategic	Customer		Future	C113	3/31/2026	84	$ -	$ -	$ -	$ -	$ 3,379,000	$ -	$ -	$ -	$ 3,379,000
AMI NY	PRJ-279	4704	Strategic	Customer		Future	C113	3/31/2027	84	$ -	$ -	$ -	$ -	$ -	$ 2,421,000	$ -	$ -	$ 2,421,000
CIS Enhancements	PRJ-8343	6434	Strategic	Customer	Customer Information System (CIS) Enhancements will deliver enhanced functionality to the existing CIS Platform. Now that National Grid has consolidated CRIS and CSS into single system (CSS), future CIS enhancements and componentization will provide more effective ways for the Company's Customer Service reps and advocates to support new billing capabilities.	Future	C903	3/31/2025	84	$ -	$ -	$ 2,761,324	$ 2,761,324	$ -	$ -	$ -	$ -	$ 2,761,324
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	12/31/2026	84	$ -	$ -	$ -	$ -	$ -	$ 4,418,118	$ -	$ -	$ 4,418,118
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	9/30/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 19,881,533	$ -	$ 19,881,533
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	6/30/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 2,761,324	$ 2,761,324
CIS Enhancements	PRJ-8343	6434	Strategic	Customer		Future	C903	3/31/2029	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 25,404,181	$ 25,404,181

Investment Name	PRJ #	INVP #	Category	Portfolio	Operational Efficiencies Achieved/Expected To Achieve	Inflight/Future	Allocation Code	Forecasted In Service Date	Amortization Period	CWIP - Inception to date	Forecast - CAPEX - FY24	FY25 CAPEX	FY26 Beginning Balance	FY26 CAPEX	FY27 CAPEX	FY28 CAPEX	FY29 CAPEX	Total
Clean Energy	PRJ-2082	5100	Strategic	Customer	Clean Energy 2.0's (CE2.0) objectives and key results (OKRs) expect to achieve an Electric Vehicle (EV) application cycle time reduction target of 10-20%. Through efficiencies in the new platform, this gives the customer service employees the ability to process more EV applications with the staff they have, to achieve growing goals. CE2.0 has also uncovered process efficiencies the EV business would need to implement to further aid in the workload of customer service employees. Energy Efficiency (EE) OKRs include comprehensive OKRs including the reduction of conversion time through data driven prioritization metrics such as early visibility of savings, reduction in program design and implementation time, and application processing and reporting overhead with a target of 27%. The new platform will also move the energy efficiency ecosystem, from account managers to vendors, into a single unified platform driving efficiencies across day-to-day activities resolving inefficiencies and governance issues. Efficiencies provided by the platform will benefit multiple areas, including the IT and Customer Energy Management (CEM) environments. Businesses will see savings through a single unified platform for tracking and process oversight, speed to market, on demand reporting, and shorter reconciliation phases.	Future	C903	3/31/2025	84	$ -	$ -	$ 12,500,000	$ 12,500,000	$ -	$ -	$ -	$ -	$ 12,500,000
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	6/15/2025	84	$ -	$ -	$ -	$ -	$ 5,319,773	$ -	$ -	$ -	$ 5,319,773
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	11/30/2025	84	$ -	$ -	$ -	$ -	$ 5,359,473	$ -	$ -	$ -	$ 5,359,473
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	4/1/2027	84	$ -	$ -	$ -	$ -	$ -	$ -	$ 11,512,942	$ -	$ 11,512,942
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	4/1/2028	84	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 6,748,966	$ 6,748,966
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	4/15/2026	84	$ -	$ -	$ -	$ -	$ -	$ 5,399,173	$ -	$ -	$ 5,399,173
Clean Energy	PRJ-2082	5100	Strategic	Customer		Future	C903	11/15/2026	84	$ -	$ -	$ -	$ -	$ -	$ 5,359,473	$ -	$ -	$ 5,359,473
Customer Experience Initiatives (ZBR)	PRJ-1718	6606	Strategic	Customer	The existing Customer Experience Initiatives (ZBR) program is proposing to undertake additional programs to enhance operational efficiencies and modernize the customer experience, leading to a reduced need for human/agent assistance from the Company's Customer Service employees. These programs include: (1) optimizing the front-office delivery model (the manner in which calls are handled) for the Company's contact center, (2) reducing calls with self service, (3) minimizing average call handling time, (4) first call resolution, (5) automating manual work, (6) optimizing back-office processes and capacity, and (7) promoting e-bill (Paperless) adoption. Improvements to process and reduction in calls, along with self service increases will enable employees to focus on assisting customers with more complex interactions and focus on driving customer satisfaction as market dynamics and customer needs evolve and change.	Future	C903	3/31/2025	84	$ -	$ -	$ 5,827,000	$ 5,827,000	$ -	$ -	$ -	$ -	$ 5,827,000

Date of Request: August 9, 2024 Request No. DPS-913
Due Date: August 19, 2024 NG Request No. NG-1123

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Customer Payment Methods

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference pages 123-124 of the Company's Electric Rate Design initial testimony, which states, "The Company has received an increased volume of inquiries from Customers' regarding our accepted methods of payment. Although the payment methods accepted are posted to the Company's website, and updated when required, the Company is proposing the inclusion of the payment methods we accept to ensure there is additional clarification regarding the acceptable forms of payment."

1. Provide a redline version of the revised electric and gas tariff(s) that will include this language.

2. Provide the list of accepted payment methods.

3. For each of the last five calendar years (2019-2023), provide the number of inquiries received by the Company regarding customer's payment options, separately by residential and non-residential.

4. Indicate if the proposed payment methods will vary between electric and gas customers.

Response:

1. The redlined tariff leaves specific to the language regarding the acceptable forms of payment are attached here as Attachment 1 for the electric tariff and Attachment 2 for the gas tariff.

2. Customers can access a list of the acceptable forms of payment on their bill and the

Company's website at https://www.nationalgridus.com/pay-bill. The acceptable methods include:

- Online using a checking or savings account;
- Mailing a check payable to National Grid;
- Credit/debit card:

    i. Using Western Union Speedpay (fees starting at $1.75 for residential customers and $5.95 for business customers); or
    ii. Over the phone through the Company's IVR system, which directs the customer to Western Union Speedpay (fees starting at $1.75 for residential customers and $5.95 for business customers).

- Automated bank account payments;
- Digital payments using Venmo, PayPal, Google Pay, or ApplePay through Speedway (fees may apply starting at $1.75 for residential customers and $5.95 for business customers);
- Using cash in-person at authorized National Grid payment locations;
- Using checks or money orders in-person at authorized Western Union locations;
- Through a customer's bank website that supports electronic bill payment;
- Using Healthfirst OTC and OTC plus cards (in-person at Walmart; or by calling the insurance company directly).

3. The chart below provides the number of inquiries received by the Company regarding customer's payment options for calendar years 2019 – 2023. The below inquiries were all made by residential customers. There were no inquiries from non-residential accounts.

PSC Case Volumes Residential - Accounts				
Year	**NiMO**	**Long Island**	**DNY**	**Total:**
2019	0	0	0	0
2020	0	0	0	0
2021	0	0	0	0
2022	0	0	1	1
2023	1	1	0	2

4. The payment methods in #2 above are available for both electric and gas customers.

Name of Respondent: Carol Teixeira

Date of Reply: August 19, 2024

GENERAL INFORMATION

2. HOW SERVICE MAY BE OBTAINED: (continued)

2.4 Whenever service is supplied from a line extension constructed in accordance with the provisions of these rules and regulations relating to line extensions or to additional or special facilities, or whenever such service is subject to a surcharge or minimum charge determined pursuant to these rules, the applicant or customer shall:

2.4.1 Make written application for service upon Company's prescribed forms.

2.4.2 Comply with all the applicable provisions of these rules including the guarantee to pay the surcharge or minimum charge.

2.5 Acceptable Forms of Payment

2.5.1 The Company accepts the following forms of payment from customers: cash, check, debit or credit card, electronic bank transfer, Healthfirst OTC and OTC Plus card.

2.5.2 An up-to-date listing of acceptable methods of payment is provided on the Company's website.

3. LIMITATION OF THE SERVICE OFFER:

3.1 Denial of Service

3.1.1 Residential applicants, as defined in Rule 1.4, Definitions.

3.1.1.1 The Company reserves the right to deny or refuse to supply service to a residential applicant who is indebted to the Company for residential service provided to a prior account in their name, unless one of the following qualifications are met:

3.1.1.1.1 The applicant makes full payment of the arrears for the residential service provided to any such prior account in their name; or

3.1.1.1.2 The applicant has pending a billing dispute with the Company or the Public Service Commission with respect to any amounts due for service to a prior account in their name; or

3.1.1.1.3 The applicant has paid any amounts required by the settlement of a billing dispute relating to a prior account in their name; or

PSC NO: 219 GAS
NIAGARA MOHAWK POWER CORPORATION
INITIAL EFFECTIVE DATE: ~~05/23/05~~07/03/24
STAMPS:

LEAF: 28
REVISION: ~~1~~2
SUPERSEDING REVISION: ~~0~~1

GENERAL INFORMATION

2. HOW SERVICE MAY BE OBTAINED: (continued)

2.4.3.3 Deposit:

2.4.3.3.1 Copies of a circular entitled "TERMS AND CONDITIONS UPON WHICH CONSUMERS' DEPOSITS ARE COLLECTED, HELD, AND MAY BE WITHDRAWN" setting forth Section 117 of the Public Service Law and Subchapter A, Chapter III, Title 16 of the New York Code of Rules and Regulations, Part 225.3 are available upon request at offices of the Company where applications for service are received.

2.5 Acceptable Forms of Payment

2.5.1 The Company accepts the following forms of payment from customers: cash, check, debit or credit card, electronic bank transfer, Healthfirst OTC and OTC Plus card.

2.5.2 An up-to-date listing of acceptable methods of payment is provided on the Company's website.

3. PRIORITY OF SERVICE:

3.1 Effective November 1, 1977, and continuing thereafter until modified or terminated by Company or order of the Public Service Commission:

3.1.1 The Company will permit the attachment of residential space heating customers in new or existing one or two family homes. Applications will also be accepted from residences for small appliance use.

3.1.1.1 The applicant will be required to contribute to the estimated cost of the service line pursuant to Rule 11. Prior to the attachment for space heating use, the applicant shall conform to the minimum insulation standards pursuant to Part 233, 16 NYCRR.

3.1.2 The Company will accept applications for new or additional commercial and industrial gas use. For estimated gas use of 50,000 Dth or more per year, the Company may require the applicant to install or have available dual fuel facilities. In the event dual fuel capability is required, adequate alternate fuel must be maintained in order to enable the customer to satisfactorily operate their facilities whenever and so long as the gas supply is interrupted.

3.1.3 Dual fuel facilities will not be required if the Company approves the process because of its unique nature whereby there is not a feasible substitute. Applications where there is no feasible substitute will generally be limited to 20,000,000 Btu per hour input. In cases where such applications would exceed this limitation, the Company will give consideration to the gas use requested giving recognition to the total amount of gas available for sale and the potential demands by other qualifying customers.

Issued By: ~~William F. Edwards~~Rudolph L. Wynter, President, Syracuse, New York

Date of Request: August 9, 2024
Due Date: August 19, 2024

Request No. DPS-915
NG Request No. NG-1125

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Strategic Account Managers

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference page 37 of the Customer's initial testimony, which states, "The Company plans to expand the number of Managed Account customers to 805, with the goal of providing a dedicated account manager to accounts that exceed 750 kW of electric demand or annual gas consumption of 25,000 dekatherms."

1. For each of the last five calendar years (2019, 2020, 2021, 2022, and 2023), provide the total number of complaints from Managed Account customers received by the Company. Include a breakdown of electric and gas accounts, and the nature of the complaints.

2. For calendar year 2024 to date, provide the total number of complaints total number of complaints from Managed Account customers received by the Company. Include a breakdown of electric and gas accounts, and the nature of the complaints.

Response:

1. The Company only tracks escalated complaints that are managed by the Company's Office of the President team. Please refer to Attachment 1 for a listing of escalated complaints from Managed Account customers tracked by the Company's Office of the President team from 2019 through 2023. During this period, there were a total of 9 escalated complaints associated with electric accounts and one escalated complaint associated with gas accounts.

2. There have been no escalated complaints from Managed Account customers tracked by the Company's Office of the President team during 2024 year to date.

Name of Respondent:	Date of Reply:
Matthew Foran	August 19, 2024

Date Received	Region	Case Number	Category	Site/Company	Description	Case Comments
2/24/2023	New York Upstate	03981131	Non-Managed	Mohawk	Customer has requested to review data related to their metering device. The customer experienced a dip in power and suspects there are some upstream impacts that are causing this issue. The customer has attempted to work with local National Grid representatives and has not been successful in getting this issue corrected.	
5/8/2019	New York Upstate	00890323	NYSPSC	Capital	This case is being refiled so that a detailed response can be provided to OCs and to Albany County. Original correspondence from Case 735804 will be attached to the Utility Notice.	
11/3/2023	New York Upstate	04793281	NYSPSC	Frontier	Consumer states they were just informed by the utility that their company electrical service is going to be shut off from 11/6/2023 - 11/23/2023 for reinstallation work on their L183. Consumer states they requested that date of the scheduled work be pushed back until December due to the short notice but was told it could not be. Consumer states their business is a reliability program for the state of NY and are in need of advanced notice for service terminations due to maintenance.	On 11/2/2023, Customer contacted National Grid to have the outage rescheduled for December 2023. National Grid informed the Customer, National Grid is taking an outage of the Dupont-Packard 183LN to replace insulators at multiple locations due to severe hardware degradation. National Grid Crews will be replacing insulators and hardware on all towers of this circuit during the outage time frame. National Grid Transmission Asset Management Department determined that the severe hardware degradation on the circuit needed to be addressed as soon as possible. The work is being completed in response to an outage that occurred on both 183LN & 184LN causing approximately 7.8K Customers and three Industrial Customers to lose power.
7/20/2020	New York Upstate	00866058	NYSPSC	Capital	After National Grid made some changes to its transmission infrastructure an inadvertent current starting go through SABICs' transformers.	
9/3/2020	New York Upstate	00866986	NYSPSC	Capital	I spoke to B_______ NYS PSC customer service representative. He asked me to send in the documented third party report which is attached.	Added PSC closing letter
1/20/2021	New York Upstate	01214558	NYSPSC	Capital	Reopened for Informal Hearing This case has been reopened to begin Mr. M________ informal hearing process. National Grid will be contacted by PSC Informal Hearing Unit Staff in the future with further information.	Customer has requested an Informal Hearing on a multi-Million dollar project that is not needed if they changed switches on their end per Mark Harbaugh.
4/27/2022	New York Upstate	02764081	Correspondence	Western	Correspondence received re: transformer ownership discount	Forwarded a letter to C______ N_____ with National Auditing Services & Consulting, LLC. They provided copy of letter confirming permission from OTB president that we can discuss account with them. The letter confirms that the customer with a SC3 with a delivery voltage of 2.2-15kV & has customer owned transformer is charged standard Tariff rate. Provided website to go to for further information. Also advised that $616.84 was a credit for late payment charge and that the next 2 bills also had late payment charges credited as a courtesy. Provided copy of 1-year statement for review.

3/20/2019	New York Upstate	00893392	QRS	Frontier	Consultant has contacted this office to request assistance with a service classification/rate dispute. Consultant states that account was activated on the SC-3 rate and based on historic usage qualifies for the SC-2D and should have been placed on the SC-2D rate from activation. Consultant is requesting a retroactive adjustment for the account at the SC-2D rate for six years or the date the account was opened plus applicable interest on the overpaid charges. Consultant correspondence requesting assistance will be attached as a file to the Utility Notice for this case.	
8/14/2023	New York Upstate	04506135	QRS	Frontier	A concrete riser and metal cover (18 diameter) was hit during a blizzard by equipment and is now above grade. The wires are going to expose and my employees can't mow around it. Please place the riser back at grade to remove the hazard	Visited site and advised M____ S____ that this is City of Buffalo Property and not our electrical. Also, we contacted the City of Buffalo traffic division to advise.

Date of Request: August 15, 2024
Due Date: August 26, 2024

Request No. DPS-956
NG Request No. NG-1207

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Data Privacy and Data Governance Full-Time Equivalents

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference the Company's proposal for an incremental 2.5 full-time equivalents (2.5) for Data Privacy and Data Governance on pages 78-80 of the Customer Panel's initial testimony and Exhibit__(CP-8).

1. For each of the last five calendar years (2019, 2020, 2021, 2022, and 2023), provide the total number of projects and/or initiatives within Niagara Mohawk that required a "Data Privacy and Data Stewardship" employee. Indicate how many of these projects were specific to Niagara Mohawk only and how many were allocated to Niagara Mohawk from the Service Company.

2. For calendar year 2024 to date, provide number of number of projects and/or initiatives within Niagara Mohawk that required a "Data Privacy and Data Stewardship" employee. Indicate how many of these projects were specific to Niagara Mohawk only and how many were allocated to Niagara Mohawk from the Service Company.

Response:

1. National Grid has not had a dedicated employee for data privacy or data stewardship and therefore has not utilized such a resource on projects over the last five years. While projects and work have required review for data privacy and stewardship issues, that review has been handled by different individuals across the Company on top of their normal day jobs. As explained in the Customer Panel’s direct testimony, the Company’s focus on promoting increased energy efficiency services, non-pipes alternatives, non-wires alternatives, and various forms of assistance to low-to-moderate income customers has created the need for dedicated resources for data privacy and data stewardship matters. Accurate customer data and the protection of that data is vital to the success of customer-facing efforts; hence, the need for the proposed FTEs.

2. In calendar year 2024 there have been six initiatives identified that are in progress or scheduled to start that currently do not have dedicated resources assigned to them but would benefit from focused resources. These are Service Company initiatives, the costs of which will be allocated to Niagara Mohawk and other operating affiliates.

   i. Match and Merge Logic: Data stewards would be used to ensure that the match and merge logic is accurate with continuous fine-tuning activities to ensure National Grid provides the single view of customer. Data privacy work would involve maintaining controls and security of data access points as they relate to responsible and safe customer data sharing practices with agencies and vendors.

   ii. Customer Hierarchy: Through this process National Grid will build a customer hierarchy that includes data from external sources matched and merged with the internal customer service system. The external dataset will also bring in non-customer data and additional attributes. Data privacy work would involve maintaining controls and security of data access points as they relate to responsible and safe customer data sharing practices with agencies and vendors.

   iii. Data Quality Metrics: Addition of data quality rules totaling over 40 data checks is needed in National Grid's Informatica Customer Data Quality tool. The results of any accounts that fail these checks will be provided to the data stewards.

   iv. Data Quality Metrics Dashboards: Create dashboards to show the high-level percentage of passed and failed metrics to show the overall impact and success of clean-up activities.

   v. Quality Clean-up: Data stewards will be provided a detailed report of customers with quality issues. The teams will coordinate outreach to the customer to gather the correct information. The source systems will then make the updates based on the outreach initiatives.

   vi. Implement Process and System Changes: Data stewards and data privacy equivalents will work with the business users to ensure any system and process document updates are complete to ensure the data is entered correctly the first time. Data privacy will also ensure that Personal Identifiable Information is not entered into any fields other than those earmarked to hold this level of data.

Name of Respondent:	Date of Reply:
Carlos Nouel	August 26, 2024

Date of Request: August 15, 2024
Due Date: August 26, 2024

Request No. DPS-957
NG Request No. NG-1208

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Data Privacy and Data Governance Full-Time Equivalents

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference the Company's proposal for an incremental 2.5 full-time equivalents (2.5) for Data Privacy and Data Governance on pages 78-80 of the Customer Panel's initial testimony and Exhibit__(CP-8).

1. Provide the following information:

   a. A detailed explanation of the current job duties and functions of the "Lead Analyst Data Governance."

   b. The time associated with each job duty/function provided in response to Question 1.a., above.

   c. Provide all changes made to these duties over the last five years.

Response:

1. As explained in the response to DPS-956, National Grid does not currently have FTEs dedicated to data governance. Because of the increase in services and programs that require the sharing of customer data, the Company requires the need of 2.5 Lead Analysts who will be dedicated to data governance and data privacy work and issues.

   Lead Analyst Data Governance, Data Privacy – 0.5 FTE

   a. As noted in the Company’s response to DPS-293, this role is driven by regulatory requirements for protection of customer data and increased energy efficiency services, non-pipes alternatives, non-wires alternatives, and various forms of assistance to low-to-moderate income customers to help advance the clean energy transition. The below bullet provides further details of the proposed job function.

- Maintain controls and security of data access points as they relate to responsible and safe customer data sharing practices with agencies, vendors, and through the NYSERDA IEDR/NYS Clean Energy agenda.

b. 50% of this 0.5 FTE's time will be associated with the duties listed above.

c. The Company currently does not have any FTEs working on these duties; therefore, there have been no changes in the last five years.

<u>Lead Analyst Data Governance, Data Stewardship – 2.0 FTE</u>

a. As noted in the Company's response to DPS-293, these roles are driven by the need to maintain the accuracy and integrity of customer data in National Grid's front office, back office, and clean energy management areas. The below bullets provide further details of the proposed job function.

- Cleanse and remediate customer data for improved communication, interactions, and service to customers. Estimated time 20%.

- Create and maintain processes, procedures, business rules and standards, and access controls to ensure that data quality, data definition, and privacy standards are met. Estimated time 15%.

- Coordinate outreach efforts with other subject matter experts to prioritize data requests and issues to ensure effective updates for mature and trusted customer data. Estimated time 15%.

b. 50% of these 2.0 FTE's time will be associated with the duties listed above and a further breakdown of time can be found above next to the actual duty/function.

c. The Company currently does not have any FTEs working on these duties; therefore, there have been no changes in the last five years.

<u>Name of Respondent</u>: Carlos Nouel

<u>Date of Reply</u>: August 26, 2024

Date of Request: August 16, 2024 Request No. DPS-971
Due Date: August 26, 2024 NG Request No. NG-1229

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: NYPSC - Chrystie Stafford

TO: National Grid

SUBJECT: Customer Service Performance Indicators (CSPI) - Call Center Staffing (Follow-Up to DPS-302)

REQUEST:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. For each month of 2024 to date, provide the following:

   a. The number of internal employees who were going through training for employment with the in-house call center(s);

   b. The number of trained, in-house, call center full-time equivalents (FTEs) who regularly take customer calls;

   c. The number of trained, in-house, customer service FTEs who answer Public Service Commission (PSC) complaints and/or regularly perform tasks other than taking calls;

   d. The number of internal customer service staff, including call-takers, who left the Company or changed their position within the Company;

   e. The average daily number of external call center employees utilized by the Company's third-party vendor(s);

   f. The number of customer service representative (CSR) positions the Company allocated for the call center(s);

   g. The number of vacant CSR positions in the call center(s).

2. For each month of 2024 to date, provide the number of hours worked for the following positions:

   a. Trained, in-house call center employees.

b. External call center employees through the Company's third-party vendor(s).

3. For each month of 2024 to date, provide the following number of FTE positions:

a. Meter readers employed at the Company, both in-house and through the Company's third-party vendor(s) (separately state in-house and third-party).

b. In-house meter readers who left the Company or changed their position within the Company to a non-meter reader position.

Response:

1. a. The table below contains the monthly totals to date of National Grid's employees in training for the NMPC call center.

	2024
January	28
February	20
March	18
April	22
May	21
June	26
July	26
August	11

b. The table below contains the monthly totals to date of National Grid's full-time representative employees for the NMPC call center.

	2024
January	113
February	111
March	116
April	121
May	118
June	126
July	130
August	140

c. To date, for 2024 the Company has 7 trained, in-house, full-time staff who answer PSC complaints and/or perform tasks related to escalated customer complaints for NMPC.

d. The monthly number of CSRs who left or changed positions to date 2024.

CY24	NMPC
January	8
February	10
March	8
April	2
May	4
June	3
July	7
August	5

e. The to date 2024 monthly average daily number of external call center employees utilized by the Company's third-party vendor(s) can be found below, by vendor.

Vendor: **iQor**

CY24	NMPC
January	38
February	31
March	31
April	27
May	26
June	28
July	32
August	32

Vendor: **Startek**

CY24	NMPC
January	53
February	48
March	50
April	50
May	53
June	61
July	72
August	65

Vendor: **TSI**

CY24	NMPC
January	104
February	98
March	97
April	116
May	117
June	115
July	135
August	122

f. The number of allotted CSR positions monthly for 2024 to date

CY24	NMPC
January	154
February	146
March	131
April	155
May	144
June	138
July	133
August	149

g. The number of vacant CSR positions monthly for 2024 to date

CY24	NMPC
January	0
February	0
March	0
April	0
May	0
June	0
July	0
August	8

2. a. The Monthly hours worked in 2024 to date by trained in-house representatives.

CY24	NMPC
January	19773
February	15981
March	21887
April	19456
May	21177
June	21201
July	23154
August	16053

b. The 2024 monthly number of hours worked to date by external call center employees through the Company's third-party vendor(s) can be found below, by vendor.

Vendor: **iQor**

CY24	NMPC
January	4861
February	4106
March	4497
April	3797
May	4603
June	3301
July	3930
August	2268

Vendor: **Startek**

CY24	NMPC
January	10114
February	8515
March	8705
April	9249
May	9652
June	10311
July	13890
August	8280

Vendor: **TSI**

CY24	NMPC
January	22558
February	18488
March	20619
April	23912
May	22604
June	21575
July	27873
August	16292

3. The table below contains the 2024 monthly break-down of meter reads FTE positions.

CY2024	**In House Meter Reads**	**External Meter Readers**	**Meter Reads Left Company**	**Meter Reads move to Non-Meter Reading Position**
January	33	0	0	0
February	33	0	0	0
March	33	0	0	0
April	34	0	0	0
May	36	0	0	0
June	36	0	0	0
July	36	0	0	0
August	36	0	0	0

Name of Respondent:
Frederick Daum

Date of Reply:
August 26, 2024

Date of Request: August 27, 2024
Due Date: September 6, 2024

Request No. DPS-992
NG Request No. NG-1307

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: PSC - Adam Polmateer

TO: National Grid

SUBJECT: Economic Development — Natural Gas Grant Programs

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

On pages 124 and 125 of the Customer Panel's direct testimony, the Company proposes to continue three natural gas economic development grant programs. The following questions relate to those programs.

1. Regarding the Company's Economic Development and the Future of Heat, provide the following information:

    a. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide the total number of applications received by the Company and how many of those applications were approved for grant funding.

    b. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide the total amount awarded for each of those grants and total spending.

    c. For the program description found on pg. 125 line 1: "Encourage customer and community investment in NPA's," provide a brief description of the project scope for each of the approved grant applications and how it relates to the program description.

    d. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide a description of how the Company determines the success of this program and an explanation of what success has been achieved by this program.

2. Regarding the Company's Sustainable Gas and Economic Development program, provide the following information:

a. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide the total number of applications received and how many of those applications were approved for grant funding.

b. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide the total amount awarded for each of those grants and total spending.

c. For the program description found on pg. 125 lines 2-5: "Does not provide funding for upgrades to the gas delivery system, but encourages the development and demonstration of sustainable and renewable gas technologies." provide a brief description of the project scope for each of the approved grant applications and how it relates to the program description.

d. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide a description of how the Company determines the success of this program and an explanation of what success has been achieved by this program.

3. Regarding the Natural Gas Manufacturing Program, provide the following information:

a. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide the total number of applications received and how many of those applications were approved for grant funding.

b. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide the total amount awarded for each of those grants and total spending.

c. For the program description found on pg. 125 lines 6-8: "provides support for initiatives that allow customers to maintain or increase their manufacturing output while reducing the amount and cost of production inputs including labor, materials and energy" provide a brief description of the project scope for each of the approved grant applications and how it relates to the program description.

d. For each of the past five calendar years (2019, 2020, 2021, 2022 and 2023), provide a description of how the Company determines the success of this program and an explanation of what success has been achieved by this program.

<u>Response</u>:

1. a.-c. No new applications were received or approved for this program during the period 2019-2023.

d. Like most of the Company’s economic development grant programs, the “Economic Development and the Future of Heat” program will be evaluated based on economic impacts, including new or retained jobs and new capital investment in the regional economy. Because no projects were completed between 2019 and 2023, the Company has not had an opportunity to evaluate the benefits of this program during that period.

2. a.-c. No new applications were received or approved for this program during the period 2019-2023.

   d. Like most of the Company's economic development grant programs, the "Sustainable Gas and Economic Development" program will be evaluated based on economic impact, including new or retained jobs and new capital investment in the regional economy. Because no projects were completed between 2019 and 2023, the Company has not had an opportunity to evaluate the benefits of this program during that period.

3. Please see Attachment 1.

Name of Respondent	Date of Reply:
Arthur Hamlin	September 5, 2024

3. Natural Gas Manufacturing Productivity Progran

	CY 2019	CY 2020	CY 2021	CY 2022	CY 2023
a. Applications Received	10	1	5	5	6
Applications Approved	11	0	4	3	3
b. Funding awarded (approved)	$106,755	$0	$92,484	$86,000	$45,432
Total Spending	$0	$0	$69,691	$3,000	$112,982

c. Application Number	Approval Year	Project Description	Jobs Created/ Retained
5076	2019	Support for "Lean Kaizen" training and foundational work to achieve ISO 9001 certification. These initiatives will allow this Albany optical products manufacturer to improve process efficiency and product quality, leading to increased productivity and new market opportunities.	32
5150	2019	This grant supported delivery of "Training Within Industry" (TWI) for front line production employees. By building a foundation for problem solving, standardized work, continuous improvement and operational excellence, this Central NY food processor will increase manufacturing productivity and improve occupational safety performance.	114
5250	2019	Cohoes-based manufacturer of process automation equipment is undertaking continuous improvement and growth projects that will focus on supply chain optimization, value chain mapping and export controls compliance, which will improve operational efficiency and increase manufacturing sales/output.	185

c. Application Number	Approval Year	Project Description	Jobs Created/ Retained
5271	2019	Scope of work will include an independent assessment of this Syracuse company's technology environment versus Department of Defense manufacturing and quality standards. The project will identify areas of weakness, current compliance risks and a roadmap for remediation.	70
5307	2019	HVAC equipment manufacturer in Albany is undertaking a multi-faceted product development initiative including supply chain optimization, quality planning and process Failure Mode and Effect Analysis (FMEA).	6
5309	2019	Support for "Lean manufacturing" assistance that will enable this North Syracuse air filtration company to reduce costs and eliminate manufacturing process waste.	105
5310	2019	"Go to Market Discovery" project will create a strategic plan for this Manlius manufacturer, to ensure top-line sales growth while stabilizing their existing customer/revenue base. Also included is assistance with the company's current sales pipeline backlog to stabilize revenue and customer base to ensure retained sales and retained jobs while exploring opportunities for future top line growth.	49

5308	2019	Manufacturer of precision electrical components is investing in Lean Six Sigma "green belt" training for quality assurance, lead time reduction and overall productivity improvement across multiple product lines.	368

c.

Application Number	Approval Year	Project Description	Jobs Created/ Retained
5315	2019	Support for a Capital Region paper manufacturer's new product development efforts, utilizing Technology Driven Market Intelligence (TDMI) to identify the benefits and market impacts of technology-based assets.	20
5351	2019	Albany industrial equipment manufacturer is implementing a comprehensive productivity/quality improvement project focusing on supply chain optimization and ISO Quality Management Systems.	220
5399	2019	Support for foundational "lean manufacturing" training for this Oneida precision manufacturer will include Lean Six Sigma, Blueprint Reading, Toyota Kata and problem solving, all designed to improve processes and eliminate waste.	39
5835	2021	Cooling technology manufacturer in Syracuse is undertaking a comprehensive productivity and growth project including warehouse optimization support, NIST cybersecurity review, and compliance assessments related to international regulations for chemical use in manufacturing.	120

5846	2021	Scope of work is focused on FDA compliance, ISO certification and Quality Management System (QMS) for internal audits and management support. The project will enable this medical equipment manufacturer to retain existing business while expanding sales to the European markets.	10

c.

Application Number	Approval Year	Project Description	Jobs Created/ Retained
5902	2021	Quality management project will enable this plastic foam manufacturer in Amsterdam to establish standards and processes that result in consistently high quality within the tight specifications and narrow window of deviation increasingly demanded by customers.	38
5954	2021	Comprehensive "lean manufacturing" project will include on-site Toyota Kata Coaching and Integrated Computer Solutions to improve efficiency/productivity and ensure NIST standard compliance, this Syracuse-based precision fabricator to work within the Department of Defense supply chain.	90
6123	2022	Central NY precision machining company is investing in comprehensive productivity and quality improvement training, including Toyota Kata Training and Coaching, Kaizen Coaching and Productivity Engineering for Plant Expansion Planning. The project will provide foundational training and skills to meet urgent quality needs and complete a lean transformation across the facility.	45

6124	2022	Comprehensive productivity improvement and top-line growth project for this Syracuse manufacturer of specialty HVAC and filtration systems, including Lean Six Sigma training, compliance testing and support for International Product Certification.	20
6172	2022	Grant funds will support process improvement/Kata coaching and Value Stream Mapping for this paper manufacturer in Pulaski, NY. Process efficiency metrics will track improvements in order confirmation, order processing, scheduling and lead times.	6

c. Application Number	Approval Year	Project Description	Jobs Created/ Retained
6369	2023	Schenectady manufacturer of advanced composites and automation equipment is investing in productivity improvement through Value Stream Mapping, a "lean" management technique that focuses on end-to-end process optimization and elimination of waste.	6
6435	2023	Scope of work includes identification and implementation of process improvements related to the company's technology platforms, business systems and performance reporting. All activities are aimed at improving the efficiency, accuracy and precision of business support processes for this Syracuse-based printing and packaging manufacturer.	20
6457	2023	This Albany manufacturer is transitioning to a new facility and will undertake several initiatives aimed at creating a more efficient plant layout, optimizing per-unit production costs, and establishing a spatial blueprint for additional investments in equipment and manufacturing capacity.	77

d. In addition to the benefits detailed in the project descriptions above, the Company measures the economic impact of this program in terms of jobs created or retained in the Niagara Mohawk gas service territory. Those estimated impacts are provided above for each project. In total, the Natural Gas Manufacturing Productivity Program has helped create or retain an estimated 1,640 jobs during the period 2019-2023.

Also, to help evaluate the effectiveness of the Company's Economic Development grant programs, an online survey is distributed to all companies and organizations that complete a project and receive a grant reimbursement. Survey responses include an estimate of cost savings per year, new annual revenue and retained annual revenue. Eight customers provided estimated benefits as follows:

Total Annual Cost Savings $1.3 million
Total Annual Revenue Increase $1.25 million
Total Retained Annual Revenue $70 million

Finally, the same survey asks grant recipients to provide feedback on the role that National Grid funding played in the completion and timing of the project. 14 customers who were surveyed responded as follows:

National Grid funding led the customer to take actions that they otherwise would not have taken: 100% positive response
National Grid funding led the customer to take actions more quickly than they otherwise would have: 93% positive response

Date of Request: August 29, 2024 Request No. DPS-1001
Due Date: September 9, 2024 NG Request No. NG-1430

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: PSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Customer Outreach - "Other Delivery Surcharge"

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

The following questions reference the Company's proposal on pages 115-116 of the Electric Rate Design Panel's initial testimony to "move all of the delivery surcharges that are currently included in the Delivery Charge line of customers' bills into a new bill line item, Other Delivery Surcharges ('ODS')."

1. Provide the Company's proposed outreach plan and associated materials regarding this proposed "ODS" line item.

    a. If the Company has not yet developed outreach materials regarding this line item, provide the date they will be available.

2. Indicate if the Company intends to update the definitions provided on customers' bill with the proposed ODS line item. If not, explain why not.

    a. Provide the proposed language the Company will use on the bill for the "ODS" line item.

    b. If the Company has not yet developed this language, provide the anticipated date it will be available.

Response:

1. See Attachment 1 for the Company's proposed Outreach Plan for the ODS. The Company has not developed outreach materials at this time, but draft materials will be developed at least 30 days prior to the anticipated effective date of the new rate plan. These materials will not be finalized until the Company receives an Order approving the ODS mechanism.

2. Yes, the Company plans to modify the definitions on the back of the bill to reflect this new ODS line item on customer bills. As the ODS is comprised of various delivery surcharges, the bill definition will refer customers to the monthly ODS statement that will be filed to identify the individual delivery surcharges and rates that are included in the ODS. An illustration of the monthly statement was provided in Exhibit ___(E-RDP-13) of the Company's initial testimony. The back of bill definition language for the ODS will be similar to the following:

"See the Company's Statement of Other Delivery Surcharges ("ODS") for applicable monthly delivery surcharges that are included in the ODS at https://www.nationalgridus.com/Upstate-NY-Business/Rates/Rate-Statements".

Name of Respondent: Carol Teixeira

Date of Reply: September 9, 2024

Request No. DPS-1001
Other Delivery Surcharges ("ODS"): Outreach Plan

Channel	Details	Timeline
Talking points for Customer Service, Account Managers & Consumer Advocates	Talking points will be provided to customer-facing groups, including the Customer Service representatives in our call centers, as well as our Account Managers and Consumer Advocates.	Within 1-2 weeks following approval
Website Updates	Information about the new ODS line item will be added to the **About Your Bill** section of the National Grid website. Updates will include: - An update to the **Interactive Bill Samples** ("Help Reading Your Bill") - Frequently Asked Questions / Bill FAQs	Within 2-3 weeks following approval
Email Content Boxes	Messages informing customers of the new line item on their bill will be included on relevant emails, including monthly emails that are sent to all customers.	Within 2-4 weeks following approval; to appear on multiple emails.
On Bill Message	An on-bill message will be placed on all customer bills with a weblink to learn more about how to read your bill	Within 2 billing cycles following approval
Bill Statement	A definition of the ODS will be added to the back of the bill and will include a link to the website where monthly rate statements can be found.	Within 1 billing cycle following approval
WeConnect Article	WeConnect is a quarterly customer newsletter with multiple features and short articles about safety precautions, energy saving tips and important news for customers. A feature for the new ODS line item will be included to explain the addition and what it means for customers.	Within 3-4 billing cycles following approval

Date of Request: August 30, 2024 Request No. DPS-1006
Due Date: September 9, 2024 NG Request No. NG-1468

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: PSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Customer Outreach & Education Expenditures - Follow Up to DPS-851

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. For Niagara Mohawk only, fill in the attached spreadsheet with the associated outreach and education expenditures in each category for each year of the past five calendar years (2019, 2020, 2021, 2022 and 2023), separately for electric and gas.

   a. If certain information is unavailable for a requested calendar year, provide the information available and indicate the time frame (e.g., rate year or fiscal year).

   b. If certain data cannot be provided for a requested category (Energy Efficiency, Energy Affordability Program, etc.) and/or subcategory (bill inserts, signage), provide a detailed explanation as to why the requested information for a specific category cannot be provided.

2. Confirm whether the outreach budget and expense information provided in the Company's response to DPS-851 is specific to Niagara Mohawk only, or also includes the outreach information for all of National Grid's New York businesses, including The Brooklyn Union Gas Company d/b/a National Grid NY (KEDNY) and KeySpan Gas East Corp. d/b/a National Grid (KEDLI).

Response:

1. a. See Attachment 1. Estimated and actual outreach and education budgets were presented and filed according to the format requested annually by the Department of Consumer Services.

   b. See response to 1a.

2. Electric outreach budget and expense information provided in the Company's response to DPS-851 is specific to Niagara Mohawk only. Natural gas outreach and expense information includes Niagara Mohawk, KEDNY, and KEDLI.

<u>Name of Respondent</u>:
Nicole Jezykowski

<u>Date of Reply</u>:
September 9, 2024

Niagara Mohawk Power Corporation
d/b/a National Grid
Cases 24-E-0322 & 24-G-0323
DPS-1006 Attachment 1

	elec	gas	elec	gas	elec	gas	elec	gas	elec	gas	elec
	Estimated Budget April 1 , 2019 - March 31, 2020	**Estimated Budget April 1 , 2019 - March 31, 2020**	**Estimated Budget January – December 2020**	**Estimated Budget January – December 2020**	**Estimated Budget April 2020 – March 2021**	**Estimated Budget April 2020 – March 2021**	**Estimated Budget January- December 2022**	**Estimated Budget January - December 2022**	**Estimated Budget January- December 2023**	**Estimated Budget January - December 2023**	**Estimated Budget January - December 2024**
Outreach Plan Total (SUM of Electric and Gas)	**$8,162,156**		**$8,512,817**		**$8,512,817**		**$9,281,840**		**$8,757,363**		**$10,96**
Outreach Plan Total (Electric and Gas separately)	$2,605,148	$5,557,008	$3,115,546	$5,397,271	$3,115,546	$5,397,271	$3,307,912	$5,973,928	$2,801,572	$5,952,191	$6,571,561
Energy Efficiency											
Bill Inserts							$59,085	$62,919	$63,000	$23,371	
Brochures/Flyers							$19,695	$31,460	$15,750	$69,698	
Direct Mail							$177,255	$314,595	$236,250	$265,826	
Educational Videos							$295,424	$283,136	$6,219	$0	
Email							$196,950	$346,055	$794	$0	
Media (Broadcast, agency)							$236,340	$471,893	$92,050	$762,898	
Newsletters									$15,414	$27,474	
Web and digital media							$687,798	$1,258,380	$408,599	$482,640	
Other (Creative Dev, Pop Signage, Web Mgt)							$296,950	$346,055	$484,924	$1,308,832	
Energy Efficiency Total	$756,284	$1,317,123	$2,054,869	$1,812,304			$1,969,497	$3,114,493	$1,323,000	$2,940,739	
Customer Service											
Bill Inserts							$153,386	$254,628	$194,700	$302,647	
Brochures/Flyers											
Direct Mail											
Educational Videos											
Email											
Media (Broadcast, agency)											
Newsletters											
Web and digital media											
Other (creative, signage, web)											
Customer Service Total	$66,058	$87,387	$65,058	$86,687			$153,386	$254,628	$194,700	$302,647	
Seasonal Campaigns											
Bill Inserts							$6,750	$8,250			
Brochures/Flyers											
Direct Mail											
Educational Videos							$10,000	$10,000			
Email							$75,000				
Media (Broadcast, agency)											
Newsletters											
Web and digital media											
Other (creative, signage, web)											
Seasonal Campaigns Total	$215,292	$297,308	$204,000	$306,000			$91,750	$18,250	$55,000	$55,000	
General											
Bill Inserts											
Brochures/Flyers											
Direct Mail											
Educational Videos											
Email											
Media (Broadcast, agency)											
Newsletters											
Web and digital media											
Other (creative, signage, web)											
General Total	$1,567,514	$3,855,190	$791,619	$3,192,280							

	elec	gas	elec	gas	elec	gas	elec	gas	elec	gas	elec
	Estimated Budget April 1 , 2019 - March 31, 2020	**Estimated Budget April 1 , 2019 - March 31, 2020**	**Estimated Budget January – December 2020**	**Estimated Budget January – December 2020**	**Estimated Budget April 2020 – March 2021**	**Estimated Budget April 2020 – March 2021**	**Estimated Budget January- December 2022**	**Estimated Budget January - December 2022**	**Estimated Budget January- December 2023**	**Estimated Budget January - December 2023**	**Estimated Budget January - December 2024**
Energy Affordability											
Bill Inserts											
Brochures/Flyers							$12,300	$22,700	$14,600	$25,400	
Direct Mail							$109,500	$40,500			
Educational Videos							$43,800	$16,200			
Email											
Media (Broadcast, agency)											
Newsletters											
Web and digital media							$127,750	$42,250			
Outbound calling HEAP							$21,600	$25,600			
Other (Robocals, Care & Share)							$29,565	$51,435	$54,239	$79,565	
Energy Affordability Total							$344,515	$198,685	$68,839	$104,965	
Service Related Communications								$87,657			
Bill Inserts							$33,033	$70,001	$6,000	$252,554	
Brochures/Flyers							$175,266	$892,495	$181,988	$226,385	
Direct Mail									$375,635	$890,743	
Educational Videos								$92,635	$0	$10,092	
Email								$154,972	$15,000	$115,704	
Media (Broadcast, agency)								$166,800	$500,000	$500,000	
Newsletters							$2,768	$19,883	$12,000	$50,982	
Web and digital media							$15,088	$188,457	$26,922	$193,230	
Other (creative, signage, web)							$52,250	$156,751	$74,088	$364,250	
Service Related Communications Total							$278,405	$1,829,651	$1,191,633	$2,603,940	
Other Communications											
Bill Inserts											
Brochures/Flyers							$3,000	$3,000			
Direct Mail							$5,371	$7,120			
Educational Videos											
Email											
Media (Broadcast, agency)							$116,759	$154,774			
Newsletters											
Web and digital media							$147,729	$195,827			
Other (creative, signage, web)											
Other Communications Total							$272,859	$360,721			
Outreach Events							$395,000		$84,400		

Notes:
The requested reporting format was standardized to annual beginning in 2022.

Reporting of outreach expense and budgets by specific communications tactic was requested in 2021 and 2022

Niagara Mohawk Power Corporation
d/b/a National Grid
Cases 24-E-0322 & 24-G-0323
DPS-1006 Attachment 1

	gas	elec	gas	elec	gas	elec	gas	elec	gas	elec	gas
	Estimated Budget January - December 2024	**Actual April 1, 2018 - March 31, 2019**	**Actual April 1, 2018 - March 31, 2019**	**Actual January – December 2019**	**Actual January – December 2019**	**Actual April 2020 - March 2021**	**Actual April 2020 - March 2021**	**Actual January- December 2022**	**Actual January- December 2022**	**Actual January- December 2023**	**Actual January- December 2023**
Outreach Plan Total (SUM of Electric and Gas)	**4,518**	**$9,202,040**		**$6,908,100**		**$9,191,890**		**$8,202,116**		**$8,316,437**	
Outreach Plan Total (Electric and Gas separately)	$4,392,958	$2,582,980	$6,619,061	$2,535,108	$4,372,992	$2,785,342	$6,406,548	$2,482,129	$5,719,987	$3,492,127	$4,824,309
Energy Efficiency											
Bill Inserts						$7,867	$15,217	$0	$10,000		
Brochures/Flyers						$3,000	$7,158	$0	.		
Direct Mail						$0	$21,000	$0	$228,861		
Educational Videos						$210,241	$66,034	$11,750	$0		
Email						$144,447	$117,207	$1,500	$37,670		
Media (Broadcast, agency)						$257,779	$149,157	$173,904	$1,282,888		
Newsletters						$0	$0	$29,120	$46,200		
Web and digital media						$717,302	$1,431,060	$771,938	$811,606		
Other (Creative Dev, Pop Signage, Web Mgt)						$136,727	$202,560	$667,608	$882,047		
Energy Efficiency Total		$1,181,841	$1,893,793	$1,529,128	$767,335	$1,477,364	$2,009,394	$1,655,820	$3,299,272		
Customer Service											
Bill Inserts						$102,891	$222,516	$177,000	$275,134		
Brochures/Flyers											
Direct Mail											
Educational Videos											
Email											
Media (Broadcast, agency)											
Newsletters											
Web and digital media											
Other (creative, signage, web)											
Customer Service Total		$8,269	$14,388	$42,760	$72,565	$102,891	$221,516	$177,000	$275,134		
Seasonal Campaigns											
Bill Inserts								$32,794	$49,192		
Brochures/Flyers											
Direct Mail								$2,000	$2,000		
Educational Videos											
Email						$38,860	$21,694				
Media (Broadcast, agency)								$135,032	$212,307		
Newsletters											
Web and digital media								$38,425	$65,295		
Other (creative, signage, web)											
Seasonal Campaigns Total		$285,000	$155,255	$138,908	$290,475	$35,590	$21,694	$208,251	$328,793		
General											
Bill Inserts											
Brochures/Flyers								$3,000	$3,000		
Direct Mail								$5,371	$7,120		
Educational Videos											
Email											
Media (Broadcast, agency)								$116,759	$154,774		
Newsletters											
Web and digital media								$147,729	$195,827		
Other (creative, signage, web)											
General Total		$1,107,690	$4,555,624	$824,312	$3,242,617			$272,859	$360,721		

	gas		elec	gas	elec	gas	elec	gas	elec	gas	elec	gas
	Estimated Budget January - December 2024		**Actual April 1, 2018 - March 31, 2019**	**Actual April 1, 2018 - March 31, 2019**	**Actual January – December 2019**	**Actual January – December 2019**	**Actual April 2020 - March 2021**	**Actual April 2020 - March 2021**	**Actual January- December 2022**	**Actual January- December 2022**	**Actual January- December 2023**	**Actual January- December 2023**
Energy Affordability												
Bill Inserts												
Brochures/Flyers									$10,372	$6,448		
Direct Mail									$8,017	$12,026		
Educational Videos												
Email												
Media (Broadcast, agency)												
Newsletters												
Web and digital media												
Outbound calling HEAP												
Other (Robocals, Care & Share)							$37,743	$54,608	$49,766	$88,727		
Energy Affordability Total									$68,155	$107,201		
Service Related Communications												
Bill Inserts								$115,615		$246,554		
Brochures/Flyers							$35,088	$35,088	$27,013	$85,885		
Direct Mail								$862,686	$146,462	$695,425		
Educational Videos								$6,020	$0	$0		
Email								$152,970	$0	$100,704		
Media (Broadcast, agency)								$266,950	$0	$0		
Newsletters								$133,411	$0	$38,982		
Web and digital media								$68,765	$2,768	$169,076		
Other (creative, signage, web)							$55,500	$196,622	$196,300	$372,962		
Service Related Communications Total							$90,588	$1,838,127	$372,543	$1,709,587		
Other Communications												
Bill Inserts												
Brochures/Flyers												
Direct Mail							$195,000	$345,000				
Educational Videos							$22,000	$22,000				
Email							$175,000	$165,000				
Media (Broadcast, agency)							$199,154	$199,154				
Newsletters												
Web and digital media							$60,265	$60,265				
Other (creative, signage, web)												
Other Communications Total							$651,419	$791,419				
Outreach Events							$0					

Notes:
The requested reporting format was standardized to annual beginning in 2022.

Reporting of outreach expense and budgets by specific communications tactic was requested in 2021 and 2022

Date of Request: September 13, 2024
Due Date: September 23, 2024

Request No. DPS-1027
NG Request No. NG-1555

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: PSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Strategic Account Managers

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. In Excel format, provide a list of customers, with personal information redacted, that currently meet the "Managed Accounts" criteria as defined on page 37 of the Customer Panel initial testimony. Indicate whether each customer meets the 750 kW in yearly average electric demand, or 25,000 Dth in annual gas consumption, or both.

2. Confirm if the current full-time equivalents (FTEs) dedicated to Managed Account customers are called "Strategic Account Managers" within the Commercial Services Team or if the "Strategic Account Managers" is a new group entirely.

3. For each of the last five calendar years (2019, 2020, 2021, 2022, and 2023), provide how many positions of the FTEs dedicated to "Managed Accounts" customers were vacant.

Response:

1. Please refer to Attachment DPS-68-1027 for a list of customers, with customer and company names redacted, that currently meet the “Managed Accounts” criteria as defined on page 37 of the Customer Panel’s direct testimony. Please note that the Company has existing relationships with some customers that do not meet these thresholds. Because of the importance of maintaining these relationships, these customers will continue to be classified as “Managed Accounts.”

2. The current full-time equivalents (“FTEs”) dedicated to Managed Account customers are called “Key Account Managers” in the new Customer Account Management UNY team. The Commercial Services team is a separate team responsible for the relationships with Large Scale Renewables developers and wholesale transmission customers.

3. For each of the last five calendar years (2019, 2020, 2021, 2022, and 2023), there were no long-term vacancies. Any FTE that moved out of a role was backfilled within a few months. In the Company's response to DPS-848, the Company provided the following table (included here for reference), which summarizes the total number of FTEs who perform(ed) Strategic Account Management activities from 2019 to present. One Corporate Affairs Program Manager position was vacant at the end of 2021 but was backfilled in 2022.

	2019	2020	2021	2022	2023	2024
1. Corporate Affairs - Program Managers	17	17	16	17	17	10
% allocation to Large Customer Account Management activities	40%	40%	40%	40%	25%	10%
Corporate Affairs - Large Customer Account Management FTE	7	7	7	7	4	1
2. Energy Efficiency - Strategic Account Partnerships Program Managers	1	2	3	3	3	0
3. Customer Account Management UNY (starting June 2024)	0	0	0	0	0	9
4. Commercial Services - Large-Scale Renewables Developers / Wholesale Transmission Customers	5	5	5	5	5	5
5. National Accounts - EE / Account Management	1	1	1	1	1	1
TOTAL FTE - Strategic Account Management	**14**	**15**	**16**	**16**	**13**	**16**

<u>Name of Respondent</u>:
Matthew Foran

<u>Date of Reply</u>:
September 23, 2024

Customer	Electric Threshold: 750 kW Annual Avg Demand	Gas Threshold: 25,000 Dth Annual Consumption	Old/New Managed Account	Exceeds Either Threshold	Meets both Electric and Gas Thresholds
Customer 1	Meets	Not Applicable	New	Yes	No
Customer 2	Doesn't Meet	Meets	New	Yes	No
Customer 3	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 4	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 5	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 6	Meets	Doesn't Meet	New	Yes	No
Customer 7	Meets	Meets	New	Yes	Yes
Customer 8	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 9	Meets	Meets	New	Yes	Yes
Customer 10	Meets	Meets	Old	Yes	Yes
Customer 11	Meets	Doesn't Meet	Old	Yes	No
Customer 12	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 13	Meets	Meets	Old	Yes	Yes
Customer 14	Meets	Meets	Old	Yes	Yes
Customer 15	Meets	Doesn't Meet	Old	Yes	No
Customer 16	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 17	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 18	Meets	Meets	Old	Yes	Yes
Customer 19	Meets	Meets	Old	Yes	Yes
Customer 20	Meets	Doesn't Meet	Old	Yes	No
Customer 21	Meets	Meets	New	Yes	Yes
Customer 22	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 23	Meets	Meets	Old	Yes	Yes
Customer 24	Meets	Meets	Old	Yes	Yes
Customer 25	Meets	Doesn't Meet	New	Yes	No
Customer 26	Meets	Meets	Old	Yes	Yes
Customer 27	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 28	Meets	Not Applicable	Old	Yes	No
Customer 29	Meets	Not Applicable	New	Yes	Not Applicable
Customer 30	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 31	Meets	Not Applicable	New	Yes	Not Applicable
Customer 32	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 33	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 34	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 35	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 36	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 37	Meets	Meets	Old	Yes	Yes
Customer 38	Meets	Meets	Old	Yes	Yes
Customer 39	Meets	Doesn't Meet	Old	Yes	No
Customer 40	Meets	Doesn't Meet	Old	Yes	No
Customer 41	Meets	Doesn't Meet	Old	Yes	No
Customer 42	Doesn't Meet	Doesn't Meet	Old	No	No

Customer 43	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 44	Meets	Meets	Old	Yes	Yes
Customer 45	Meets	Meets	Old	Yes	Yes
Customer 46	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 47	Meets	Not Applicable	New	Yes	Not Applicable
Customer 48	Meets	Not Applicable	New	Yes	Not Applicable
Customer 49	Meets	Doesn't Meet	Old	Yes	No
Customer 50	Meets	Doesn't Meet	New	Yes	No
Customer 51	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 52	Meets	Not Applicable	New	Yes	Not Applicable
Customer 53	Meets	Meets	Old	Yes	Yes
Customer 54	Meets	Doesn't Meet	Old	Yes	No
Customer 55	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 56	Meets	Doesn't Meet	Old	Yes	No
Customer 57	Meets	Meets	Old	Yes	Yes
Customer 58	Meets	Meets	Old	Yes	Yes
Customer 59	Meets	Meets	Old	Yes	Yes
Customer 60	Meets	Doesn't Meet	Old	Yes	no
Customer 61	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 62	Meets	Doesn't Meet	New	Yes	No
Customer 63	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 64	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 65	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 66	Meets	Doesn't Meet	Old	Yes	No
Customer 67	Meets	Doesn't Meet	Old	Yes	No
Customer 68	Meets	Meets	New	Yes	Yes
Customer 69	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 70	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 71	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 72	Meets	Doesn't Meet	New	Yes	No
Customer 73	Meets	Doesn't Meet	Old	Yes	No
Customer 74	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 75	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 76	Doesn't Meet	Meets	New	Yes	No
Customer 77	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 78	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 79	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 80	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 81	Doesn't Meet	Meets	New	Yes	No
Customer 82	Meets	Doesn't Meet	Old	Yes	No
Customer 83	Meets	Meets	Old	Yes	Yes
Customer 84	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 85	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 86	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 87	Meets	Meets	New	Yes	Yes
Customer 88	Doesn't Meet	Not Applicable	Old	No	Not Applicable

Customer 89	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 90	Meets	Not Applicable	New	Yes	Not Applicable
Customer 91	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 92	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 93	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 94	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 95	Meets	Not Applicable	New	Yes	Not Applicable
Customer 96	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 97	Meets	Meets	Old	Yes	Yes
Customer 98	Doesn't Meet	Meets	New	Yes	No
Customer 99	Meets	Not Applicable	New	Yes	Yes
Customer 100	Meets	Meets	Old	Yes	Yes
Customer 101	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 102	Meets	Not Applicable	New	Yes	Not Applicable
Customer 103	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 104	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 105	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 106	Meets	Doesn't Meet	New	Yes	No
Customer 107	Meets	Doesn't Meet	Old	Yes	No
Customer 108	Not Applicable	Meets	Old	Yes	Not Applicable
Customer 109	Meets	Meets	Old	Yes	Yes
Customer 110	Meets	Meets	New	Yes	Yes
Customer 111	Doesn't Meet	Meets	Old	Yes	No
Customer 112	Doesn't Meet	Meets	New	Yes	No
Customer 113	Meets	Meets	Old	Yes	Yes
Customer 114	Meets	Doesn't Meet	New	Yes	No
Customer 115	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 116	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 117	Doesn't Meet	Meets	Old	Yes	No
Customer 118	Doesn't Meet	Meets	Old	Yes	No
Customer 119	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 120	Doesn't Meet	Not Applicable	New	No	Not Applicable
Customer 121	Meets	Doesn't Meet	Old	Yes	No
Customer 122	Meets	Meets	Old	Yes	Yes
Customer 123	Meets	Doesn't Meet	New	Yes	No
Customer 124	Meets	Meets	Old	Yes	Yes
Customer 125	Meets	Doesn't Meet	Old	Yes	No
Customer 126	Meets	Meets	Old	Yes	Yes
Customer 127	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 128	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 129	Meets	Doesn't Meet	Old	Yes	Not Applicable
Customer 130	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 131	Doesn't Meet	Meets	New	Yes	No
Customer 132	Meets	Doesn't Meet	New	Yes	No
Customer 133	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 134	Doesn't Meet	Not Applicable	Old	No	Not Applicable

Customer 135	Meets	Doesn't Meet	New	Yes	No
Customer 136	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 137	Meets	Doesn't Meet	New	Yes	No
Customer 138	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 139	Meets	Doesn't Meet	Old	Yes	No
Customer 140	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 141	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 142	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 143	Meets	Meets	Old	Yes	Yes
Customer 144	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 145	Doesn't Meet	Meets	Old	Yes	No
Customer 146	Doesn't Meet	Meets	New	Yes	No
Customer 147	Meets	Doesn't Meet	New	Yes	No
Customer 148	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 149	Meets	Meets	New	Yes	Yes
Customer 150	Meets	Meets	New	Yes	Yes
Customer 151	Meets	Meets	Old	Yes	Yes
Customer 152	Meets	Doesn't Meet	Old	Yes	Not Applicable
Customer 153	Meets	Doesn't Meet	Old	Yes	No
Customer 154	Meets	Not Applicable	New	Yes	No
Customer 155	Meets	Not Applicable	New	Yes	Not Applicable
Customer 156	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 157	Doesn't Meet	Meets	Old	Yes	No
Customer 158	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 159	Meets	Not Applicable	New	Yes	Not Applicable
Customer 160	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 161	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 162	Meets	Doesn't Meet	Old	Yes	No
Customer 163	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 164	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 165	Meets	Not Applicable	New	Yes	No
Customer 166	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 167	Meets	Doesn't Meet	New	Yes	No
Customer 168	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 169	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 170	Meets	Meets	Old	Yes	Yes
Customer 171	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 172	Meets	Meets	Old	Yes	Yes
Customer 173	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 174	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 175	Meets	Meets	New	Yes	Yes
Customer 176	Meets	Meets	Old	Yes	Yes
Customer 177	Meets	Doesn't Meet	New	Yes	No
Customer 178	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 179	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 180	Meets	Meets	Old	Yes	Yes

Customer 181	Meets	Meets	Old	Yes	Yes
Customer 182	Meets	Doesn't Meet	New	Yes	No
Customer 183	Meets	Doesn't Meet	Old	Yes	No
Customer 184	Meets	Meets	Old	Yes	Yes
Customer 185	Meets	Meets	Old	Yes	Yes
Customer 186	Meets	Doesn't Meet	New	Yes	No
Customer 187	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 188	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 189	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 190	Meets	Meets	Old	Yes	Yes
Customer 191	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 192	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 193	Meets	Doesn't Meet	New	Yes	No
Customer 194	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 195	Meets	Doesn't Meet	Old	Yes	No
Customer 196	Meets	Doesn't Meet	Old	Yes	No
Customer 197	Doesn't Meet	Meets	Old	Yes	No
Customer 198	Meets	Meets	New	Yes	Yes
Customer 199	Doesn't Meet	Meets	New	Yes	No
Customer 200	Not Applicable	Meets	Old	Yes	No
Customer 201	Doesn't Meet	Meets	New	Yes	No
Customer 202	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 203	Meets	Doesn't Meet	Old	Yes	No
Customer 204	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 205	Meets	Doesn't Meet	New	Yes	No
Customer 206	Meets	Doesn't Meet	New	Yes	No
Customer 207	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 208	Meets	Meets	New	Yes	Yes
Customer 209	Meets	Doesn't Meet	New	Yes	No
Customer 210	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 211	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 212	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 213	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 214	Meets	Not Applicable	New	Yes	Not Applicable
Customer 215	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 216	Meets	Meets	New	Yes	Yes
Customer 217	Meets	Doesn't Meet	New	Yes	No
Customer 218	Meets	Meets	Old	Yes	Yes
Customer 219	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 220	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 221	Meets	Doesn't Meet	New	Yes	No
Customer 222	Doesn't Meet	Not Applicable	New	No	Not Applicable
Customer 223	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 224	Meets	Meets	Old	Yes	Yes
Customer 225	Meets	Doesn't Meet	New	Yes	No
Customer 226	Meets	Not Applicable	Old	Yes	Not Applicable

Customer 227	Meets	Doesn't Meet	New	Yes	No
Customer 228	Meets	Doesn't Meet	New	Yes	No
Customer 229	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 230	Meets	Doesn't Meet	New	Yes	No
Customer 231	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 232	Doesn't Meet	Not Applicable	New	No	Not Applicable
Customer 233	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 234	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 235	Doesn't Meet	Meets	Old	Yes	No
Customer 236	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 237	Meets	Meets	Old	Yes	Yes
Customer 238	Meets	Doesn't Meet	Old	Yes	No
Customer 239	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 240	Meets	Doesn't Meet	New	Yes	No
Customer 241	Meets	Meets	Old	Yes	Yes
Customer 242	Meets	Meets	Old	Yes	Yes
Customer 243	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 244	Meets	Doesn't Meet	New	Yes	No
Customer 245	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 246	Meets	Doesn't Meet	New	Yes	No
Customer 247	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 248	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 249	Meets	Meets	Old	Yes	Yes
Customer 250	Meets	Meets	New	Yes	Yes
Customer 251	Meets	Doesn't Meet	Old	Yes	No
Customer 252	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 253	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 254	Meets	Not Applicable	New	Yes	Not Applicable
Customer 255	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 256	Meets	Doesn't Meet	New	Yes	No
Customer 257	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 258	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 259	Meets	Doesn't Meet	Old	Yes	No
Customer 260	Meets	Doesn't Meet	Old	Yes	No
Customer 261	Not Applicable	Meets	New	Yes	Not Applicable
Customer 262	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 263	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 264	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 265	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 266	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 267	Meets	Doesn't Meet	New	Yes	No
Customer 268	Meets	Doesn't Meet	New	Yes	No
Customer 269	Meets	Doesn't Meet	Old	Yes	No
Customer 270	Doesn't Meet	Meets	New	Yes	No
Customer 271	Meets	Doesn't Meet	Old	Yes	No
Customer 272	Meets	Meets	Old	Yes	Yes

Customer 273	Meets	Meets	Old	Yes	Yes
Customer 274	Meets	Meets	Old	Yes	Yes
Customer 275	Meets	Meets	Old	Yes	Yes
Customer 276	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 277	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 278	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 279	Meets	Not Applicable	New	Yes	Not Applicable
Customer 280	Doesn't Meet	Meets	Old	Yes	No
Customer 281	Meets	Not Applicable	New	Yes	Not Applicable
Customer 282	Meets	Meets	Old	Yes	Yes
Customer 283	Meets	Meets	Old	Yes	Not Applicable
Customer 284	Meets	Meets	Old	Yes	Yes
Customer 285	Doesn't Meet	Meets	New	Yes	No
Customer 286	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 287	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 288	Meets	Not Applicable	New	Yes	Not Applicable
Customer 289	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 290	Meets	Doesn't Meet	Old	Yes	Not Applicable
Customer 291	Meets	Meets	Old	Yes	Yes
Customer 292	Meets	Doesn't Meet	Old	Yes	No
Customer 293	Meets	Meets	New	Yes	Yes
Customer 294	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 295	Doesn't Meet	Meets	New	Yes	No
Customer 296	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 297	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 298	Meets	Doesn't Meet	Old	Yes	No
Customer 299	Meets	Not Applicable	Old	Yes	No
Customer 300	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 301	Doesn't Meet	Meets	Old	Yes	No
Customer 302	Meets	Not Applicable	New	Yes	Not Applicable
Customer 303	Meets	Doesn't Meet	Old	Yes	No
Customer 304	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 305	Meets	Not Applicable	New	Yes	Not Applicable
Customer 306	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 307	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 308	Doesn't Meet	Meets	Old	Yes	No
Customer 309	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 310	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 311	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 312	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 313	Meets	Meets	Old	Yes	Yes
Customer 314	Meets	Doesn't Meet	New	Yes	No
Customer 315	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 316	Meets	Doesn't Meet	Old	Yes	No
Customer 317	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 318	Meets	Doesn't Meet	New	Yes	No

Customer 319	Meets	Doesn't Meet	New	Yes	No
Customer 320	Meets	Meets	Old	Yes	Yes
Customer 321	Meets	Meets	Old	Yes	Yes
Customer 322	Meets	Doesn't Meet	Old	Yes	No
Customer 323	Meets	Meets	New	Yes	Yes
Customer 324	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 325	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 326	Doesn't Meet	Meets	Old	Yes	No
Customer 327	Meets	Meets	Old	Yes	Not Applicable
Customer 328	Meets	Not Applicable	New	Yes	Not Applicable
Customer 329	Meets	Doesn't Meet	New	Yes	No
Customer 330	Meets	Doesn't Meet	Old	Yes	No
Customer 331	Meets	Doesn't Meet	Old	Yes	No
Customer 332	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 333	Meets	Doesn't Meet	Old	Yes	No
Customer 334	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 335	Meets	Doesn't Meet	Old	Yes	No
Customer 336	Meets	Meets	Old	Yes	Yes
Customer 337	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 338	Meets	Doesn't Meet	Old	Yes	No
Customer 339	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 340	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 341	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 342	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 343	Meets	Doesn't Meet	New	Yes	No
Customer 344	Meets	Meets	Old	Yes	Yes
Customer 345	Meets	Doesn't Meet	New	Yes	No
Customer 346	Meets	Meets	Old	Yes	Yes
Customer 347	Meets	Doesn't Meet	Old	Yes	No
Customer 348	Meets	Doesn't Meet	Old	Yes	No
Customer 349	Meets	Not Applicable	New	Yes	Not Applicable
Customer 350	Meets	Not Applicable	New	Yes	Not Applicable
Customer 351	Meets	Not Applicable	New	Yes	Not Applicable
Customer 352	Meets	Doesn't Meet	Old	Yes	No
Customer 353	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 354	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 355	Meets	Doesn't Meet	New	Yes	No
Customer 356	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 357	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 358	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 359	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 360	Meets	Meets	Old	Yes	Yes
Customer 361	Meets	Meets	New	Yes	Yes
Customer 362	Meets	Doesn't Meet	New	Yes	No
Customer 363	Meets	Meets	Old	Yes	Yes
Customer 364	Meets	Not Applicable	Old	Yes	No

Customer 365	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 366	Meets	Doesn't Meet	New	Yes	No
Customer 367	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 368	Meets	Not Applicable	New	Yes	Not Applicable
Customer 369	Meets	Not Applicable	New	Yes	Not Applicable
Customer 370	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 371	Meets	Doesn't Meet	Old	Yes	No
Customer 372	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 373	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 374	Meets	Meets	Old	Yes	Yes
Customer 375	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 376	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 377	Meets	Not Applicable	New	Yes	Not Applicable
Customer 378	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 379	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 380	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 381	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 382	Meets	Meets	New	Yes	Yes
Customer 383	Meets	Doesn't Meet	Old	Yes	No
Customer 384	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 385	Meets	Doesn't Meet	Old	Yes	No
Customer 386	Meets	Not Applicable	New	Yes	Not Applicable
Customer 387	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 388	Meets	Meets	Old	Yes	Yes
Customer 389	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 390	Meets	Doesn't Meet	New	Yes	No
Customer 391	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 392	Meets	Doesn't Meet	New	Yes	No
Customer 393	Meets	Meets	New	Yes	Yes
Customer 394	Meets	Doesn't Meet	Old	Yes	No
Customer 395	Doesn't Meet	Meets	Old	Yes	No
Customer 396	Meets	Meets	New	Yes	Yes
Customer 397	Meets	Not Applicable	New	Yes	Not Applicable
Customer 398	Meets	Doesn't Meet	New	Yes	No
Customer 399	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 400	Meets	Not Applicable	New	Yes	Not Applicable
Customer 401	Meets	Doesn't Meet	New	Yes	No
Customer 402	Meets	Doesn't Meet	New	Yes	No
Customer 403	Meets	Not Applicable	New	Yes	Not Applicable
Customer 404	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 405	Meets	Doesn't Meet	New	Yes	No
Customer 406	Meets	Meets	Old	Yes	Yes
Customer 407	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 408	Meets	Doesn't Meet	Old	Yes	No
Customer 409	Meets	Doesn't Meet	New	Yes	No
Customer 410	Meets	Not Applicable	New	Yes	Not Applicable

Customer 411	Meets	Doesn't Meet	New	Yes	No
Customer 412	Meets	Doesn't Meet	Old	Yes	No
Customer 413	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 414	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 415	Meets	Not Applicable	New	Yes	No
Customer 416	Meets	Not Applicable	New	Yes	Not Applicable
Customer 417	Meets	Doesn't Meet	New	Yes	No
Customer 418	Meets	Meets	Old	Yes	Yes
Customer 419	Meets	Meets	Old	Yes	Yes
Customer 420	Meets	Meets	Old	Yes	Yes
Customer 421	Doesn't Meet	Meets	New	Yes	No
Customer 422	Meets	Meets	Old	Yes	Yes
Customer 423	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 424	Meets	Doesn't Meet	New	Yes	No
Customer 425	Meets	Meets	Old	Yes	Yes
Customer 426	Meets	Meets	Old	Yes	Yes
Customer 427	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 428	Doesn't Meet	Meets	New	Yes	Not Applicable
Customer 429	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 430	Meets	Meets	Old	Yes	Yes
Customer 431	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 432	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 433	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 434	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 435	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 436	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 437	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 438	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 439	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 440	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 441	Meets	Meets	New	Yes	Yes
Customer 442	Meets	Meets	New	Yes	Yes
Customer 443	Meets	Not Applicable	New	Yes	Not Applicable
Customer 444	Meets	Not Applicable	New	Yes	Not Applicable
Customer 445	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 446	Doesn't Meet	Meets	New	Yes	No
Customer 447	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 448	Meets	Not Applicable	New	Yes	Not Applicable
Customer 449	Meets	Meets	Old	Yes	Yes
Customer 450	Meets	Doesn't Meet	Old	Yes	No
Customer 451	Meets	Meets	Old	Yes	Yes
Customer 452	Meets	Meets	Old	Yes	Yes
Customer 453	Doesn't Meet	Not Applicable	New	No	Not Applicable
Customer 454	Meets	Meets	Old	Yes	Yes
Customer 455	Meets	Doesn't Meet	Old	Yes	No
Customer 456	Meets	Doesn't Meet	Old	Yes	No

Customer 457	Meets	Meets	Old	Yes	Yes
Customer 458	Meets	Doesn't Meet	New	Yes	No
Customer 459	Meets	Doesn't Meet	New	Yes	No
Customer 460	Meets	Meets	New	Yes	Yes
Customer 461	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 462	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 463	Meets	Doesn't Meet	New	Yes	No
Customer 464	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 465	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 466	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 467	Meets	Not Applicable	New	Yes	No
Customer 468	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 469	Doesn't Meet	Meets	New	Yes	No
Customer 470	Meets	Meets	Old	Yes	Yes
Customer 471	Meets	Meets	New	Yes	Yes
Customer 472	Meets	Meets	New	Yes	Yes
Customer 473	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 474	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 475	Meets	Meets	New	Yes	Yes
Customer 476	Meets	Meets	Old	Yes	Yes
Customer 477	Meets	Not Applicable	New	Yes	Not Applicable
Customer 478	Meets	Doesn't Meet	New	Yes	No
Customer 479	Meets	Meets	Old	Yes	Not Applicable
Customer 480	Meets	Not Applicable	New	Yes	Not Applicable
Customer 481	Meets	Meets	Old	Yes	Yes
Customer 482	Meets	Meets	New	Yes	Yes
Customer 483	Meets	Meets	Old	Yes	Yes
Customer 484	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 485	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 486	Meets	Meets	Old	Yes	Not Applicable
Customer 487	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 488	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 489	Meets	Meets	New	Yes	Yes
Customer 490	Meets	Doesn't Meet	New	Yes	No
Customer 491	Meets	Meets	Old	Yes	Yes
Customer 492	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 493	Meets	Meets	Old	Yes	Yes
Customer 494	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 495	Meets	Meets	Old	Yes	Yes
Customer 496	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 497	Doesn't Meet	Meets	New	Yes	No
Customer 498	Meets	Meets	Old	Yes	Yes
Customer 499	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 500	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 501	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 502	Meets	Doesn't Meet	Old	Yes	No

Customer 503	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 504	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 505	Meets	Doesn't Meet	Old	Yes	No
Customer 506	Meets	Not Applicable	Old	Yes	No
Customer 507	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 508	Doesn't Meet	Meets	New	Yes	No
Customer 509	Meets	Doesn't Meet	Old	Yes	No
Customer 510	Meets	Doesn't Meet	Old	Yes	No
Customer 511	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 512	Meets	Meets	Old	Yes	Yes
Customer 513	Meets	Meets	New	Yes	Yes
Customer 514	Meets	Not Applicable	New	Yes	Not Applicable
Customer 515	Meets	Meets	Old	Yes	Yes
Customer 516	Meets	Meets	Old	Yes	Yes
Customer 517	Meets	Meets	Old	Yes	Yes
Customer 518	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 519	Meets	Doesn't Meet	New	Yes	No
Customer 520	Meets	Meets	Old	Yes	Yes
Customer 521	Meets	Meets	Old	Yes	Yes
Customer 522	Meets	Meets	Old	Yes	Yes
Customer 523	Meets	Meets	Old	Yes	Yes
Customer 524	Meets	Meets	Old	Yes	Yes
Customer 525	Meets	Not Applicable	New	Yes	Not Applicable
Customer 526	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 527	Meets	Meets	Old	Yes	Yes
Customer 528	Meets	Doesn't Meet	Old	Yes	No
Customer 529	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 530	Meets	Meets	Old	Yes	Yes
Customer 531	Meets	Not Applicable	New	Yes	No
Customer 532	Meets	Meets	Old	Yes	Yes
Customer 533	Meets	Meets	Old	Yes	Yes
Customer 534	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 535	Meets	Doesn't Meet	New	Yes	No
Customer 536	Doesn't Meet	Meets	New	Yes	No
Customer 537	Meets	Meets	Old	Yes	Yes
Customer 538	Meets	Meets	Old	Yes	Yes
Customer 539	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 540	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 541	Meets	Doesn't Meet	Old	Yes	No
Customer 542	Meets	Doesn't Meet	New	Yes	No
Customer 543	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 544	Meets	Not Applicable	New	Yes	Not Applicable
Customer 545	Meets	Doesn't Meet	Old	Yes	No
Customer 546	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 547	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 548	Meets	Not Applicable	New	Yes	No

Customer 549	Meets	Meets	Old	Yes	Yes
Customer 550	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 551	Meets	Meets	Old	Yes	Yes
Customer 552	Meets	Not Applicable	Old	Yes	No
Customer 553	Meets	Meets	Old	Yes	Yes
Customer 554	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 555	Meets	Meets	Old	Yes	Yes
Customer 556	Meets	Meets	Old	Yes	Yes
Customer 557	Meets	Doesn't Meet	New	Yes	No
Customer 558	Meets	Meets	Old	Yes	Yes
Customer 559	Meets	Doesn't Meet	New	Yes	No
Customer 560	Meets	Meets	Old	Yes	Yes
Customer 561	Doesn't Meet	Meets	Old	Yes	No
Customer 562	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 563	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 564	Meets	Meets	Old	Yes	Yes
Customer 565	Meets	Meets	Old	Yes	Yes
Customer 566	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 567	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 568	Meets	Meets	Old	Yes	Yes
Customer 569	Meets	Doesn't Meet	New	Yes	No
Customer 570	Meets	Doesn't Meet	Old	Yes	No
Customer 571	Meets	Meets	Old	Yes	Yes
Customer 572	Meets	Meets	Old	Yes	Yes
Customer 573	Doesn't Meet	Meets	Old	Yes	No
Customer 574	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 575	Meets	Meets	Old	Yes	Yes
Customer 576	Meets	Not Applicable	New	Yes	No
Customer 577	Meets	Not Applicable	New	Yes	Not Applicable
Customer 578	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 579	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 580	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 581	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 582	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 583	Meets	Meets	Old	Yes	Yes
Customer 584	Meets	Meets	Old	Yes	Yes
Customer 585	Meets	Meets	Old	Yes	Yes
Customer 586	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 587	Doesn't Meet	Meets	Old	Yes	No
Customer 588	Meets	Meets	Old	Yes	Yes
Customer 589	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 590	Meets	Doesn't Meet	New	Yes	No
Customer 591	Meets	Doesn't Meet	New	Yes	No
Customer 592	Meets	Meets	Old	Yes	Yes
Customer 593	Meets	Meets	Old	Yes	Not Applicable
Customer 594	Meets	Not Applicable	Old	Yes	Not Applicable

Customer 595	Meets	Not Applicable	New	Yes	Not Applicable
Customer 596	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 597	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 598	Meets	Doesn't Meet	Old	Yes	No
Customer 599	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 600	Meets	Doesn't Meet	Old	Yes	No
Customer 601	Meets	Doesn't Meet	New	Yes	No
Customer 602	Meets	Meets	New	Yes	Yes
Customer 603	Meets	Meets	Old	Yes	Yes
Customer 604	Meets	Meets	Old	Yes	Yes
Customer 605	Meets	Meets	Old	Yes	Yes
Customer 606	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 607	Meets	Meets	Old	Yes	Yes
Customer 608	Meets	Meets	Old	Yes	Yes
Customer 609	Meets	Meets	Old	Yes	Yes
Customer 610	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 611	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 612	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 613	Meets	Doesn't Meet	New	Yes	No
Customer 614	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 615	Meets	Doesn't Meet	New	Yes	No
Customer 616	Meets	Doesn't Meet	New	Yes	No
Customer 617	Meets	Meets	New	Yes	Yes
Customer 618	Meets	Meets	Old	Yes	Yes
Customer 619	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 620	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 621	Meets	Doesn't Meet	Old	Yes	No
Customer 622	Meets	Doesn't Meet	Old	Yes	No
Customer 623	Doesn't Meet	Meets	New	Yes	No
Customer 624	Meets	Meets	Old	Yes	Yes
Customer 625	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 626	Meets	Meets	Old	Yes	Yes
Customer 627	Meets	Meets	Old	Yes	Yes
Customer 628	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 629	Meets	Meets	Old	Yes	Yes
Customer 630	Meets	Meets	Old	Yes	Yes
Customer 631	Meets	Meets	Old	Yes	Yes
Customer 632	Meets	Meets	Old	Yes	Yes
Customer 633	Meets	Meets	Old	Yes	Yes
Customer 634	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 635	Meets	Doesn't Meet	New	Yes	No
Customer 636	Meets	Doesn't Meet	New	Yes	No
Customer 637	Meets	Doesn't Meet	Old	Yes	No
Customer 638	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 639	Meets	Meets	Old	Yes	Yes
Customer 640	Meets	Meets	Old	Yes	Yes

Customer 641	Meets	Doesn't Meet	Old	Yes	No
Customer 642	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 643	Meets	Doesn't Meet	Old	Yes	No
Customer 644	Meets	Doesn't Meet	Old	Yes	No
Customer 645	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 646	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 647	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 648	Meets	Doesn't Meet	New	Yes	No
Customer 649	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 650	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 651	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 652	Meets	Meets	Old	Yes	Yes
Customer 653	Meets	Meets	New	Yes	Yes
Customer 654	Meets	Meets	Old	Yes	Yes
Customer 655	Meets	Meets	New	Yes	Yes
Customer 656	Meets	Doesn't Meet	New	Yes	No
Customer 657	Meets	Meets	Old	Yes	Yes
Customer 658	Not Applicable	Doesn't Meet	Old	No	Not Applicable
Customer 659	Meets	Doesn't Meet	Old	Yes	No
Customer 660	Meets	Doesn't Meet	Old	Yes	No
Customer 661	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 662	Meets	Meets	Old	Yes	Yes
Customer 663	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 664	Meets	Meets	Old	Yes	Yes
Customer 665	Meets	Meets	Old	Yes	Yes
Customer 666	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 667	Meets	Doesn't Meet	New	Yes	No
Customer 668	Meets	Doesn't Meet	Old	Yes	No
Customer 669	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 670	Meets	Doesn't Meet	New	Yes	No
Customer 671	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 672	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 673	Meets	Doesn't Meet	Old	Yes	No
Customer 674	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 675	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 676	Meets	Meets	New	Yes	Yes
Customer 677	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 678	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 679	Meets	Meets	Old	Yes	Yes
Customer 680	Meets	Doesn't Meet	New	Yes	No
Customer 681	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 682	Meets	Meets	New	Yes	Yes
Customer 683	Meets	Meets	New	Yes	Yes
Customer 684	Meets	Doesn't Meet	Old	Yes	No
Customer 685	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 686	Meets	Meets	Old	Yes	Yes

Customer 687	Meets	Doesn't Meet	New	Yes	No
Customer 688	Meets	Meets	Old	Yes	Yes
Customer 689	Meets	Meets	New	Yes	Yes
Customer 690	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 691	Meets	Meets	Old	Yes	Yes
Customer 692	Meets	Meets	Old	Yes	Yes
Customer 693	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 694	Meets	Doesn't Meet	New	Yes	No
Customer 695	Doesn't Meet	Not Applicable	Old	No	Not Applicable
Customer 696	Meets	Meets	New	Yes	Yes
Customer 697	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 698	Meets	Doesn't Meet	New	Yes	No
Customer 699	Meets	Meets	New	Yes	Yes
Customer 700	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 701	Meets	Not Applicable	New	Yes	Not Applicable
Customer 702	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 703	Meets	Meets	Old	Yes	Yes
Customer 704	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 705	Doesn't Meet	Meets	New	Yes	No
Customer 706	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 707	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 708	Meets	Meets	Old	Yes	Yes
Customer 709	Meets	Meets	Old	Yes	Yes
Customer 710	Meets	Meets	Old	Yes	Yes
Customer 711	Meets	Doesn't Meet	Old	Yes	No
Customer 712	Meets	Meets	Old	Yes	Yes
Customer 713	Meets	Doesn't Meet	New	Yes	No
Customer 714	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 715	Meets	Meets	New	Yes	Yes
Customer 716	Meets	Not Applicable	New	Yes	Not Applicable
Customer 717	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 718	Meets	Not Applicable	New	Yes	Not Applicable
Customer 719	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 720	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 721	Doesn't Meet	Meets	New	Yes	No
Customer 722	Meets	Meets	Old	Yes	Yes
Customer 723	Meets	Meets	New	Yes	Yes
Customer 724	Meets	Doesn't Meet	New	Yes	No
Customer 725	Meets	Not Applicable	New	Yes	Not Applicable
Customer 726	Meets	Meets	Old	Yes	Yes
Customer 727	Meets	Not Applicable	New	Yes	No
Customer 728	Meets	Meets	Old	Yes	Yes
Customer 729	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 730	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 731	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 732	Meets	Not Applicable	Old	Yes	Not Applicable

Customer 733	Meets	Not Applicable	New	Yes	Not Applicable
Customer 734	Doesn't Meet	Doesn't Meet	Old	No	No
Customer 735	Doesn't Meet	Meets	New	Yes	No
Customer 736	Meets	Meets	Old	Yes	Yes
Customer 737	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 738	Meets	Meets	New	Yes	Yes
Customer 739	Meets	Not Applicable	New	Yes	Not Applicable
Customer 740	Meets	Not Applicable	New	Yes	No
Customer 741	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 742	Meets	Meets	Old	Yes	Yes
Customer 743	Doesn't Meet	Meets	New	Yes	No
Customer 744	Meets	Meets	Old	Yes	Yes
Customer 745	Meets	Not Applicable	Old	Yes	Not Applicable
Customer 746	Meets	Not Applicable	Old	Yes	Not Applicable

Date of Request: September 13, 2024 Request No. DPS-1028
Due Date: September 23, 2024 NG Request No. NG-1556

Niagara Mohawk Power Corporation d/b/a National Grid
Case No. 24-E-0322 & 24-G-0323
Data Request

Request for Information

FROM: PSC - Chelsea Laquittara

TO: National Grid

SUBJECT: Strategic Account Managers

Request:

In all interrogatories, any requests for workpapers or supporting calculations shall be construed as requesting any Word, Excel, or other computer spreadsheet models in original electronic format with all formulae intact and unlocked.

1. In its response to DPS-855, the Company states that "The expanded target list of 805 managed accounts includes additional enterprises that met or exceeded either 750 kW in yearly average demand or 25,000 Dth in annual gas consumption." For each of the following, provide the number of accounts on the "expanded list," separately for electric and gas:

    a. New accounts meeting this criteria;

    b. Existing accounts that temporarily increased its load to meet the criteria; and

    c. Existing accounts that have consistently met or exceeded either 750 kW in yearly average demand or 25,000 Dth in annual gas consumption.

    d. Include in your response how many customers in Question 1.a., 1.b., and 1.c., above, meet both 750 kW in yearly average demand and 25,000 Dth in annual gas consumption.

2. Indicate how long (e.g., how many days, months, or years) the customer's load must meet or exceed either 750 kW in yearly average demand or 25,000 Dth in annual gas consumption to be considered a "Managed Account" customer.

Response:

1. The number of accounts on the “expanded list” include the following:

    a. New accounts meeting the specified criteria:

- 178 new accounts meet the electric threshold of 750 kW yearly average demand.
- 66 new accounts meet the gas threshold of 25,000 Dth annual consumption.

b. No accounts temporarily increased their load for the purpose of meeting either load threshold.

c. Existing accounts that have consistently met or exceeded either 750 kW in yearly average demand or 25,000 Dth in annual gas consumption:

- 429 existing accounts meet the electric threshold of 750 kW yearly average demand.
- 172 existing accounts meet the gas threshold of 25,000 Dth annual consumption.

d. The number of customers in Question 1.a. and 1.c., above, that meet both 750 kW in yearly average demand and 25,000 Dth in annual gas consumption are as follows:

- 42 new accounts meet both thresholds.
- 150 existing accounts meet both thresholds.

Please note that the counts in 1d. above only include customers in territories where National Grid is the distribution company for both electricity and gas.

2. The Company has not established an official guideline for periodic review of its managed account list. An annual review of the load thresholds and other factors, such as emerging strategic/specialized needs, may make sense to consider any proposed additions to the managed account list or modifying the management of certain accounts.

Name of Respondent:
Matthew Foran

Date of Reply:
September 23, 2024

Exhibit__(SCSP-2)
SCSP's Proposed
Customer Service Performance Indicator
Targets and NRAs

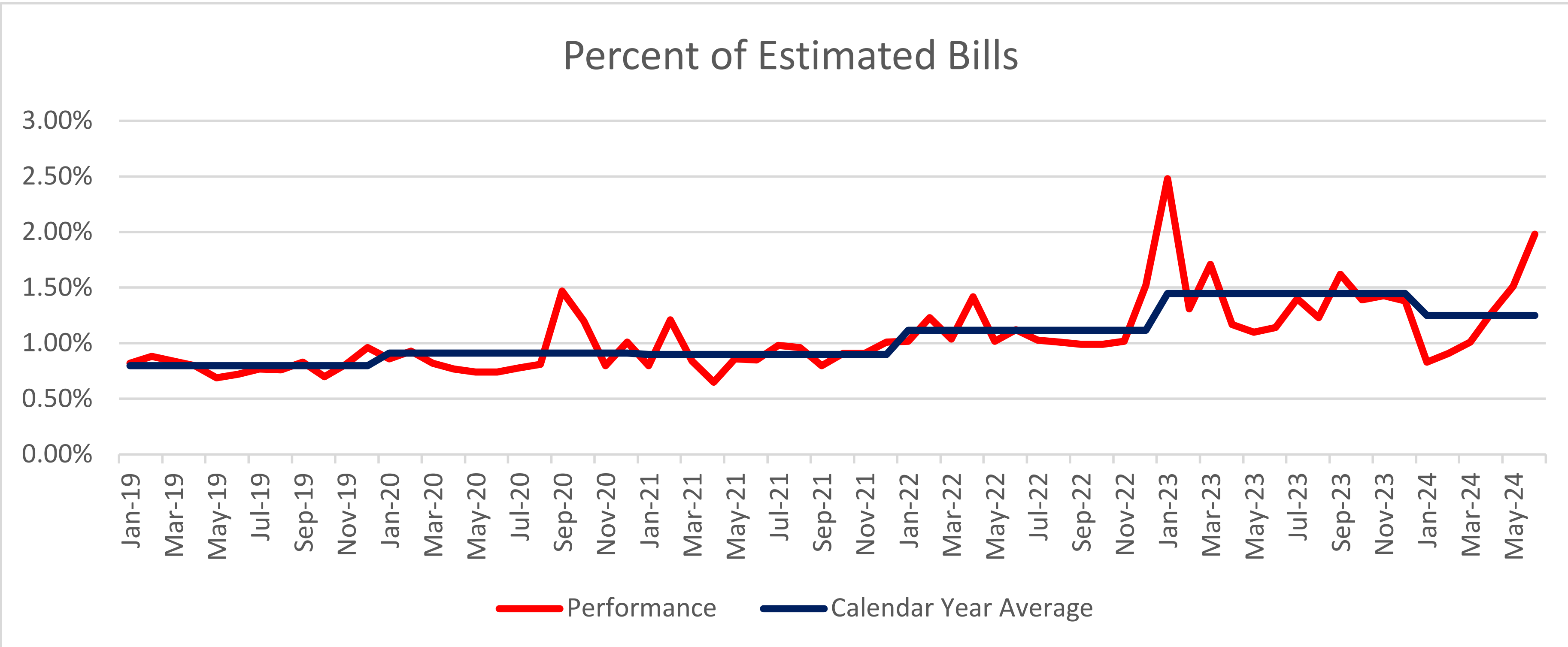
Proposed
Customer Service Performance Indicator
Targets and NRAs

Estimated Bills	
Target	NRA in Basis Points
≤1.5%	0
>1.5%	3
≥1.7%	6
≥2.0%	12
PSC Complaint Rate	
Target	NRA in Basis Points
≤1.0	0
>1.0	3
≥1.2	6
≥1.4	12
Residential Customer Satisfaction Survey	
Target	NRA in Basis Points
≥82.0%	0
<82.0%	3
≤81.0%	6
≤79.9%	12
Small/Medium Commercial and Industrial Customer Satisfaction Survey	
Target	NRA in Basis Points
≥82.0%	0
<82.0%	3
≤81.0%	6
≤79.9%	12
Call Answer Rate	
Target	NRA in Basis Points
≥79.2%	0
<79.2%	3
≤77.0%	6
≤74.9%	12

Exhibit__(SCSP-3)

NMPC's

Estimated Bills


Percent of Estimated Bills
3.00%
2.50%
2.00%
1.50%
1.00%
0.50%
0.00%
Jan-19
Mar-19
May-19
Jul-19
Sep-19
Nov-19
Jan-20
Mar-20
May-20
Jul-20
Sep-20
Nov-20
Jan-21
Mar-21
May-21
Jul-21
Sep-21
Nov-21
Jan-22
Mar-22
May-22
Jul-22
Sep-22
Nov-22
Jan-23
Mar-23
May-23
Jul-23
Sep-23
Nov-23
Jan-24
Mar-24
May-24
Performance
Calendar Year Average

Exhibit__(SCSP-4)
National Institute of Standards and Technology
Publication 1270

NIST Special Publication 1270

Towards a Standard for Identifying and Managing Bias in Artificial Intelligence

Reva Schwartz
Apostol Vassilev
Kristen Greene
Lori Perine
Andrew Burt
Patrick Hall

This publication is available free of charge from:
https://doi.org/10.6028/NIST.SP.1270

National Institute of Standards and Technology
U.S. Department of Commerce

NIST Special Publication 1270

Towards a Standard for Identifying and Managing Bias in Artificial Intelligence

Reva Schwartz
National Institute of Standards and Technology
Information Technology Laboratory

Apostol Vassilev
National Institute of Standards and Technology
Information Technology Laboratory
Computer Security Division

Kristen Greene
National Institute of Standards and Technology
Information Technology Laboratory
Information Access Division

Lori Perine
National Institute of Standards and Technology
Information Technology Laboratory
& The University of Maryland

Andrew Burt
Patrick Hall
BNH.AI

This publication is available free of charge from:
https://doi.org/10.6028/NIST.SP.1270

March 2022

U.S. Department of Commerce
Gina M. Raimondo, Secretary

National Institute of Standards and Technology
James K. Olthoff, Performing the Non-Exclusive Functions and Duties of the Under Secretary of Commerce for Standards and Technology & Director, National Institute of Standards and Technology

National Institute of Standards and Technology Special Publication 1270
Natl. Inst. Stand. Technol. Spec. Publ. 1270, 86 pages (March 2022)
CODEN: NSPUE2

This publication is available free of charge from:
https://doi.org/10.6028/NIST.SP.1270

Executive Summary

As individuals and communities interact in and with an environment that is increasingly virtual, they are often vulnerable to the commodification of their digital footprint. Concepts and behavior that are ambiguous in nature are captured in this environment, quantified, and used to categorize, sort, recommend, or make decisions about people's lives. While many organizations seek to utilize this information in a responsible manner, biases remain endemic across technology processes and can lead to harmful impacts regardless of intent. These harmful outcomes, even if inadvertent, create significant challenges for cultivating public trust in artificial intelligence (AI).

While there are many approaches for ensuring the technology we use every day is safe and secure, there are factors specific to AI that require new perspectives. AI systems are often placed in contexts where they can have the most impact. Whether that impact is helpful or harmful is a fundamental question in the area of Trustworthy and Responsible AI. Harmful impacts stemming from AI are not just at the individual or enterprise level, but are able to ripple into the broader society. The scale of damage, and the speed at which it can be perpetrated by AI applications or through the extension of large machine learning MODELS across domains and industries requires concerted effort. Current attempts for addressing the harmful effects of AI bias remain focused on computational factors such as representativeness of datasets and fairness of machine learning algorithms. These remedies are vital for mitigating bias, and more work remains. Yet, as illustrated in Fig. 1, human and systemic institutional and societal factors are significant sources of AI bias as well, and are currently overlooked. Successfully meeting this challenge will require taking all forms of bias into account. This means expanding our perspective beyond the machine learning pipeline to recognize and investigate how this technology is both created within and impacts our society.

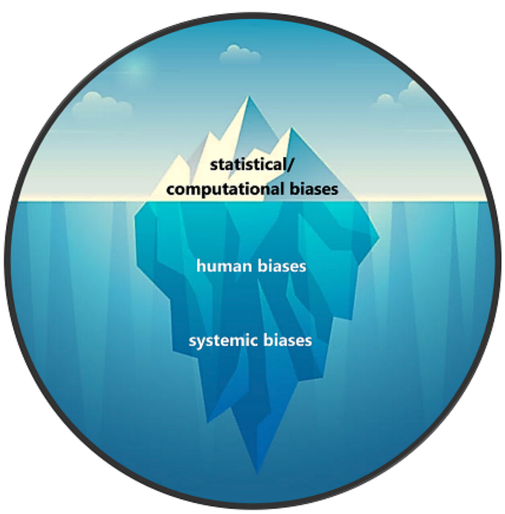


Fig. 1. The challenge of managing AI bias

Trustworthy and Responsible AI is not just about whether a given AI system is biased, fair or ethical, but whether it does what is claimed. Many practices exist for responsibly producing AI. The importance of transparency, datasets, and test, evaluation, validation, and verification (TEVV) cannot be overstated. Human factors such as participatory design techniques and multi-stakeholder approaches, and a human-in-the-loop are also important for mitigating risks related to AI bias. However none of these practices individually or in concert are a panacea against bias and each brings its own set of pitfalls. What is missing from current remedies is guidance from a broader SOCIO-TECHNICAL perspective that connects these practices to societal values. Experts in the area of Trustworthy and Responsible AI counsel that to successfully manage the risks of AI bias we must operationalize these values and create new norms around how AI is built and deployed. This document, and work by the National Institute of Standards and Technology (NIST) in the area of AI bias, is based on a socio-technical perspective.

The intent of this document is to surface the salient issues in the challenging area of AI bias, and to provide a first step on the roadmap for developing detailed socio-technical guidance for identifying and managing AI bias. Specifically, this special publication:

- describes the stakes and challenge of bias in artificial intelligence and provides examples of how and why it can chip away at public trust;
- identifies three categories of bias in AI — systemic, statistical, and human — and describes how and where they contribute to harms;
- describes three broad challenges for mitigating bias — datasets, testing and evaluation, and human factors — and introduces preliminary guidance for addressing them.

Bias is neither new nor unique to AI and it is not possible to achieve zero risk of bias in an AI system. NIST intends to develop methods for increasing assurance, GOVERNANCE and practice improvements for identifying, understanding, measuring, managing, and reducing bias. To reach this goal, techniques are needed that are flexible, can be applied across contexts regardless of industry, and are easily communicated to different stakeholder groups. To contribute to the growth of this burgeoning topic area, NIST will continue its work in measuring and evaluating computational biases, and seeks to create a hub for evaluating socio-technical factors. This will include development of formal guidance and standards, supporting standards development activities such as workshops and public comment periods for draft documents, and ongoing discussion of these topics with the stakeholder community.

Key words

bias, trustworthiness, AI safety, AI lifecycle, AI development

Acknowledgments

The authors wish to thank everyone who responded to our call and submitted comments to the draft version of this paper. The received comments and suggested references were essential for improving the paper and the future direction of this work. We also want to thank the many people who assisted with the updating of the document, including our NIST colleagues, and other reviewers who took the time to provide their constructive feedback. We thank Kyle Fox for his insightful comments, discussions, and invaluable input.

Audience

The intended primary audience for this document includes individuals and groups who are responsible for designing, developing, deploying, evaluating, and governing AI systems. The document is informed and motivated by segments of the public who experience potential harm or inequities due to bias in AI systems, or are affected by biases that are newly introduced or amplified by AI systems.

Background

This document is a result of an extensive literature review, conversations with experts from the areas of AI bias, fairness, and socio-technical systems, a workshop on AI bias,[1] and public comments on the draft version.[2] Insights derived from the public comments have been integrated throughout this document. An overview and analysis of themes from the public comments will be posted.[3] Intermediate follow-on work to this publication will include development of formal guidance for assessing and managing the risks of AI bias, and a series of public workshops to discuss these topics with the stakeholder community and build consensus.

Trademark Information

NIST Special Publications

The National Institute of Standards and Technology (NIST) promotes U.S. innovation and industrial competitiveness by advancing measurement science, standards, and technology in ways that enhance economic security and improve our quality of life. Among its broad range of activities, NIST contributes to the research, standards, evaluations, and data required to advance the development, use, and assurance of trustworthy artificial intelligence (AI).

[1] For more information about this workshop see https://www.nist.gov/news-events/events/2020/08/bias-ai-workshop.

[2] Public comments are available at https://www.nist.gov/artificial-intelligence/comments-received-proposal-identifying-and-managing-bias-artificial.

[3] Updated information for all of these resources can be found on the NIST AI Bias webpage, located at https://www.nist.gov/artificial-intelligence/ai-fundamental-research-free-bias.

The Information Technology Laboratory (ITL) at NIST develops tests, test methods, reference data, proof of concept implementations, and technical analyses to advance the development and productive use of information technology. ITL's responsibilities include the development of management, administrative, technical, and physical standards and guidelines.

This special publication focuses on addressing and managing risks associated with bias in the design, development, and use of AI. It is one of a series of documents and workshops related to the NIST AI Risk Management Framework (AI RMF) and is intended to advance the trustworthiness of AI technologies. As with other documents in the AI RMF series, this publication provides reference information and technical guidance on terminology, processes and procedures, and test and evaluation, validation, and verification (TEVV). While practical guidance[4] published by NIST may serve as an informative reference, this guidance remains voluntary.

The content of this document reflects recommended practices. This document is not intended to serve as or supersede existing regulations, laws, or other mandatory guidance.

[4]The term 'practice guide,' 'guide,' 'guidance' or the like, in the context of this paper, is a consensus-created, informative reference intended for voluntary use; it should not be interpreted as equal to the use of the term 'guidance' in a legal or regulatory context." This document does not establish any legal standard or any other legal requirement or defense under any law, nor have the force or effect of law.

How to read this document

Section 1 lays out the purpose and scope of NIST's work in AI bias. Section 2 describes three categories of bias and how they may occur in the commission, design, development, and deployment of AI technologies that can be used to generate predictions, recommendations, or decisions (such as the use of algorithmic decision systems), and how AI systems may impact individuals and communities or create broader societal harms. Section 3 describes the challenge of bias related to three core areas: datasets; test, evaluation, validation and verification; and human factors, and provides general guidance for managing AI bias in each of those areas.

This document uses terms such as AI technology, AI system, and AI applications interchangeably. Terms related to the machine learning pipeline, such as AI model or algorithm are also used in this document interchangeably. Depending on context, when the term "system" is used it may refer to the broader organizational and/or social ecosystem within which the technology was designed, developed, deployed, and used, instead of the more traditional use related to computational hardware or software.

Important reading notes:

- The document includes a series of vignettes, shown in red callout boxes, to help exemplify how and why AI bias can reduce public trust. Interesting nuances/aspects are highlighted in blue callout boxes, important takeaways are shown as framed text.
- Terms that are displayed as small caps in the text are defined in the GLOSSARY. Clicking on a word shown in small caps, e.g. MODEL, takes the reader directly to the definition of that term in the Glossary. From there, one may click on a page number shown at the end of the definition to return.
- March 24, 2022 update: the following changes are introduced with respect to the original version of this document published on March 15, 2022:
  - Fixed typos in the text of Fig. 5 and Fig. 7.
  - Removed duplicates and fixed poorly formatted entries in the **References**.
  - Corrected a statement in the text of VIGNETTE on p.7 regarding the work cited in [36].

Contents

List of Figures

1. Purpose and Scope

In August 2019, fulfilling an assignment in an Executive Order on AI,[5] NIST released "A Plan for Federal Engagement in Developing Technical Standards and Related Tools" [1]. Based on broad public and private sector input, this plan recommended a deeper, more consistent, and long-term engagement in AI standards "to help the United States to speed the pace of reliable, robust, and trustworthy AI technology development." NIST research in AI continues along this path to focus on how to measure, evaluate, and enhance the trustworthiness of AI systems and the responsible practices for designing, developing, and deploying such systems. Working with the AI community, NIST has identified the following technical and socio-technical characteristics needed to cultivate trust in AI systems: accuracy, explainability and interpretability, privacy, reliability, robustness, safety, and security resilience—and that harmful biases are mitigated or controlled.

While AI has significant potential as a transformative technology, it also poses inherent risks. Since trust and risk are closely related, NIST's work in the area of trustworthy and responsible AI centers around development of a voluntary Risk Management Framework (RMF). The unique challenges of AI require a deeper understanding of how AI risks differ from other domains. The NIST AI RMF is intended to address risks in the design, development, use, and evaluation of AI products, services, and systems for such tasks as recommendation, diagnosis, pattern recognition, and automated planning and decision-making. The framework is intended to enable the development and use of AI in ways that will increase trustworthiness, advance usefulness, and address potential harms. NIST is leveraging a multi-stakeholder approach to creating and maintaining actionable practice guides via the RMF that is broadly adoptable.

AI risk management

AI risk management seeks to minimize anticipated and emergent negative impacts of AI systems, including threats to civil liberties and rights. One of those risks is bias. Bias exists in many forms, is omnipresent in society, and can become ingrained in the automated systems that help make decisions about our lives. While bias is not always a negative phenomenon, certain biases exhibited in AI models and systems can perpetuate and amplify negative impacts on individuals, organizations, and society. These biases can also indirectly reduce public trust in AI. There is no shortage of examples where bias in some aspect of AI technology and its use has caused harm and negatively impacted lives, such as in hiring, [2–7] health care, [8–17] and criminal justice [18–30]. Indeed, there are many instances in which the deployment of AI technologies have been accompanied by concerns about whether and how societal biases are being perpetuated or amplified [31–46].

Public perspectives

Depending on the application, most Americans are likely to be unaware of when they are

[5] Exec. Order No. 13,859, 84 Fed. Reg. 3,967 (Feb. 11, 2019), https://www.federalregister.gov/documents/2019/02/14/2019-02544/maitaining-american-leadership-in-artificial-intelligence.

interacting with AI enabled technology [47]. However, there is a general view that there needs to be a "higher ethical standard" for AI than for other forms of technology [48]. This mainly stems from the perceptions and fears about loss of control and privacy [46, 49–51].

Bias is tightly associated with the concepts of transparency and fairness in society. For much of the public, the assumptions underlying algorithms are rarely transparent. The complex web of code and decisions that went into the design, development, and deployment of AI rarely is easily accessible or understandable to non-technical audiences. Nevertheless, many people are affected by—or their data is used as inputs for—AI technologies and systems without their consent, such as when they apply to college, [52] for a new apartment, [53] or search the internet. When individuals feel that they are not being fairly judged when applying for jobs [2–5, 7, 54–56] or loans [57–59] it can reduce public trust in AI technology [60, 61].

When an end user is presented with information online that stigmatizes them based on their race, age, or gender, or doesn't accurately perceive their identity, it causes harm [34, 36, 37, 41]. Consumers can be impacted by price gouging practices resulting from an AI application, even when it is not used to make decisions directly affecting that individual [43].

2. AI Bias: Context and Terminology

For purposes of this publication, the term Artificial Intelligence (AI) refers to a large class of software-based systems that receive signals from the environment and take actions that affect that environment by generating outputs such as content, predictions, recommendations, classifications, or decisions influencing the environments they interact with, among other outputs [62]. Machine learning (ML) refers more specifically to the "field of study that gives computers the ability to learn without being explicitly programmed," [63] or to computer programs that utilize data to learn and apply patterns or discern statistical relationships. Common ML approaches include, but are not limited to, regression, random forests, support vector machines, and artificial neural networks. ML programs may or may not be used to make predictions of future events. ML programs also may be used to create input for additional ML programs. AI includes ML within its scope.

While AI holds great promise, the convenience of automated classification and discovery within large datasets can come with significant downsides to individuals and society through the amplification of existing biases. Bias can be introduced purposefully or inadvertently into an AI system, or it can emerge as the AI is used in an application. Some types of AI bias are purposeful and beneficial. For example, the ML systems that underlie AI applications often model our implicit biases with the intent of creating positive experiences for online shopping or identifying content of interest [64, 65]. The proliferation of recommender systems and other modeling and predictive approaches has also helped to expose the many negative social biases baked into these processes, which can reduce public trust [66–69].

AI is neither built nor deployed in a vacuum, sealed off from societal realities of discrimination or unfair practices. Understanding AI as a socio-technical system acknowledges that the processes used to develop technology are more than their mathematical and computational constructs. A socio-technical approach to AI takes into account the values and behavior modeled from the datasets, the humans who interact with them, and the complex organizational factors that go into their commission, design, development, and ultimate deployment.

2.1 Characterizing AI bias

2.1.1 Contexts for addressing AI bias

Statistical context

In technical systems, bias is most commonly understood and treated as a statistical phenomenon. Bias is an effect that deprives a statistical result of representativeness by systematically distorting it, as distinct from a random error, which may distort on any one occasion but balances out on the average [70]. The International Organization for Standardization (ISO) defines bias more generally as: "the degree to which a reference value deviates from the truth"[71]. In this context, an AI system is said to be biased when it exhibits systematically inaccurate behavior. This statistical perspective does not sufficiently encompass or communicate the full spectrum of risks posed by bias in AI systems.

Legal context

This section was developed in response to public comments. Stakeholder feedback noted that the discussion of bias in AI could not be divorced from the treatment of bias in the U.S. legal system and how it relates to laws and regulations addressing discrimination and fairness, especially in the areas of consumer finance, housing, and employment.[6,7] There currently is no uniformly applied approach among the regulators and courts to measuring impermissible bias in all such areas. Impermissible discriminatory bias generally is defined by the courts as either consisting of disparate treatment, broadly defined as a decision that treats an individual less favorably than similarly situated individuals because of a protected characteristic such as race, sex, or other trait, or as disparate impact, which is broadly defined as a facially neutral policy or practice that disproportionately harms a group based on a protected trait.[8]

> This section is presented not as legal guidance, rather as a reminder for developers, deployers, and users of AI that they must be cognizant of legal considerations in their work, particularly with regard to bias testing. This section provides basic background understanding of some of the many ways bias is treated in some federal laws.

As it relates to disparate impact, courts and regulators have utilized or considered as acceptable various statistical tests to evaluate evidence of disparate impact. Traditional methods of statistical bias testing look at differences in predictions across protected classes, such as race or sex. In particular, courts have looked to statistical significance testing to assess whether the challenged practice likely caused the disparity and was not the result of chance or a nondiscriminatory factor.[9]

[6]Many laws, at the federal, state and even municipal levels focus on preventing discrimination in a host of areas. *See e.g.* Title VII of the Civil Rights Act, regarding discrimination on the basis of sex, religion, race, color, or national origin in employment, the Equal Credit Opportunity Act, focused, broadly, on discrimination in finance, the Fair Housing Act, focused on discrimination in housing, and the Americans with Disabilities Act, focused on discrimination related to disabilities, among others. Other federal agencies, including the U.S. Equal Employment Opportunity Commission, the Federal Trade Commission, the U.S. Department of Justice, and the Office Federal Contract Compliance Programs are responsible for enforcement and interpretation of these laws.

[7]Note that the analysis in this section is not intended to serve as a fully comprehensive discussion of the law, how it has been interpreted by the courts, or how it is enforced by regulatory agencies, but rather to provide an initial high-level overview.

[8]*See* 42 U.S.C. 2000e-2(a) (2018) and 42 U.S.C. 2000e-2(k) (2018), respectively.

[9]The Uniform Guidelines on Employment Selection Procedures (UGESP) state "[a] selection rate for any race, sex, or ethnic group which is less than four-fifths (4/5ths) (or eighty percent) of the rate for the group

It is important to note, however, that the tests used to measure bias are not applied uniformly within the legal context. In particular, federal circuit courts are split on whether to require a plaintiff to demonstrate both statistical and practical significance to make out a case of disparate impact. Some decisions have expressly rejected practical significance tests in recent years while others have continued to endorse their utility. This split illustrates that while the legal context provides several examples of how bias and fairness has been quantified and adjudicated over the last several decades, the relevant standards are still evolving.

It is also important to note that critical differences exist between traditional disparate impact analyses described above and illegal discrimination as it relates to people with disabilities, particularly under the Americans with Disabilities Act (ADA). Claims under the ADA are frequently construed as "screen out" rather than as "disparate impact" claims. "Screen out" may occur when an individual with a disability performs poorly on an evaluation or assessment, or is otherwise unable to meet an employer's job requirements, because of a disability and the individual loses a job opportunity as a result. In addition, the ADA's prohibition against denial of reasonable accommodation, for example, may require an employer to change processes or procedures to enable a particular individual with a disability to apply for a job, perform a job, or enjoy the benefits and privileges of employment. Such disability-related protections are particularly important to AI systems because testing an algorithm for bias by determining whether such groups perform equally well may fail to detect certain kinds of bias. Likewise, eliminating group discrepancies will not necessarily prevent screen out or the need for reasonable accommodation in such systems.

Cognitive and societal context

The teams involved in AI system design and development bring their cognitive biases, both individual and group, into the process [72]. Bias is prevalent in the assumptions about which data should be used, what AI models should be developed, where the AI system should be placed — or if AI is required at all. There are systemic biases at the institutional level that affect how organizations and teams are structured and who controls the decision making processes, and individual and group heuristics and cognitive/perceptual biases throughout the AI lifecycle (as described in Section 2.4). Decisions made by end users, downstream decision makers, and policy makers are also impacted by these biases, can reflect limited points of view and lead to biased outcomes [73–78]. Biases impacting human decision making are usually implicit and unconscious, and therefore unable to be easily controlled or mitigated [79]. Any assumption that biases can be remedied by human control or awareness is not a recipe for success.

with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact." 29 C.F.R. § 1607.4(D)

2.1.2 Categories of AI bias

Based on previous academic work to classify AI bias [80–90] and discussions with thought leaders in the field, it is possible to identify three dominant categories of AI bias. This three-way categorization helps to expand our understanding of AI bias beyond the computational realm. By defining and describing how systemic and human biases present within AI, we can build new approaches for analyzing, managing, and mitigating bias and begin to understand how these biases interact with each other. Correspondingly, Fig. 2 presents three categories of AI bias. Definitions for these terms are found in the GLOSSARY.[10] This list of biases, while not exhaustive, constitutes prominent risks and vulnerabilities to consider when designing, developing, deploying, evaluating, using, or auditing AI applications.

Systemic
Systemic biases result from procedures and practices of particular institutions that operate in ways which result in certain social groups being advantaged or favored and others being disadvantaged or devalued. This need not be the result of any conscious prejudice or discrimination but rather of the majority following existing rules or norms. Institutional racism and sexism are the most common examples [91]. Other systemic bias occurs when infrastructures for daily living are not developed using universal design principles, thus limiting or hindering accessibility for persons with disabilities. Systemic bias is also referred to as institutional or historical bias. These biases are present in the datasets used in AI, and the institutional norms, practices, and processes across the AI lifecycle and in broader culture and society. See VIGNETTE for more examples.

[10] Definitions for each category of bias were often selected based on either recently published papers on the topic, or seminal work within the domain the term is most associated with. When multiple definitions were identified, the most relevant definition was selected or adapted. The references provided are not intended to indicate specific endorsement or to assign originator credit.

Systemic bias in gender identification

Beyond personal identity, human faces encode a number of conspicuous traits such as nonverbal expression, indicators of sexual attraction and selection, and emotion. Facial recognition technology (FRT) is used in many types of applications including gender identification, which compares morphological distances between faces to classify human faces by gender. The degree of sexual dimorphism between men and women appears to vary with age and ethnic group. As a consequence, accuracy of FRT gender identification can vary with respect to the age and ethnic group [92]. Prepubescent male faces are frequently misclassified as female, and older female faces are progressively misclassified as male [92]. Studies have highlighted that human preferences for sexually dimorphic faces may be evolutionarily novel [93, 94]. One study found differing levels of facial sexual dimorphism in samples taken from countries located in Europe, South America, and Africa [95]. Buolamwini and Gebru examined the suitability of using skin types as a proxy for demographic classifications of ethnicity or race and found that skin type is not an adequate proxy for such classifications. Multiple ethnicities can be represented by a given skin type, and skin type can vary widely within a racial or ethnic category. For example, the skin types of individuals identifying as Black in the U.S. can represent many hues, which also can be represented in ethnic Hispanic, Asian, Pacific Islander and American indigenous groups. Moreover, racial and ethnic categories tend to vary across geographies and over time [36]. While training data based on a limited or non-representative sample of a group results in lower accuracy in categorizing members of that group, the degree of sexual monomorphism or dimorphism within that group also affects accuracy. Additional biases can occur due to a lack of awareness about the multiplicity of gender [96].

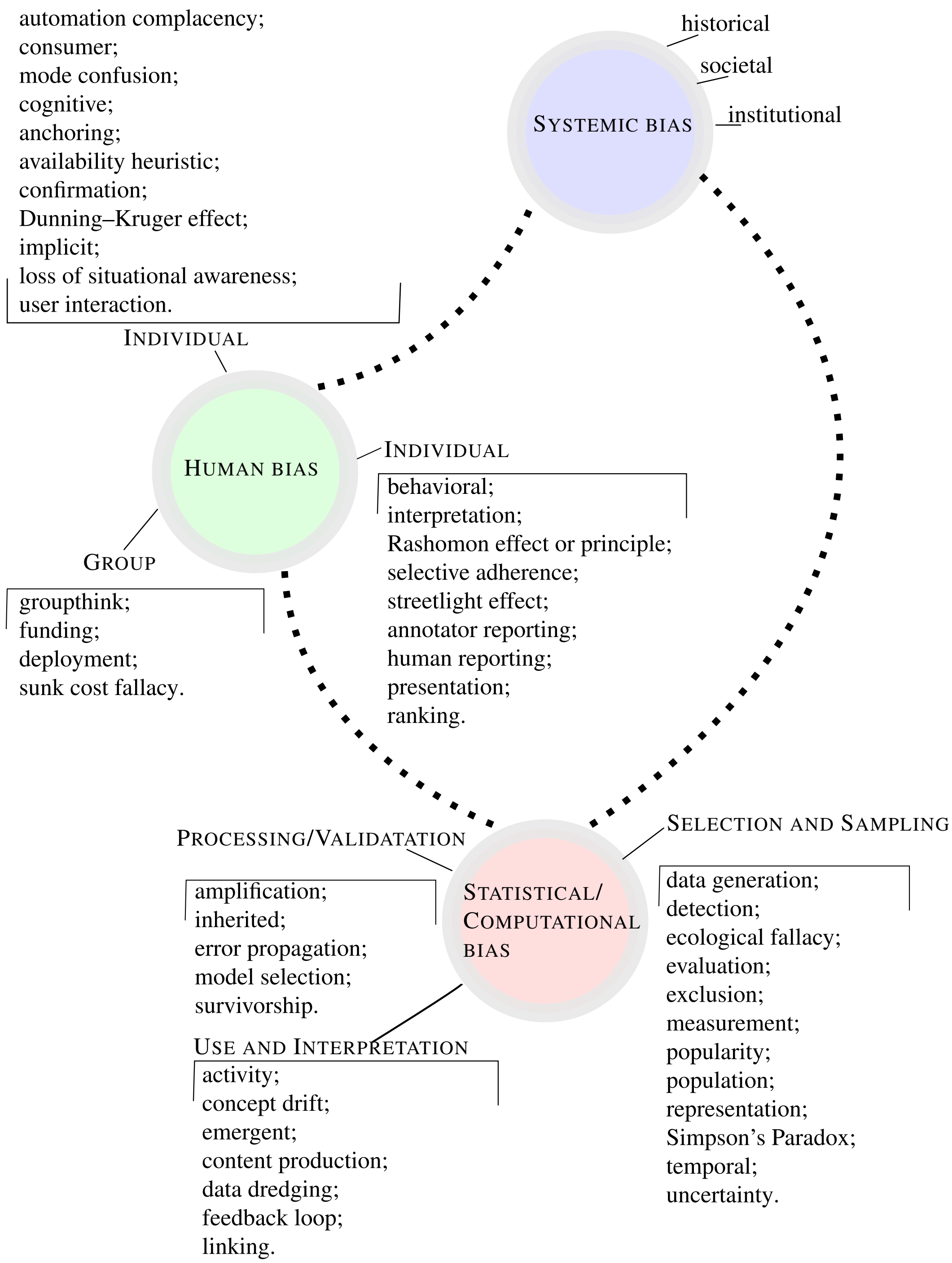


Fig. 2. Categories of AI Bias. The leaf node terms in each subcategory in the picture are hyperlinked to the GLOSSARY. Clicking them will bring up the definition in the Glossary. To return, click on the current page number (8) printed right after the glossary definition.

Statistical and Computational

Statistical and computational biases stem from errors that result when the sample is not representative of the population. These biases arise from systematic as opposed to random error and can occur in the absence of prejudice, partiality, or discriminatory intent [97]. In AI systems, these biases are present in the datasets and algorithmic processes used in the development of AI applications, and often arise when algorithms are trained on one type of data and cannot extrapolate beyond those data. The error may be due to heterogeneous data, representation of complex data in simpler mathematical representations, wrong data, and algorithmic biases such as over- and under-fitting, the treatment of outliers, and data cleaning and imputation factors.

Human

Human biases reflect systematic errors in human thought based on a limited number of heuristic principles and predicting values to simpler judgmental operations [98]. These biases are often implicit and tend to relate to how an individual or group perceives information (such as automated AI output) to make a decision or fill in missing or unknown information. These biases are omnipresent in the institutional, group, and individual decision making processes across the AI lifecycle, and in the use of AI applications once deployed. There is a wide variety of human biases. Cognitive and perceptual biases show themselves in all domains and are not unique to human interactions with AI. Rather, they are a fundamental part of the human mind. There is an entire field of study centered around biases and heuristics in thinking, decision-making, and behavioral economics for example [98]. Such research investigates phenomena such as ANCHORING BIAS, availability heuristic or bias, CONFIRMATION BIAS, and framing effects, among many others. It should be noted that heuristics are adaptive mental shortcuts that can be helpful, allowing complexity reduction in tasks of judgement and choice, yet can also lead to cognitive biases [98]. Human heuristics and biases are implicit; as such, simply increasing awareness of bias does not ensure control over it. Here we focus on broader examples of human bias in the AI space.

2.2 How AI bias contributes to harms

Technology based on AI has tighter connections to and broader impacts on society than traditional software. Applications that utilize AI are often deployed across sectors and contexts for decision-support and decision-making. In this role, they can replace humans and human processes for high-impact decisions. For example, AI-based hiring technologies and the models that underlie them replace people-oriented hiring processes and are implemented in any sector that seeks to automate their recruiting and employment pipeline [99–101]. Yet, ML models tend to exhibit "unexpectedly poor behavior when deployed in real world domains" without domain-specific constraints supplied by human operators [102]. These contradictions are a cause for considerable concern with large language models (or so-called foundation models) due to their considerable EPISTEMIC and ALEATORIC uncertainty[103] (as described in Section 3.2.1)—among other factors. Methods for capturing the poor performance, harmful impacts and other results of these models currently are imprecise and non-comprehensive.

Values

While ML systems are able to model complex phenomena, whether they are capable of learning and operating in line with our societal values remains an area of considerable research and concern [55, 60, 104–109]. Systemic and implicit biases such as racism and other forms of discrimination can inadvertently manifest in AI through the data used in training, as well as through the institutional policies and practices underlying how AI is commissioned, developed, deployed, and used. Statistical/algorithmic and human cognitive and perceptual biases enter the engineering and modeling processes themselves, and an inability to properly validate model performance leaves these biases exposed during deployment [61, 102, 110, 111]. These biases collide with the cognitive biases of the individuals interacting with the AI systems as users, experts in the loop, or other decision makers. Teams that develop and deploy AI often have inaccurate expectations of how the technology will be used and what human oversight can accomplish, especially when deployed outside of its original intent [112, 113]. Left unaddressed, these biases and accompanying contextual factors can combine into a complex and pernicious mixture. These biases can negatively impact individuals and society by amplifying and reinforcing discrimination at a speed and scale far beyond the traditional discriminatory practices that can result from implicit human or institutional biases such as racism, sexism, ageism or ableism.

2.3 A Socio-technical Systems Approach

Likely due to expectations based on techno-solutionism and a lack of mature AI process governance, organizations often default to overly technical solutions for AI bias issues. Yet, these mathematical and computational approaches do not adequately capture the societal impact of AI systems [61, 73, 75, 111]. The limitations of a computational-only perspective for addressing bias have become evident as AI systems increasingly expand into our lives.

The reviewed literature suggests that the expansion of AI into many aspects of public life requires extending our view from a mainly technical perspective to one that is socio-technical in nature, and considers AI within the larger social system in which it operates [7, 19, 31, 37, 74, 75, 78, 114–119]. Using a socio-technical approach to AI bias makes it possible to evaluate dynamic systems of bias and understand how they impact each other and under what conditions these biases are attenuated or amplified. Adopting a socio-technical perspective can enable a broader understanding of AI impacts and the key decisions that happen throughout, and beyond, the AI lifecycle–such as whether technology is even a solution to a given task or problem [3, 108]. Reframing AI-related factors such as datasets, TEVV, participatory design, and human-in-the-loop practices through a socio-technical lens means understanding how they are both functions of society and, through the power of AI, can impact society. A socio-technical approach also enables analytic approaches that take into account the needs of individuals, groups and society.

Techno-solutionism
As computational technologies have evolved, there has been an increasing tendency to believe that technical solutions alone are sufficient for addressing complex problems that may have social, political, ecological, economic, and/or ethical dimensions. This approach to problem-solving, often termed techno-solutionism,[120] assumes that the "right" code or algorithm can be applied to any problem and ignores or minimizes the relevance of human, organizational, and societal values and behaviors that inform design, deployment, and use of technology.

In the context of socio-technical AI systems, techno-solutionism promotes a viewpoint that is too narrow to effectively address bias risks. One control, for example, used in model risk management to mitigate against techno-solutionism and other anti-patterns, is to establish, document, and review the anticipated real-world value of an AI system.

Socio-technical approaches in AI are an emerging area, and identifying measurement techniques to take these factors into consideration will require a broad set of disciplines and stakeholders. Identifying contextual requirements for evaluating socio-technical systems is necessary. Developing scientifically supportable guidelines to meet socio-technical requirements will be a core focus.

AI bias extends beyond computational algorithms and models, and the datasets upon which they are built. The assumptions and decisions made within the processes used to develop technology are key factors, as well as how AI technology is used and interpreted once deployed. The idea that quantitative measures are better and more objective than other observations is known as the MCNAMARA FALLACY. This fallacy, and the related concept TECHNOCHAUVINISM [35], are at the center of many of the issues related to algorithmic bias. Traditional ML approaches attempt to turn ambiguity, context, human subjectivity, and categorical observations into objectively measurable quantities based on numerical mathematical models of their representations. This well-intentioned process enables data-driven modeling but it also inadvertently creates new challenges for socio-technical systems. Representing these complex human phenomena with mathematical models comes at the cost of disentangling the context necessary for understanding individual and societal impact and contributes to a fallacy of objectivity [121]. Science has made great strides in understanding the limitations of human cognition, including how humans perceive, learn, and store visual, aural, and textual information, and make decisions under risk. Yet, significant gaps remain. Thus, any mathematical attempt to model such human traits is limited and incomplete. This is a key challenge in model causality and predicting human interpretation of model output. And without proper governance, excising context and flattening the categories into numerical constructs makes traceability more difficult [122].

Finding approaches in TEVV to compensate for these limitations in the underlying modeling technology and bringing back the necessary context is an *important area of study.*

2.4 An Updated AI Lifecycle

Improving trust in AI by mitigating and managing bias starts with identifying a structure for how it presents within AI systems and uses. Organizations that design and develop AI technology use the AI lifecycle to keep track of their processes and ensure delivery of high-performing functional technology—but not necessarily to identify harms or manage them. This document has adapted a four-stage AI lifecycle from other stakeholder versions.[11] The intent is to enable AI designers, developers, evaluators and deployers to relate

[11] AI lifecycles utilized as key guidance in the development of the four-stage approach are: Centers of Excellence (CoE) at the U.S. General Services Administration [70] [IT Modernization CoE. (n.d.)], the Organisation for Economic Co-operation and Development [106] [Organisation for Economic Co-operation and Development. (2019).]. Another model of the AI lifecycle is currently under development with the Joint Technical Committee of the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC). *See* Information technology — Artificial intelligence — AI system life cycle processes, ISO/IEC CD 5338 (under development, 1st ed.), https://www.iso.org/standard/81118.html.

lifecycle processes with AI bias categories and effectively facilitate its identification and management. The academic literature and best practice guidelines strongly encourage a multi-stakeholder approach to developing AI applications using a lifecycle. Guidance for how organizations can enable this approach is described in Section 3.3.2 and focuses on participatory design methods such as human-centered design.

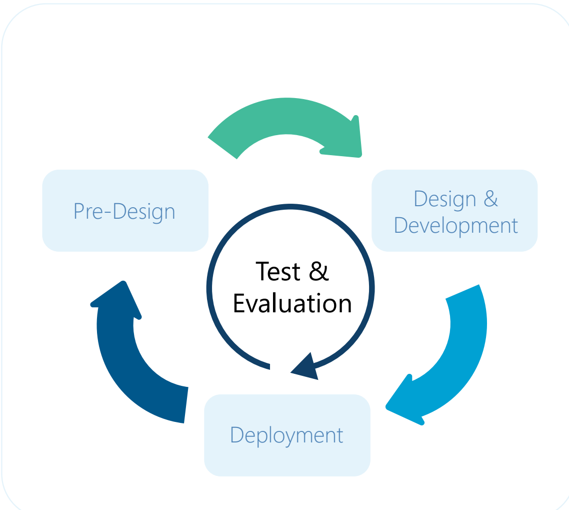


Fig. 3. The AI Development Lifecycle

AI Lifecycles are iterative, and begin in the **Pre-Design** stage, where planning, problem specification, background research, and identification of data take place. Decisions here include how to frame the problem, the purpose of the AI component, and the general notion that there is a problem requiring or benefiting from AI. Central to these decisions is who (individuals or groups) makes them and which individuals or teams have the most power or control over them. These early decisions and who makes them can reflect systemic biases within organizational settings, individual and group heuristics, and limited points of view. Systemic biases are also reflected in the datasets selected within pre-design. All of these biases can affect later stages and decisions in complex ways, and lead to biased outcomes [3, 74–78].

The **Design and Development** stage typically starts with analysis of the requirements and the available data. Based on this, a model is designed or selected. A compatibility analysis should be performed to ensure that potential sources of bias are identified and plans for mitigation are put into place. As model implementation progresses and is trained on selected data, the effectiveness of bias mitigation should be evaluated and adjusted.During development the organization should periodically assess the completeness of bias identification processes as well as the effectiveness of mitigation. Finally, at the end of the development stage, and before deployment, a thorough assessment of bias mitigation is necessary to ensure the system stays within pre-specified limits. The overall model specification must include the identified sources of bias, the implemented mitigation techniques and related performance assessments before the model can be released for deployment.

The **Deployment stage** is when the AI system is released and used. Once humans begin to interact with the AI system the performance of the system must be monitored and reassessed to ensure proper function. Teams should engage in continuous monitoring and have detailed policies and procedures for how to handle system output and behavior. System retraining may be necessary to correct adverse events, or decommission may be necessary. Since the lifecycle is iterative there are numerous opportunities for technology development teams to carry out multi-stakeholder consultation and ensure their applications are not causing unintended effects or harms. Specific guidance for governing systems under these conditions is the subject of Section 3.4.1.

The **Test and Evaluation** stage is continuous throughout the entire AI Development Lifecycle. Organizations are encouraged to perform continuous testing and evaluation of all AI system components and features where bias can contribute to harmful impacts. For example, if during deployment the model is retrained with new data for a specific context, the model deployer should work with the model producer to assess actual performance for bias evaluation. Multi-stakeholder engagement is encouraged to ensure that the assessment is balanced and comprehensive. If deviations from desired goals are observed, the findings should feed into the model **Pre-Design** stage to ensure appropriate adjustments are made in data curation and problem formulation. Any proposed changes to the design of the model should then be evaluated together with the new data and requirements to ensure compatibility and identification of any potential new sources of bias. Then another round of design and implementation commences to formulate corresponding requirements for the new model capabilities and features and for additional datasets. During this stage, the model developer should perform continuous testing and evaluation to ensure that bias mitigation maintains effectiveness in the new setting, as the model is optimized and tested for performance. Once released, the deploying organization should use documented model specifications to test and evaluate bias characteristics during deployment in the specific context. Ideally, this evaluation should be performed together with other stakeholders to ensure all previously identified problems are resolved to everyone's satisfaction.

> The most accurate model is not necessarily the one with the least harmful impact [123].

3. AI Bias: Challenges and Guidance

Through a review of the literature, and various multi-stakeholder processes, including public comments, workshops, and listening sessions, NIST has identified three broad areas that present challenges for addressing AI bias. The first challenge relates to **dataset** factors such as availability, representativeness, and baked-in societal biases. The second relates to issues of measurement and metrics to support testing and evaluation, validation, and verification (**TEVV**). The third area broadly comprises issues related to **human factors**, including societal and historic biases within individuals and organizations, as well as challenges related to implementing human-in-the-loop. This section outlines some key challenges associated with each of these three areas, along with recommended guidance.

It must be noted that TEVV does not amount to a full application of the scientific method. TEVV is an engineering construct that seeks to detect and remediate problems in a post-hoc fashion. The scientific method compels more holistic design thinking through rigorous experimental design, hypothesis generation, and hypothesis testing. In particular, anecdotal evidence and the frequency of publicly-recorded AI bias incidents indicate that solid experimental design techniques that focus on structured data collection and selection and minimization of CONFIRMATION BIAS are being downplayed in many AI projects. CONSTRUCT VALIDITY is particularly important in AI system development. AI development teams should be able to demonstrate that the application is measuring the concept it intends to measure. It is important for all stakeholders, including AI development teams, to know how to evaluate scientific claims. That said, all the bias mitigants and governance processes outlined in this document do show promise. Interestingly, they are often borrowed from practices outside of core AI and ML — even technical guidance related to improved experimental design and more rigorous application of the scientific method. None are a panacea. All have pitfalls. NIST plans to work with the trustworthy and responsible AI communities to explore the proposed mitigants and governance processes, and build associated formal technical guidance over the coming years in concert with these communities.

> The challenge of bias in AI is complex and multi-faceted. While there are many approaches for mitigating this challenge there is no quick fix.The recommendations in this document include a sampling of potentially promising techniques. These approaches, individually or in concert, are not a panacea against bias and each brings its own strengths and weaknesses.

3.1 Who is Counted? Datasets in AI Bias

3.1.1 Dataset Challenges

AI design and development practices rely on large scale datasets to drive ML processes. This ever-present need can lead researchers, developers, and practitioners to first "go where the data is," and adapt their questions accordingly [124]. This creates a culture focused more on which datasets are available or accessible, rather than what dataset might be most suitable [108]. As a result, the data used in these processes may not be fully representative of populations or the phenomena that are being modeled. The data that is collected can differ significantly from what occurs in the real world [76, 77, 117]. For example, sampling bias occurs when data is collected from responses to online questionnaires or is scraped from social media. The datasets which result are based on samples that are neither randomized nor representative of a population other than the users of a particular online platform. Such datasets are not generalizable, yet frequently are used to train ML applications which are deployed for use in broader socio-technical contexts, even though data representing certain societal groups may be excluded [116]. Systemic biases may also be manifested in the form of availability bias when datasets that are readily available but not fully representative of the target population (including proxy data) are used and reused as training data. Disadvantaged groups including indigenous populations, women, and disabled people are consistently underrepresented [37, 116, 125, 126]. Similarly, datasets used in natural language processing (NLP) often differ significantly from their real-world applications, [127] which can lead to discrimination [128] and systematic gaps in performance. Other issues arise due to the common ML practice of reusing datasets. Under such practices, datasets may become disconnected from the social contexts and time periods of their creation. Scholars are beginning to examine the ethical and adverse impact implications of using data collected at a specific time for a specific purpose for uses that were not originally intended. Decontextualizing data raises questions related to privacy, consent, and internal validity of ML model results [129].

Even when datasets are representative, they may still exhibit entrenched historical and systemic biases, improperly utilize protected attributes, or utilize culturally or contextually unsuitable attributes. Developers sometimes exclude protected attributes, associated with social groups which have historically been discriminated against. However, this does not remedy the problem, since the information can be inadvertently inferred in other ways through proxy or latent variables. Latent variables such as gender can be inferred through browsing history, and race can be inferred through zip code. So models based on such variables can still negatively impact individuals or classes of individuals [73]. Thus, the proxies used in development may be both a poor fit for the concept or characteristic seeking to be measured, and reveal unintended information about persons and groups. There is also sensitivity related to attributes and inferences that do not receive protection under civil rights laws, but which may enable discrimination when inferred and used by an ML model, such as low income status. Alternately, when there is not sufficient knowledge or awareness of the socio-technical context of a process or phenomenon, the attributes that are collected for use in an ML application may not be universally applicable for modeling the different social groups or cultures who are analyzed using the application. For example, using (past) medical costs to predict the need for future health interventions leads to severe under-prediction of healthcare needs in groups that do not have sufficient access to health care, such as African Americans [14].

Protected attributes: A host of laws and regulations have been established to prohibit discrimination based on grounds such as race, sex, age, religious affiliation, national origin, and disability status, among others. Local laws can apply protections across a wide variety of groups and activities.

Once end users start to interact with an AI system, any early design and development decisions that were poorly or incompletely specified or based on narrow perspectives can be exposed, leaving the process vulnerable to additive statistical or human biases [77]. By not designing to compensate for activity biases, algorithmic models may be built on data from only the most active users, likely creating downstream system activity that does not reflect the intended or real user population [130, 131] resulting in potentially harmful impacts. In one example, by considering that ads for jobs in Science, Technology, Engineering and Mathematics (STEM) might be seen most often by men due to how marketing algorithms optimize for cost in ad placement, the women who were the intended audience of the ads never saw them [132] cf., VIGNETTE for details. Furthermore, feedback loops can result in disparity amplification in which marginalized individuals or groups are less likely to use an AI system and the subsequent training data are based on the most frequent users. For example, non-native English speakers are less likely to use a voice-enabled personal assistant and people living in transit deserts are often dependent on ride-hailing services. So, the experiences of these groups do not match the intended purpose or operation of the AI system.

3.1.2 Dataset Guidance

A key question that must be asked for the development and deployment of an AI system is: *do datasets exist that are fit or suitable for the purpose of the various applications, domains and tasks for which the AI system is being developed and deployed?* Not only is the predictive behavior of the ML system determined by the data, but the data also largely defines the machine learning task itself [61]. The question of dataset fit or suitability requires attention to three factors: statistical methods for mitigating representation issues; processes to account for the socio-technical context in which the application is being deployed; and awareness of the interaction of human factors with the AI technical system at all stages of the AI lifecycle. When datasets are available, the set of metrics for demonstrating fairness are many, context-specific, and unable to be reduced to a concise mathematical definition [133].

Statistical Factors AI bias problems are exacerbated by the variety of statistical biases that are prevalent in the large scale datasets used in ML modeling. When these models are deployed for decision-based applications, often in high-risk settings and off-label uses, harms can be perpetuated and amplified.

A major trend for addressing AI bias is to focus on balanced statistical representation in the datasets used in modeling processes. Simple but effective techniques, such as class imbalance measures or label imbalance measures, or analysis using statistical phenomena such as SIMPSON'S PARADOX,[134] can be used to detect bias in datasets, and sometimes help mitigate it [85, 135–138]. Numerous studies and software libraries invoke data rebalancing processes (e.g., [139]). Causal models and graphs may also be used to detect direct discrimination in the data [61, 85].

Generalized linear models require that variables are independent with little multicollinearity and that residuals are normally distributed and homoscedastic. Furthermore, common algorithmic techniques such as L^1 and L^2 regularization in ML cost functions assume that the variables are unimodal. However, data is often heterogeneous and multimodal especially when populations are not disaggregated by gender, age, race, or income.

Thus, it is important to document and communicate the limitations of the applicability of AI outputs, whether a model is used for benchmarking, prediction, or classification. In many cases, practitioners train models on benchmark datasets and use them on real data in specific applications. However, it may not be possible to fully address mathematically the imbalances in representation and the heterogeneous nature of real-world heterogeneous datasets. A recent study highlighted serious errors in commonly used benchmark dataset [140]. Consequently, a model trained on biased and erroneous data may lead to biased and inaccurate predictions. Moreover, training a model on one dataset and using it to operate on another requires special care to account for potential differences in the distributions of the datasets that may further exacerbate the unfairness and errors of the model.

Accounting for Socio-technical Factors

While statistical methods are indeed necessary, they are not sufficient for addressing the AI bias challenges associated with datasets. Modeling processes have the intent of making contextual concepts measurable. Once the context has been removed, however, it is difficult to get it back, leading AI models to learn from inexact representations. Just as building codes are designed based on general principles, but designed to incorporate the specific geographic characteristics of a region, so too must the use of datasets in ML applications be adapted to take into the full spectrum of socio-technical factors of the context in which they are deployed.

> Word embeddings represent text data as positions in a high-dimensional mathematical space. Such a representation allows arithmetic (measurable comparisons) to be performed on words [141]. However, when text data are simplified as mathematical objects, contextual information including homographs or idioms that do not fit neatly into the model may be lost. When asked to compute "doctor" - "father" + "mother" using this arithmetic, an AI system might respond with "nurse." Is the AI system's answer due to historical gender stereotypes in professions or due to the natural, close association of the gender-specific verb "nurse" with mother? In other scenarios, even when attempts are made to explicitly remove bias from training data, biases may still exist because of deep, complex connections within the text data [80, 142].

Attention to the socio-technical factors for an AI system is essential at all phases of the lifecycle, most importantly in design, development, and deployment. In the design phase, socio-technical analysis provides insights into social variations in the dynamics or characteristics of a phenomenon. This can help better frame questions for analysis and enable assessment of dataset fit. A socio-technical perspective in the development phase facilitates selection of data sources and attributes, and explicitly integrates impact assessment as a complement to algorithmic accuracy. Studies have shown how it is possible to mathematically address statistical bias in a dataset, then develop an algorithm which performs with high accuracy, yet produce outcomes that are harmful to a social class and diametrically opposed to the intended purpose of the AI system [14]. The need for new ways to measure the impact of AI systems is a current theme in the literature and the trustworthy and responsible AI research community. The practice of deploying AI in off-label uses, that is AI systems being applied to a task or within a social or organizational context for which it was not designed, must be approached with caution, especially in high-risk settings. Socio-technical analysis can help determine if such use, with modification, is both ethically and technically feasible. In all cases, a socio-technical perspective implicates adopting processes that include involving stakeholders, examining cultural dynamics and norms, and assessing societal impacts.

> AI technologies can be perfectly accurate and still contribute to harmful outcomes.

Interaction of human factors and datasets Systemic institutional biases are captured in the datasets used to build the models underlying AI applications. These biases are compounded by the decisions and assumptions made by AI design and development teams about which datasets to use [129]. These decisions affect who and what gets counted, and who and what does not get counted. The issue of "flattening" the societal and behavioral factors within the datasets themselves is problematic, but often overlooked [66, 129, 143, 144]. The problem is further exacerbated by the variety of statistical biases that are prevalent in the large scale datasets used in ML modeling.

Human biases, whether conditioned socially or unconscious cognitive bias, are factors in data selection, curation, preparation and analysis processes. A person who annotates training data (for example, for gesture recognition and sentiment analysis) may impart their own perception biases. A person who chooses which data sources and variables to leave in or take out may do so in a way that aligns with a held belief. Data typically needs to be cleaned in some way, removing outliers and spurious data. Missing data may be imputed (replacing the missing values with nearest neighbors or extrapolated values) or removed entirely. Missing data may be more frequent in marginalized populations. Furthermore, because of compounding collection biases, missing and spurious data is often not random. Data analysis decisions such as the cardinal treatment of ordinal data in a Likert-scale or rating-scale data may lead to a biased estimator [145]. Processes for documenting potential sources of human bias are essential but often overlooked elements for characterizing AI model transparency and explainability, in addition to addressing AI bias and fairness. As with statistical factors and socio-technical analysis, incorporating awareness and documentation in the AI lifecycle helps to define limitations and ensure ethically and socially appropriate uses that do not perpetuate or amplify harms. See Section 3.3 for a more thorough discussion of challenges and guidance related to human factors and AI bias.

3.2 How do we know what is right? TEVV Considerations for AI Bias

3.2.1 TEVV Challenges

Delegating decision-making to algorithms is appealing because ML systems produce more consistent decisions compared to humans [146]. However, AI systems do not work in a vacuum. Operational context, such as the jurisdiction and industry vertical in which a system operates, serves to frame fairness goals. Even the algorithm itself relies on data for training and performance tuning, which in turn can be assessed by a fairness metric. Therefore, when we consider the computational approaches to mitigating bias, we must take into consideration these three components together: algorithms, data, and fairness metrics.

AI systems regularly model concepts that are—at best—only partially observable or capturable by data. Without direct measures for these highly complex considerations, AI development teams use proxies, which can create many risks [147]. For example, for "criminality," a measurable index or construct, might be created from other information, such as arrests and convictions, which are used as PROXY variables for predicting a certain outcome—in this case, whether a certain individual is likely to be a repeat offender. In algorithmic hiring, an AI system might be developed using input variables such as "length of time in prior employment," "productivity," and "number of lost hours" as measurable proxies in lieu of the not directly measurable concept of "employment suitability." The algorithm might also include a predictor variable such as distance from the employment site [148] because it might correlate with employees quitting their job due to long commutes or bad traffic. However, since "distance from the employment site" might disadvantage candidates from certain neighborhoods, and "length of time in prior employment" might disadvantage candidates who are unable to find stable transportation (or relate to other socio-economic factors) the AI system will contribute to biased outcomes.

Epistemic and aleatoric uncertainty

ML distinguishes two types of predictive uncertainty: EPISTEMIC and ALEATORIC [149]. For example, models produced by deep learning ML systems exhibit epistemic uncertainty in the parameters of the computed model. The model parameters are typically computed as the result of a nonconvex minimization of an appropriately chosen cost function. It is well known from mathematics that such a formulation of the problem does not have a unique solution [150, 151]. While epistemic uncertainty can be reduced by increasing the amount of representative training data, it cannot be fully eliminated. This can impact the behavior of a deep learning system in deployment when used with real-world data, especially when there is a mismatch in the distributions of the real and training data [102]. This can lead to undesirable effects on many of the AI system's critical attributes (e.g., robustness, resilience), including inducing harmful bias. Even convex problems (e.g., multiple linear regression) may suffer from epistemic uncertainty when a decision variable is not included in the model.

Another inherent type of uncertainty associated with machine learning is ALEATORIC.

It represents the uncertainty inherent in the data, e.g., the uncertainty in the label assigning process of the training dataset. Aleatoric uncertainty is the irreducible part of the predictive uncertainty. Since these two types of uncertainties (EPISTEMIC and ALEATORIC) are highly context-dependent, changing the context may blur the difference between them or even cause one to turn into the other. Thus, their characterization as reducible and irreducible is not absolute. For example, datasets containing overlapping samples with different attributes could be embedded into higher dimensions so that the samples are clearly separated, thus reducing aleatoric uncertainty at the expense of epistemic uncertainty - because the model would likely overfit the existing data in the larger space. Some of the difficulty in distinguishing epistemic and aleatoric uncertainty is that ML models are (implicit) mathematical representations of the data on which they are trained [152].

The growth of Large Language Models

Large LANGUAGE MODELS (LLMs) have become the dominant trend in deep learning today and are expected to continue to grow in importance [103, 153]. Although LLMs have been able to achieve impressive advances in performance on a number of important tasks, they come with significant risks that could potentially undermine public trust in the technology. LLMs create significant challenges for both EPISTEMIC and ALEATORIC uncertainty. Relying on large amounts of uncurated web data increases aleatoric uncertainty [154]. In-depth knowledge of the data and its statistical properties is critically important for detecting bias in the predictive output of ML models.

> Identifying sources of bias is the first step in any bias mitigation strategy.

Epistemic uncertainty and large-scale AI models
With the availability of large and fast computing resources, massive artificial neural networks are becoming increasingly common. In particular, some language models now consist of trillion-dimensional parameter spaces trained on hundreds of gigabytes of data. The training data, often scraped from internet sources, commonly has known gender, racial, cultural, and socio-economic biases [154, 155]. Alternative approaches to large-sized language datasets have been proposed to mitigate harmful bias, but such an approach may introduce other human biases in the selection of values-targeted datasets. Beyond the systemic and selection biases, large language models also highlight EPISTEMIC UNCERTAINTY. Stochastic gradient descent (or other accelerated methods) methods [151] are used to find a set of parameters that minimize a cost function associated with the model, but deep neural networks exhibit complicated nonlinearities which result in many potential local minima. A trillion-dimensional manifold may have a huge, unknown number of minima [156]. Furthermore, to fit these parameters into computer memory, it is often necessary to use half-precision floating-point numbers [157], introducing rounding error which may undermine stability in the numerical methods [158]. As a result, the model may demonstrate unknown and erratic behavior and challenges for reproducibility and explainability [159].

In the quest for fitting larger and larger models into existing finite computational resources, LLMs rely on techniques, e.g., reduced-precision numerical representations of models, that further increase the epistemic uncertainty of deep learning models, [160] cf., VIGNETTE. Early practice has shown that concerns about the use of LLMs are indeed valid, with preliminary experimental results showing LLMs exhibit significant bias [154, 161, 162]. To reduce risks from the use of LLMs, future work in this area should move towards efforts to fully understand and characterize their behavior, and to devise effective mitigation measures against the biases they bring.

Processes
While datasets exhibit numerous biases that lead to harmful impacts, they feed directly into other system level processes that determine what is important to model. For AI systems to determine this importance, and effectively categorize and sort the firehose of data for downstream recommendations and decisions, contextual information is flattened and unobservable phenomena are quantified through the development of indices and use of proxies. The use of data attributes with names like “criminality,” “hireability,” “creditworthiness,” or similar can be indicative of experimental design problems that give rise to harmful bias.

The software designers and data scientists working in design and development are often highly focused on system performance and optimization. This focus can inadvertently be a source of bias in AI systems. For example, during model development and selection, modelers will almost always select the most accurate models. Yet, as Forde et al describe in their paper, [163] selecting models based solely on accuracy is not necessarily the best approach for bias reduction. Furthermore, the choice of the model's objective function, upon which a model's definition of accuracy is based, can reflect bias. Not taking context into consideration during model selection can lead to biased results for sub-populations (for example, disparities in health care delivery). Relatedly, systems that are designed to use aggregated data about groups to make predictions about individual behavior—a practice initially meant to be a remedy for non-representative datasets[18]—can lead to biased outcomes. This bias, known as ECOLOGICAL FALLACY, occurs when an inference is made about an individual based on their membership within a group (for example, predicting college performance risk based on an individual's race [52]). These unintentional weightings of certain factors can cause algorithmic results that exacerbate and reinforce societal inequities.

> Natural language processing (NLP) is a powerful computational approach to allow machines to meaningfully understand human spoken and written languages. Powering activities such as algorithmic search, speech translation, and even conversational text generation, NLP is able to help us communicate with computer systems to carry out a variety of tasks. The set of harms that can arise from the use of NLP however has become a recent concern in the area of trustworthy AI [80, 90, 154, 164, 165]. Hovy and Prabhumoye describe five sources of bias in NLP and potential ways to counteract it [166].

Spurious Correlations

The speed and scope of machine learning processes can unfortunately expand the development of systems based on questionable scientific underpinnings that learn spurious correlations related to human characteristics. For example, the German public radio outlet BR24 examined a system that purportedly assessed tone of voice, language, gestures, and facial expressions to create a personality profile for use in hiring processes [6]. The analysis showed the AI system was easily manipulated by superficial changes to its inputs, awarding candidates higher scores when they wore glasses or when a bookshelf was in the background, diminishing claims that the system analyzed human expressions, and raising concerns about shortcut learning [167]. Indeed, many AI systems now attempt to make inferences about individuals based on their facial characteristics that are not scientifically supportable, such as their propensity for committing crimes or even their sexual orientation [121, 168–172]. The basis for drawing conclusions about emotional state from facial characteristics ranges from unscientific and debunked theories to emerging experimental studies [173], presenting concerning challenges to AI systems that claim to make such judgements. By mechanizing human characteristics these systems can obfuscate significant uncertainty and result in harmful biases. AI-based hiring systems that claim to glean information about candidates from audio and video have been shown to increase bias in outcome decisions and may present untenable trade-offs between bias mitigation and prediction accuracy [174]. AI systems marketed as making predictions based on facial expressions often generate decisions based on biased experimental design premises [168] or spurious patterns learned by the system (e.g., shortcut learning). These cases illustrate the risks associated with using AI systems for tasks like sentiment or affect analysis, along with using systems to infer spurious correlations more broadly, which can perpetuate biases across groups and, in several instances can be scientifically unsound [175]. AI systems in consequential or sensitive areas should not be built on the basis of spurious correlations. They can provide faux-objective justification for biased outcomes. A socio-technical perspective broadens awareness of these risky computational approaches.

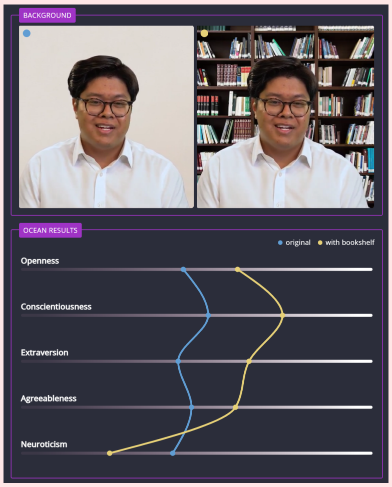


Fig. 4. The output of an AI system altered by background content.

The rise of predictive analytics as a mechanism for identifying patterns in human behavior is a recent example of a process that can produce biased outcomes and therefore should be used carefully. These applications can be highly effective at identifying key insights in data that are unable to be gleaned by humans [176]. This technology is also often presented and perceived as a way to reduce human cognitive biases and make decisions more fair and objective [27, 177, 178]. In well defined and constrained settings these technologies can result in accurate and fair outcomes. However, the assumption that AI-based systems are more objective, especially in high stakes decision making, remains unclear. Categorizing unobservable behavior and phenomena leads to increased uncertainty in system performance. Measuring whether the patterns identified by these applications are real or a result of spurious correlations is difficult. Adding to the challenge is the reality that these systems are built and placed within organizational settings along with their accompanying — often unstated — policies and priorities, and used by subject matter experts and decision makers who have their own implicit heuristics and biases [179]. A fallacy of objectivity can often surround these processes, and may create conditions where technology's capacity and capabilities are oversold [121]. See VIGNETTE for an example.

Algorithmic effects

Algorithmic complexity can vary greatly across AI models. The number of parameters, which mathematically encode the training data, may be as few as one and as many as one trillion. Simple models with fewer parameters are often used because they tend to be less expensive to build, more explainable and more transparent, and easier to implement. However, such models can exacerbate statistical biases because restrictive assumptions on the training data often do not hold with nuanced demographics. Furthermore, designers who must make decisions on what variables to include or exclude can impart their own cognitive biases into the model [110, 180]. Complex models are often used on nonlinear, multimodal data such as text and images. Such models may capture latent systemic bias in ways that are difficult to recognize and predict. Expert systems, another AI paradigm, may encode cognitive and perceptual biases in the knowledge accumulated by practitioners from which the system is designed to emulate.

Validity

Ultimately, AI systems should demonstrate that they perform accurately, but how do we know what constitutes a "right answer"? Validating performance is a difficult but necessary endeavor for any system being deployed to the public and effective management and mitigation of AI bias. Many difficulties and flaws can arise in system validation. A common challenge in system testing is a lack of ground truth, or noisy labeling and other annotation factors which make it difficult to know what is accurate. The use of proxy variables compounds this difficulty, since what is being measured isn't directly observable. Performing system tests under optimal conditions — or conditions that are not close to the deployed state — is another challenging design flaw. System performance metrics are also difficult to generalize and can lead to issues with unintended use. Due to these challenges, subject matter experts should be relied upon during validation to create and oversee the most realistic possible validation processes [102]. Also the practice of "stratified performance evaluations," [102] where system performance is analyzed across segments in the training or test data, whether demographic segments or otherwise, is a basic consideration for understanding system validity across a population of users.

Validation and deployment

Validation also means ensuring that the system is not being used in unintended ways. DEPLOYMENT BIAS happens when an AI model is used in ways not intended by developers. Emergent bias happens where the model is used in unanticipated contexts. Developers of an algorithm used by major U.S. cities to assist in coordinating housing to homeless people began phasing it out after several cities inappropriately used the algorithm as an assessment tool rather than as the presecreening tool as it was designed [181]. In another instance, the Chicago Police Department decommissioned an algorithm designed to predict the risk that an individual might be involved in future gun violence, citing unintended use and misapplication of the model [182].

It is not uncommon for deployment to be used as system testing. Depending on the context, institutional review may not be required to carry out this type of testing [183]. Without system validation, an AI system could be released that is technically flawed or fails to establish appropriate underlying mechanisms for proper functioning [184–186]. A system could be deployed in a negligent manner, be based on pseudoscience or spurious correlations, prey on the user, or generally exaggerate claims. In such cases, the goal should not be to ensure applications are bias-free, but to reject the development outright in order to prevent disappointment or harm to the user as well as to the reputation of the provider. Such systems may also run afoul of existing legal frameworks that proscribe unfair, deceptive, and predatory practices (UDAP).[12] This type of scenario may reinforce public distrust of AI technology since untested or technically flawed systems can contribute to bias and other harmful outcomes.

AI systems as magic

A further validation challenge of AI systems stems from their accessibility and hype. Physicist Richard Feynman referred to practices that superficially resemble science but do not follow the scientific method as cargo cult science. A core tenet of the scientific method is that hypotheses should be testable, experiments should be interpretable, and models should be falsifiable or at least verifiable. Commentators have drawn similarities between AI and cargo cult science citing its black box interpretability, reproducibility problem, and trial-and-error processes [187, 188]. High-level machine learning libraries and reduced costs of cloud computing have made AI more affordable and easier to develop. As a result, AI development is becoming increasingly democratized. Still, AI itself remains largely opaque—deep neural networks and Bayesian inference require advanced mathematics to understand. The DUNNING–KRUGER EFFECT is a cognitive bias in which a person with limited knowledge in a domain may vastly overestimate their understanding of that domain.

[12] *See, e.g.,* Federal Trade Commission Act, Section 5.

> Even among experts, data-driven technologies can exacerbate CONFIRMATION BIAS, particularly when they are implicitly guided by expected outcomes. An analysis that examined hundreds of AI algorithms for identifying COVID found that few of them were effective [189].

The danger is that with enough tweaking of hyperparameters across many candidate AI models, one of them may appear to be highly accurate even when measured against standard performance datasets. DATA DREDGING (also known as p-hacking) is a statistical bias in which testing huge numbers of hypotheses of a dataset may appear to yield statistical significance even when the results are statistically nonsignificant.

Fig. 5 provides examples of how the three categories of bias — systemic, statistical and computational, and human - interact and contribute to harms within the data and processes used in AI applications, and the validation procedures for determining performance.

	Systemic Biases	Statistical and Computational Biases	Human Biases
Datasets *Who is counted, and who is not counted?*	Issues with latent variables Underrepresentation of marginalized groups	Sampling and selection bias Using proxy variables because they are easier to measure Automation bias	Observational bias (streetlight effect) Availability bias (anchoring) McNamara fallacy
Processes and Human Factors *What is important?*	Automation of inequalities Underrepresentation in determining utility function Processes that favor the majority/minority Cultural bias in the objective function (best for individuals vs best for the group)	Likert scale (categorical to ordinal to cardinal) Nonlinear vs linear Ecological fallacy Minimizing the L1 vs. L2 norm General difficulty in quantifying contextual phenomena	Groupthink leads to narrow choices Rashomon effect leads to subjective advocacy Difficulty in quantifying objectives may lead to McNamara fallacy
TEVV *How do we know what is right?*	Reinforcement of inequalities (groups are impacted more with higher use of AI) Predictive policing more negatively impacted Widespread adoption of ridesharing/self-driving cars/etc. may change policies that impact population based on use	Lack of adequate cross-validation Survivorship bias Difficulty with fairness	Confirmation bias Automation bias

Fig. 5. How biases contribute to harms

3.2.2 TEVV Guidance

To mitigate the risks stemming from epistemic and aleatoric uncertainties, model developers should work closely with the organizations deploying them. Teams should work to ensure periodic model updates, and test and recalibrate model parameters on updated representative datasets to meet the business objectives while staying within desired performance targets and acceptable levels of bias. From a Bayesian inference perspective, this can be seen as updating the prior of the model to help avoid issues that may arise from using stale priors. Organizations are recommended to employ appropriate governance procedures to adequately capture this cross-organizational need and ensure no negative impacts from using the AI technology.

Algorithms

In ML, it is not meaningful to assign bias to the model or algorithm itself without contextual information about the specific tasks on which they may be used. This links the model and algorithm to the dataset on which they are trained and tested (see VIGNETTE for how contextual factors can play a role in bias). The catchphrase "bias in, bias out" is widely used to describe the heavy dependence of the algorithmic behavior on the data. For example, in a natural language processing context, hate speech detection models use dialect markers as toxicity predictors, which can result in bias against minority groups [190]. In another context, an algorithm designed to deliver gender-neutral advertisements about jobs in STEM resulted in gender bias due to younger women being considered a valuable subgroup and more expensive as the targets for advertisements [85, 132].

Methods that help to reduce algorithmic bias are another helpful construct for understanding it. Specific methods for algorithmic mitigation of bias for many different machine learning tasks have been delineated or surveyed in recent studies [85, 191–194]. When considering approaches to mitigating algorithmic bias in a specific task context, recent literature categorizes debiasing methods into one of three categories [61, 85, 191, 194]:

1. **Pre-processing**: transforming the data so that the underlying discrimination is mitigated. This method can be used if a modeling pipeline is allowed to modify the training data.

2. **In-processing**: techniques that modify the algorithms in order to mitigate bias during model training. Model training processes could incorporate changes to the objective (cost) function or impose a new optimization constraint.

3. **Post-processing**: typically performed with the help of a holdout dataset (data not used in the training of the model). Here, the learned model is treated as a black box and its predictions are altered by a function during the post-processing phase. The function is deduced from the performance of the black box model on the holdout dataset. This technique may be useful in adapting a pre-trained large language model to a dataset and task of interest.

The limits of algorithmic transparency in eliminating bias
Automated decision-making is appealing but comes with risks that can result in discriminatory outcomes. Researchers investigated settings where ads are allocated by algorithm and found instances where historically–discriminated–against–groups are less likely to see desirable ads [132]. In this setting, a field test was performed with an ad that was intended to promote job opportunities and training in STEM. The STEM career ad campaign was motivated by widespread concern about a shortage of underrepresented groups in the STEM sector, particularly women. The assumption is that disseminating information about STEM careers to women and encouraging women to enter this field helps to address this problem. However, since women are far more likely to make decisions about household purchases, they are more valuable targets for advertising, creating pricing differentials for ad displays. The result of the ad campaign was that 20%+ more men than women viewed the ad, with the largest difference in the 25-54 year old age group.
The findings in this study help demonstrate the difficulty of evaluating algorithms for preventing discrimination, and the need for a socio-technical lens on the challenge. It is insufficient to look for bias in the algorithm alone. Relatedly, according to Lambrecht [132]:

"One popular policy prescription has been a focus on algorithmic transparency where algorithmic codes are made public. Such policies are gaining increasing momentum - for example, the Federal Trade Commission (FTC) launched a new unit focused on algorithmic transparency, ... however, that algorithmic transparency would not have helped regulators to foresee uneven outcomes. The reason is that an examination of the algorithmic code would likely have revealed an algorithm focused on minimizing ad costs for advertisers. Without appropriate knowledge about the economic context and how such cost–minimization might affect the distribution of advertising, such 'transparency' would not have been particularly helpful."

While transparency into AI system mechanisms is rarely a direct bias mitigant, as explained above, transparency enables many critical AI governance functions. Transparency is very important, but should not be mistaken for fairness.

In sectors of the U.S. economy where the Equal Credit Opportunity Act,[13] influential court cases,[14] or other legal and regulatory matters invoke the legal doctrine of Disparate Treatment, debiasing efforts may be less likely to explicitly include pre-, in-, and post-processing approaches, and instead rely on alternative modeling approaches. In consumer

[13] CFPB Supervision & Examination Manual, pt. II, § C, Equal Credit Opportunity Act (Oct. 2015).
[14] *e.g.*, Ricci v. DeStefano, 557 U.S. 557 (2009).

finance and employment litigation, where the practice of bias remediation, e.g., debiasing, has been pursued for decades, practitioners are more likely to consider adjustments to input variables or model hyperparameters to improve bias testing results or real-world outcomes. Demographic group membership, necessary for bias testing purposes, is often inferred using the Bayesian improved surname geocoding (BISG) process (see [195]).

> Modeling algorithms or debiasing techniques that rely on demographic information, as most pre-, in-, and post-processing methods do, may pose higher risks in regulated environments where disparate treatment must be avoided [196].

Fairness metrics

From a computational standpoint, defining a fairness metric for ML requires developing a formal mathematical model to achieve desired predictive goals on a given dataset and associated task. Numerous fairness metrics are proposed in the literature [85, 191, 194, 197–199]. Much of the work in determining fairness criteria involves supervised learning, but the labeled data required for these tasks may not be readily available. This is particularly true for large language models, where the sheer scale of the datasets used for training is prohibitive for proper data labeling. This has a direct impact on both representativeness of the training data and, in turn, its impact on the representativeness of the generated model might exacerbate discriminatory outcomes, as large language models are adapted to specific datasets and tasks. Moreover, even if datasets are representative they may still exhibit biases or improperly utilize protected attributes, which in turn may lead to discrimination. Proxies may be used for hiding protected attributes and care should be taken to avoid discrimination resulting from badly chosen proxies [59, 136, 147, 200, 201]. And, even if proxies are used to hide protected attributes, they may still reveal sensitive information about individuals or groups [195, 202].

Recent literature [203] considers alternative learning tasks, e.g. unsupervised learning and reinforcement learning where only intermediate feedback is provided to the model, and tries to balance the effects of short- and long-term rewards. Several open questions still remain about the use and representativeness of synthetically generated data, in applications where little data is available. An emerging related line of research is to use simulations to evaluate the long-term impact of machine learning systems by incorporating elements of system level dynamics, feedback loops, and other long-term effects to make fair decisions in dynamic environments [204].

> Another challenge, with serious social ramifications, is how to measure fairness in the emergent class of deployed generative models, such as large language models, computer vision systems, or deep fakes, whose outputs are free form text, audio or video [205].

While academic research into mathematical notions of fairness has blossomed in recent years, procedures for testing fairness in regulatory and litigation settings such as employment and consumer finance have been operational for decades, and reached a level of maturity before the recent increase in interest on the topic. In these areas, statistical tests can be applied to determine whether some automated decision-making system is acting outside the bounds of applicable law. t-tests, χ^2-tests, analysis of regression coefficients, and other traditional statistical tests can be used to show a statistically significant difference between ML system outcomes across demographic groups. In some cases, measurements of differential validity are also used to ensure that applicants and employees receive roughly equal service from systems in employment, where system performance quality is evaluated across demographic groups.[15]

Credible attempts at bias mitigation should maintain alignment with acknowledged legal standards.

Generally, the majority of fairness metrics are observational as they can be expressed using probability statements involving the available random variables [61]. These metrics can be classified into many categories: fairness through unawareness, individual fairness, demographic parity, disparate impact, differential validity, proxy discrimination, equality of opportunity, etc. However, not all critically important lines of inquiry can be answered through observations alone. Moreover, depending on the relationship between a protected attribute and the data, certain observational definitions of fairness can increase discrimination. Hence, research to improve fairness metrics continues. For instance, a counterfactual fairness definition has been developed [199] to capture the intuition that a decision is fair towards an individual if it is the same in both the actual world and a counterfactual world—where the individual belongs to a different demographic group. Simulations can also be used to gain counterfactual information about how the data would have varied if a different data collection or decision-making policy had been in place [204]. As algorithmic discrimination can arise from the encoding of spurious correlations and noisy local dependencies into ML systems during training, there is currently great focus on causal tools [206] and how they can formally incorporate effects of hypothetical actions to solve a wide range of fairness modeling problems. Until causal methods are more widely available and adopted, minimizing the number of input variables, and ensuring that there is no strong correlation amongst them and a logical relationship to the prediction target, is a mitigation tactic for proxy discrimination and other AI risks.

[15] *See, e.g.,* U.S. v. Ga. Power Co., 474 F.2d 906 (5th Cir. 1973).

When deciding which fairness metric to adopt, it is important to recognize the impossibility of satisfying certain mathematical fairness constraints at once except in highly constrained special cases [207]. For example, there is an inherent incompatibility between two conditions: calibration and balancing the positive and negative classes. These conditions cannot be satisfied simultaneously unless under certain constraints [78]. While not all mathematical fairness desiderata can be achieved simultaneously, it is important to note that mitigated bias and good performance can be achieved simultaneously [208].

The plethora of fairness metric definitions illustrates that fairness cannot be reduced to a concise mathematical definition. Fairness is dynamic, social in nature, application and context specific, and not just an abstract or universal statistical problem. Therefore, it is important to adopt a socio-technical approach to fairness in order to have realistic fairness definitions for different contexts as well as task-specific datasets for machine learning model development and evaluation.

3.3 Who makes decisions and how do they make them? Human Factors in AI Bias

3.3.1 Human Factors Challenges

As ML algorithms have evolved in accuracy and precision, computational systems have moved from being used purely for decision support—or for explicit use by and under the control of a human operator—to automated decision making with limited input from humans. Computational decision support systems augment another, typically human, system in making decisions. Comparatively, for algorithmic decision systems there is less human involvement, with the AI system itself more in the “driver’s seat,” and able to produce outcomes with little human involvement to govern the impact. The growth and prevalence of algorithmic decision systems has helped to drive a decreased sense of trust in AI among the public [209]. This distrust is exacerbated by the reality that historical and social biases are baked-in to the data and assumptions used in the algorithmic models generating automated decisions. As a result, these algorithmic models have a higher probability of producing and amplifying unjust outcomes (e.g. for racial and ethnic minorities in areas such as criminal justice) [18–30, 210]. The systemic biases embedded in algorithmic models can also be exploited and used as a weapon at scale, causing catastrophic harm [211–214]. Organizations that deploy AI models and systems without assessing and managing these risks can not only harm their users but jeopardize their reputations.

Deployment Context of Use

AI systems are designed and developed to be used in specific real world settings, but are often tested in idealized scenarios. Once deployed, the original intent, idea, or impact assessment can drift as the application is repurposed or used in unforeseen ways, and in settings or contexts for which it was not originally intended. Different deployment contexts means a new set of risks to be considered. Engaging with the broad set of stakeholder communities that may be impacted by the deployment of these technologies—before the decision is made to build the AI system—is an important consideration and strongly recommended. For more on context of use and what it encompasses from a human-centered design perspective, see subsequent Section 3.3.2.

One major purpose, and a significant benefit, of automated technology is that it can make sense of information more quickly and consistently than humans. AI systems are also often perceived as a way to make public interest decisions more fair, or to reduce (or eliminate) biased human decision making and bring about a more equitable society [27]. These perspectives have led to the deployment of automated and predictive modeling tools within trusted institutions and high-stakes settings such as hiring or criminal justice. In such settings, automated decisions that incorporate negative biases can perpetuate harms more quickly, extensively, and systematically than human and societal biases on their own.

Human-in-the-loop

Most algorithmic decision systems are socio-technical systems. They are inextricably tied to human social behavior, from the datasets used by ML processes and the decisions made by those who build them, to the interactions with the humans who provide the insight and oversight to make such systems actionable. The default assumption is that placing a human "in-the-loop" of such systems can ensure that adverse events do not occur. Current perceptions about the role and responsibility of the human-in-the-loop with AI are often implicit, and expectations about level of performance for these systems are often based on untested or outdated hypotheses. The bulk of academic literature available in this domain often relates to humans working with automated systems that pre-date the broad scale use of ML.

Some human-in-the-loop systems are deployed for use by subject matter experts. In this expert-driven scenario, professionals with expertise in a specific domain work in conjunction with an automated system towards a specific end goal—usually a consequential decision about another individual(s). Depending on the purpose of the system, the expert may interact with the ML model but is rarely part of the design or development of the system itself. These experts are not necessarily familiar with ML, data science, computer science, or other fields traditionally associated with AI design or development. For example, for AI systems that are deployed in the domain of medicine, the experts are the physicians and bring their expertise about medicine—not data science, data modeling and engineering, or other computational factors.

The perception that a human (expert or otherwise) can effectively and objectively oversee the use of algorithmic decision systems is a problematic assumption. More work needs to be done to understand the complex institutional and societal structures where these systems are developed and placed. Humans carry their own significant cognitive biases and HEURISTICS into the operation of AI systems and exactly how they can assist remains an understudied area. One challenge with human-in-the-loop scenarios is finding a configuration that enables a system to be used in a way that optimally leverages, instead of *replaces*, the subject matter expertise of the human. This is difficult since subject matter experts and AI developers often lack a common vernacular, which can contribute to miscommunication and misunderstood expectations and capabilities on both sides of the human-AI system.

Expert-system configurations are complex, even without the aid of a highly advanced AI. Experts and operators can often be placed into AI-based system settings without explicit declarations for governing authority over the specific task and outcome. With the promise of approaches that are more quantitative, subject matter experts may inadvertently activate the McNamara fallacy and leverage the AI system to take the pressure off of their often more subjective processes for the presumed objectivity of automation (this bias is often referred to as automation complacency). Expert users may also subconsciously find ways to leverage this perceived objectivity as cover, or even justification, for their implicit biases [215–217] and inadvertently make decisions that are inaccurate and harmful. Relatedly, AI developer communities may subconsciously presume that experts' methods have been validated to a greater degree than is the case. These kinds of implicit individual and group actions may create conditions that indirectly encourage the use of technology that is not quite ready for use, especially in high-stakes settings [3, 78, 218]. Researchers recommend that AI development teams work in tighter conjunction with subject matter experts and practitioner end users, who in turn, must "consider a deliberate and modest approach" when utilizing automated output [219].

Expert-driven ML and human-in-the-loop practices are not intended to serve as a form of oversight on AI systems and accompanying results. Experts bring their particular subject matter knowledge to the process, and are not necessarily trained to govern the use of an AI system they played no role in developing. But current legal and governance structures actively rely on humans—either expert or otherwise—to serve as a mechanism for protecting society from faulty, mistaken, and/or dangerous algorithmic decisions. The fundamental assumption of such structures is that a human overseer, simply by virtue of being human, will be able to provide adequate governance for systems.[16] The reality however is

[16]This is most frequently emphasized in governance frameworks that associate human-in-the-loop decisions as posing less risk, as opposed to fully automated decision making. See, for example, the role of general human intervention in minimizing risks for AI systems in the FDA's "Good Machine Learning Practice for Medical Device Development: Guiding Principles," https://www.fda.gov/medical-devices/software-medical-device-samd/good-machine-learning-practice-

that without significant procedural and cultural support, optimistic expectations about how humans are able to serve in this administrative capacity are not borne out in practice. The literature provides a thorough review of the flaws of human oversight policies [112].

General public
The challenge of interpretable systems is also a factor for consumer or citizen use of AI applications. It is presumed that trust can improve if the public is able to interrogate and engage with AI systems in a more transparent manner. In their article on public trust in AI, Knowles and Richards state "... members of the public do not need to trust individual AIs at all; what they need instead is the sanction of authority provided by suitably expert auditors that AI can be trusted" [220]. Developing such an authority requires standard practices, metrics, and norms from a socio-technical perspective. The NIST AI Risk Management Framework will help create standard practices, metrics and norms in consensus with the AI community.

Reliance on various downstream professionals to act as a governor on automated processes in complex societal systems is not a viable approach.

3.3.2 Human Factors Guidance

Impact assessments
The decision to deploy AI technology is a function of organizational incentives. AI is designed and developed within a set of organizational norms and policies. One recent proposed approach for ensuring that technology is developed in an ethical and responsible manner is the algorithmic impact assessment. Identifying and addressing potential biases is an important step in the assessment process. There is currently momentum for AI researchers to include statements about potential societal impacts [221] when submitting their work to journals or conferences. Similar to privacy impact assessments, which are relied upon by data protection and privacy frameworks to gauge and respond to data privacy risks, such impact assessments provide a high-level structure that enables organizations to frame the risks of each algorithm or deployment while also accounting for the specifics of each use case. Engaging in impact assessment can also serve as a forcing mechanism for

medical-device-development-guiding-principles; NHTSA's "Automated Driving Systems 2.0 Voluntary Guidance," https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/13069a-ads2.0_090617_v9a_tag.pdf. In the military context, even more emphasis has been placed on human intervention, such as in "AI Principles: Recommendations on the Ethical Use of Artificial Intelligence," Department of Defense Defense Innovation Board, https://media.defense.gov/2019/Oct/31/2002204458/-1/-1/0/DIB_AI_PRINCIPLES_PRIMARY_DOCUMENT.PDF; see also Brig. Gen. (ret.) Jean Michel Verney et al., "Human-On-the-Loop," Joint Air & Space Power Conference 2021, https://www.japcc.org/human-on-the-loop/.

organizations to articulate any risks, and then to generate documentation of any mitigation activities in the event that any harms—and associated oversight—do arise[17] [222–226]. A misstep with impact assessments is to only apply them once at the beginning of a long and iterative process in which goals and outcomes can change over time. To overcome the challenge of the point-in-time nature of impact assessments, impact assessments must be applied at some reasonable cadence when used with iterative and evolving AI systems. Another concern with impact assessments is that the technology groups, or others who will be assessed, may have undue influence on building or using the assessment.

Multi-stakeholder engagement

The practice of technology development is also complicated by the role of power and decision making within the organizational structure [227]. A consistent theme from the literature is the benefit of engaging a variety of stakeholders and maintaining diversity along social lines where bias is a concern (racial diversity, gender diversity, age diversity, diversity of physical ability) [228, 229]. These kinds of practices can lead to broadening perspectives, and in turn, more thorough evaluation of the societal impacts of technology-based applications. Using the demographic traits of organizational personnel to identify problematic aspects within development culture and practice is not sufficient and may not be fair. Identifying downstream impacts may take time and require the involvement of end-users, practitioners, subject matter experts, and interdisciplinary professionals from the law and social science. Expertise matters, and these stakeholders can bring their varied experiences to bear on the core challenge of identifying harmful outcomes and context shifts within the specific setting the AI system will be deployed.

Technology or datasets that seem non-problematic to one group may be deemed disastrous by others. The manner in which different user groups can game certain applications may also not be so obvious to the teams charged with bringing an AI-based technology to market. These kinds of impacts can sometimes be identified in early testing stages, but are usually very specific to the contextual end-use and will change over time. Acquiring these types of resources for risk and associated impacts does not necessarily require a huge allocation, but it does require deliberate planning and guidance. This is also a place where innovation in approaching bias could improve practice. These factors are part of changing norms and creating an organizational risk culture where teams improve capacity for considering the impact of the technology they design and develop, and communicating about these impacts more broadly.

Diversity, Equity & Inclusion

Without prioritizing diversity, equity, and inclusion in the teams involved in training and deploying AI systems it is difficult to move beyond a focus on system optimization or to address design considerations and risks beyond a narrow subset of users. Consider for example how character limits impact some languages and cultures more so than others; in

[17] H.R. 2231, 116th Cong. (2019), https://www.congress.gov/bill/116th-congress/house-bill/2231/text.

recognition of this effect, Twitter increased its character limit from 140 to 280 characters [230]. In another example, a recent exercise by the same social media company found that AI used to filter image content disfavored people with white hair and memes written in non-latin scripts [231, 232].

As recent research has shown that developers with similar demographic backgrounds make similar misjudgements, [72] ensuring that individuals involved in training, testing, and deploying the system have a diversity of experience, expertise and backgrounds is a critical risk mitigant that can help organizations manage the potential harms of AI. The human heuristics and biases that lead to examples such as these are implicit; as such, simply increasing awareness of bias does not ensure control over it. As previously described in Section 3.3, heuristics are adaptive mental shortcuts than can often be beneficial to reduce complexity in tasks of judgement and choice, yet also lead to cognitive biases.

The concepts and reasoning behind diversity, equity, and inclusion in the workplace are closely tied to the need for broad multi-stakeholder engagement during all aspects of the AI lifecycle. Numerous studies have touted the benefits of increased diversity, equity, and inclusion in the workplace [233–236]. Yet, the AI field noticeably lacks diversity [237]. To extend the benefits of diversity, equity, and inclusion to both the users and developers of AI systems, commentators and experts now recommend that bias mitigation efforts should be multifaceted, empowering a diverse group of individuals who reflect a range of backgrounds, perspectives and expertise, which in turn can help to broaden the views of AI system designers and engineers [238, 239]. In particular, diversity, equity and inclusion efforts can help organizations better understand: how the system is likely to impact a wide variety of users, how such users might interact with the system in practice, the potential harms and benefits of systems across users and groups, whether troubleshooting efforts—such as the recourse channels described below—are likely to be effective in practice, as well as how the system might impact broader populations beyond direct users of the system, among others.

Practice Improvements

By taking a lifecycle approach it is possible to identify junctures where well-developed guidance, assurance, and governance processes can assist business units and data and social scientists to collaboratively integrate processes to reduce bias without being cumbersome or blocking progress. Several technology companies are developing or utilizing guidance to improve organizational decision making and make the practice of AI development more responsible by implementing processes such as striving to identify potential bias impacts of algorithmic models. One approach is to enumerate institutional assumptions when developing algorithmic decision systems and map these assumptions to the expectations of the groups impacted by the technology–which requires deliberate multi-stakeholder and community engagement. "Cultural effective challenge" is a practice that seeks to create an environment where technology developers can actively challenge and question steps in modeling and engineering to help root out statistical biases and the biases inherent in human decision making [240]. Requiring AI practitioners to defend their techniques, within a demographically and professionally diverse setting, can incentivize new ways of thinking, stimulate improved practices, and help create change in approaches by individuals and organizations [227].

Human–AI configuration

AI systems are often deliberately placed into high-risk settings to counteract the known subjectivity and bias of humans. Yet considerable questions remain about how to optimally configure humans and automation. An approach to human-in-the-loop that takes into consideration the broad set of socio-technical factors is necessary, especially in the context of AI bias. The list of relevant sub-topics span fields such as human factors, psychology, organizational behavior, and human-AI interaction, and building bridges between these and the technology communities is still necessary. NIST seeks to develop formal guidance about how to implement human-in-the-loop processes that do not amplify or perpetuate the many human, systemic and computational biases that can degrade outcomes in this complex setting. Identifying system configurations and necessary qualifications for their components that result in outcomes that are accurate and trustworthy will be a key focus.

System and procedural transparency

A consistent finding in the literature is that AI systems need to be more explainable and interpretable. The proliferation of tools such as datasheets and model cards are intended to fill that gap [241, 242]. Bias intersects with transparency in complex ways. Groups who invent and produce technology have specific intentions for its use and are unlikely to be aware of all the ways a given application will be used and repurposed once deployed. Transparency tools are especially helpful for addressing the problem of unintended use, but even when AI systems are used as intended there are significant individual differences in how humans interpret AI model output. This issue becomes particularly relevant when deploying systems for use by subject matter experts, who are less interested in *how* a system works and more concerned with *why* a system provided a given output. When system designers do not take these perceptual differences into consideration it can lead to misinterpretation of output, which is especially problematic in high-risk settings [243, 244]. Coordinated guidance is necessary to ensure that transparency tools are effectively supporting the professionals who use them and not indirectly contributing to processes that could amplify bias.

There are techniques to flag factors in datasets and modeling processes that can produce biased outcomes or cause noncompliance with legal requirements. The intent here is that flagging information for somebody along the AI lifecycle or the end user will serve as a system check. Yet, flagging such information for downstream users does not always result in a directly positive outcome, and can in fact create the opposite[181, 245]. Developing guidance in this area will require more information about the settings under which human biases may amplify harmful outcomes, and where humans can work optimally with and complement an AI-based system. These questions, like those related to AI system design, are notably dependent on setting (e.g., aircraft, cyber-physical systems, public safety and forensics, manufacturing), operator (e.g., expert, trained, naive), and task (e.g., recognition, event detection, forecasting, reasoning).

Keeping humans at the center of AI design

Human-centered design (HCD) is an approach to the design and development of a system or technology that aims to improve the ability of users to effectively and efficiently use a product. HCD seeks to improve the user experience of an entire system, involving all aspects of a technology, from hardware design to software design. HCD is a methodology that has been successfully applied to a myriad of important domains, and NIST itself has authored several HCD handbooks tailored for particular domains, e.g.:, biometrics and public safety [246, 247].

HCD is an ongoing, iterative process in which project teams design, test, and continually refine a system, placing users at the core of the process. Humans and their needs drive the process, rather than having a techno-centric focus. HCD works as part of other development lifecycles, including waterfall, spiral and agile models. User-centered design, HCD, participatory design, co-design, and value-sensitive design all have key similarities; at the highest level, they seek to provide humans with designs that are ultimately beneficial to their lives. Furthermore, by placing humans at the center of such approaches, they naturally lend themselves to a deeper focus on larger societal considerations such as fairness, bias, values, and ethics. HCD works to create more usable products that meet the needs of its users. This, in turn, reduces the risk that the resulting system will under-deliver, pose risks to users, result in user harms, or fail.

The HCD process is illustrated in Fig. 6 below.

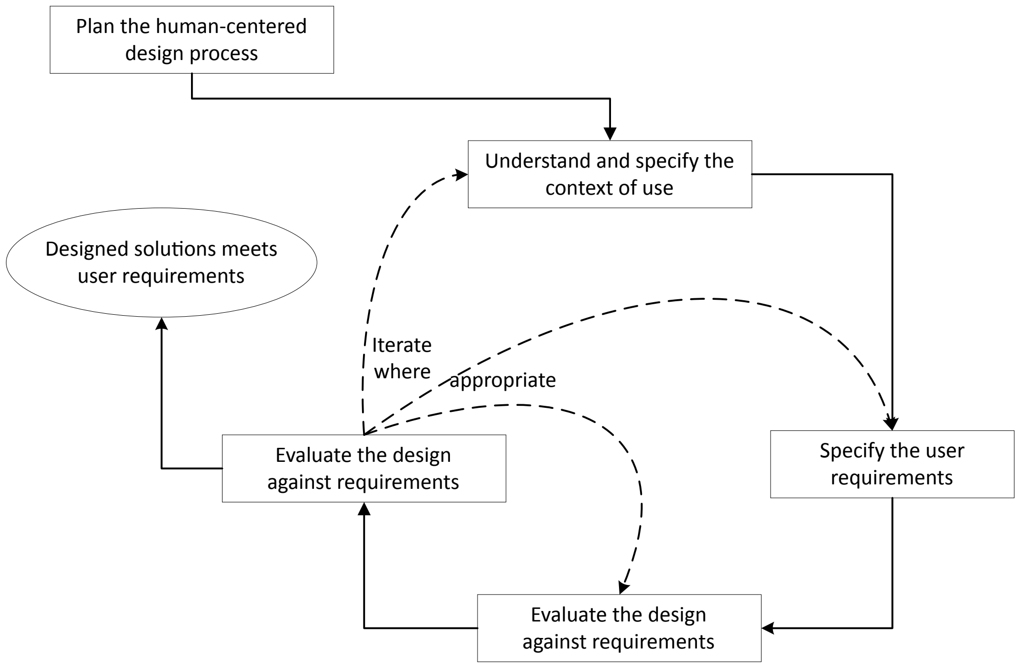


Fig. 6. Human-centered Design Process [ISO 9241-210:2019]

As defined in International Organization for Standardization (ISO) standard 9241-210:2019 [248], HCD involves:

- an explicit understanding of users, tasks and environments–the context of use;
- the involvement of users throughout design and development;
- a design driven and refined by human-centered evaluation;
- an iterative process whereby a prototype is designed, tested and modified;
- addressing the whole user experience;
- a design team including multidisciplinary skills and perspectives.

Based on the ISO standard, a HCD methodology for the development of AI systems could iteratively comprise the following, as shown in Fig. 7:

- Defining the Context of Use, including operational environment, user characteristics, tasks, and social environment;

- Determining the User & Organizational Requirements, including business requirements, user requirements, and technical requirements;
- Developing the Design Solution, including the system design, user interface, and training materials; and
- Conducting the Evaluation, including usability and conformance testing.

Although all components of HCD are critical, the context of use has key socio-technical considerations for AI systems. The socio-technical dynamics and conditions under which an AI system is used must be considered at the front end of any project to ensure that the design of the system will meet the needs of users, the objectives of the organization, and larger societal needs once the system is implemented in a real-world environment. A deep understanding of contextual factors is important throughout the AI lifecycle. Context of use does not simply involve the users' context of use, it involves a much broader view of context: the organizational environment in which the AI system is being developed (including existing systems and products); the operational environment in which the system will be used; and the larger societal environment in which the system will be implemented. For example, some intended users of AI systems may not have consistent or reliable access to fundamental internet technologies (a phenomenon widely described as the "digital divide" [249, 250]), leading to biases in how different communities access a system. Similarly, those with disabilities may experience difficulties interacting with AI systems. Crucially, such difficulties often cannot be mitigated by mathematical or software de-biasing approaches, and failure to address these important design issues may pose legal risks, for example in employment related activities affecting persons with disabilities.[18]

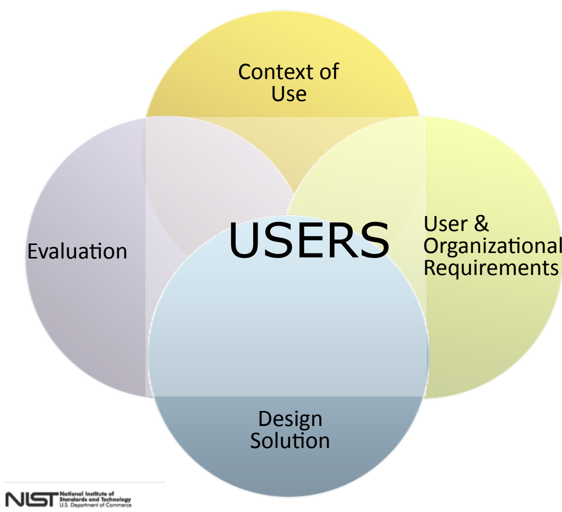


Fig. 7. Human-centered Design Process for AI Systems

[18]Congress has recognized that objects, systems, and processes often are not designed with individuals with disabilities in mind. By ensuring that these protections apply at the individual rather than group level, Congress further recognized that the means of placing an individual with disabilities on equal footing with others may require an individualized solution—one person with a disability may require a reasonable accommodation, and a different individual with a disability may require a different accommodation or no accommodation at all. Some disabilities are so heterogeneous that even two individuals with the same disability may need different accommodations. In the employment context, an algorithm may screen out a particular individual, and therefore may violate the Americans with Disabilities Act, regardless of whether broadly defined groups of individuals with disabilities tend to be assessed highly by a given algorithm.

A growing number of researchers have pointed out the benefits of socio-technical approaches. For example, Ferrer et al [251] note: “This challenge could be addressed through a socio-technical approach which can consider both the technical dimensions and the complex social contexts in which these systems are deployed. Building public confidence and greater democratic participation in AI systems requires ongoing development of not just explainable AI but of better Human-AI interaction methods and socio-technical platforms, tools and public engagement to increase critical public understanding and agency.”

Research to integrate HCD with the standard design, development, evaluation, and deployment processes of today’s AI systems is relatively recent. In their chapter on HCD of AI in the Handbook of Human Factors and Ergonomics, Margetis et al state that “A core concept of HCD is that of actively involving end-users and appropriate stakeholders in the process. In the context of AI, this means placing humans in the loop, not only through meaningful human control [252], but also through their active participation in the preparation, learning, and decision-making phases of AI [253].” Human-centered AI (HCAI) is an emerging area of scholarship that reconceptualizes HCD in the context of AI, providing human-centered AI design metaphors and suggested governance structures to develop reliable, safe, and trustworthy AI systems [254]. Schneiderman envisages HCAI as ”bridg[ing] the gap between ethics and practice with specific recommendations for making successful technologies that augment, amplify, empower, and enhance humans rather than replace them. This shift in thinking could lead to a safer, more understandable, and more manageable future. An HCAI approach will reduce the prospects for out-of-control technologies, calm fears of robot-driven unemployment, and diminish the threats to privacy and security. A human-centered future will also support human values, respect human dignity, and raise appreciation for the human capacities that bring creative discoveries and inventions.”

3.4 How do we manage and provide oversight? Governance and AI Bias

Governance processes impact nearly every aspect of managing AI bias. For that reason, it is essential to view governance as a holistic implementation tier, socio-technical in nature, and informing each phase of the bias management process. It is also important to note that governance does not simply focus on technical artifacts, such as AI systems alone, but also on organizational processes and cultural competencies that directly impact the individuals involved in training, deploying and monitoring such systems. While there are a number of components to effective governance for managing bias in AI systems, we focus here on organizational measures and culture.

3.4.1 Governance Guidance

Monitoring
AI systems may perform differently than expected once deployed, which can lead to differential treatment of individuals from different groups. A key measure to control this risk is to deploy additional systems that monitor for potential bias issues, which can alert the proper personnel when potential problems are detected. Without such monitoring in place,

it can be difficult to know if deployed system performance in the real world matches up to the measurements conducted in a laboratory environment, or whether newly collected data match the distribution of the training data. A key consideration for the success of live monitoring for bias is the collection of data from the active user population, especially data related to user demographics such as age and gender, to enable calculation of assessment measures. These type of data can have a variety of privacy implications and may be subject to legal restrictions on what types of data can be collected and under what conditions.

Recourse Channels

Availability of feedback channels allow system end users to flag incorrect or potentially harmful results, and seek recourse for errors or harms. A number of legal frameworks prioritize the ability of users to appeal and override unfavorable decisions, and are applied in a subset of algorithmic systems deployed in areas like consumer finance. Because appeal and override recourse often requires a logical description of the questionable ML decision, these processes are tightly connected to AI system explainability and interpretability. Though not without criticism [255], adverse action notices for negative consumer credit decisions, as mandated by the Equal Credit Opportunity Act and the Fair Credit Reporting Act, are an example of an explanation and appeal process[19][256]. Additional appeal and override processes could include options for customers to interact with a human instead of an AI system or options to avoid similar AI-generated content in the future. Embedding such processes and technologies into AI systems allows users to appeal wrong decisions (or even suggestions) while also empowering technology development teams to remediate potential incidents at or near their inception point.

Policies and Procedures

In the context of AI systems, ensuring that written policies and procedures address key roles, responsibilities, and processes at all stages of the AI model lifecycle is critical to managing and detecting potential overall issues of AI system performance.[20] Policies and procedures can enable consistent development and testing practices, which in turn can help to ensure that results from AI systems are repeatable and that related risks are consistently mapped, measured and managed. Without such policies, the management of AI bias can easily become subjective and inconsistent across organizations, which can exacerbate risks over time rather than minimize them—if, for example, irreconcilably different metrics are used across systems. Policies may:

- define the key terms and concepts related to AI systems and the scope of their intended impact;
- address the use of sensitive or otherwise potentially risky data;

[19] *See* 15 U.S.C., § 1691(d).
[20] Bd. Governors Fed. Rsrv. Sys., Supervisory Guidance on Model Risk Management, SR Letter 11-7 (Apr. 4, 2011).

- detail standards for experimental design, data quality, and model training;
- outline how the risks of bias should be mapped and measured, and according to what standards;
- detail processes for model testing and validation;
- detail the process of review by legal or risk functions;
- set forth the periodicity and depth of ongoing auditing and review;
- outline requirements for change management; and
- detail any plans related to incident response for such systems, in the event that any significant risks do materialize during deployment.

Documentation

Clear documentation practices can help to systematically implement policies and procedures, standardizing how an organization's bias management processes are implemented and recorded at each stage. Standardized documentation can, in turn, help to ensure accountability, as described in further detail below. Model documents should contain interpretable descriptions of system mechanisms, enabling oversight personnel to make informed, risk-based decisions about the system's potential to perpetuate bias. Documentation also serves as a single repository for important information, supporting not only internal oversight of AI systems and related business processes, but also enhancing system maintenance, and serving as a valuable resource for any necessary corrective or debugging activities.[21]

Model documentation is especially important in the context of accountability. The use of documentation templates with specific requirements enables practitioners to walk through workflows as they are prescribed in written policies and procedures, or by other best practices. Omission of key documentation elements can indicate a lack of adherence to written policies and procedures on the part of system developers or testers. Some model documentation templates also include contact information for developers and stakeholders [241, 242]. The act of adding contact information to a document describing a work product can enable more efficient oversight and communications. This type of practice should also lead to greater concern and responsibility for the quality of the product, which in turn, can impact bias management efforts within an organization.

[21] Off. Comptroller Currency, Comptroller's Handbook: Model Risk Management (Aug. 2021), https://www.occ.gov/publications-and-resources/publications/comptrollers-handbook/files/model-risk-management/index-model-risk-management.html.

Accountability

Accountability plays a critical role in governance efforts [257]. Governance without accountability is, in practice, unlikely to be effective. Ensuring that a specific team, and often, a specific individual – such as a Chief Model Risk Officer, as is now common in large consumer finance organizations – is responsible for bias management in AI systems is a fundamental accountability mechanism.[22] Ensuring individuals or teams bear responsibility for risks and associated harms provides a direct incentive for their mitigation. Put simply, when someone's boss is accountable for bias issues, they too are accountable for bias issues—and this phenomenon promulgates down to front-line practitioners. Accountability for AI bias cannot lie on the shoulders of a single individual, which is why accountability mandates should also be embedded within and across the various teams involved in the training and deployment of AI systems. Existing technical and procedural frameworks for accountability related to AI include general governance procedures, and application of system monitoring, data quality measures, computer security countermeasures, and nondiscrimination mechanisms, among others [258, 259].

Fundamentally, accountability requires a clear assessment of the role of the AI system itself. For example, decision-support systems, which may be claimed not to result in direct decision-making and therefore pose less risks, can easily become overly relied upon by users, or misused or abused. In these cases, the AI system would generate similar harms as if it were engaging in decision-making directly. Model or algorithmic audits [260] can be used to assess and document such crucial accountability considerations. There are several notions of audits commonly discussed in the responsible and trustworthy AI communities. Audit may refer to a traditional internal audit function employed to track issues of model risk, as in traditional model governance. Audit may refer to a structured and principled application of lessons learned in financial audit practices to AI systems [261]. Alternatively, audit may refer to some general documentation and transparency approach. Audits can be an effective accountability, bias, and general risk mitigation mechanism. Indeed, laws are being passed that demand bias audits of AI-based systems used in employment [262]. However, audits currently exist in a wide range of forms with varying levels of quality and consensus [263]. Audits will be addressed in future NIST documents related to the AI risk management framework.

Culture & Practice

For AI governance to be effective, it needs to be embedded throughout the culture of an organization. While organizational culture and practice can be defined in a variety of ways, the central theme of most such definitions emphasize beliefs, norms and values - or, in other words, the behavior an organization prioritizes in practice, even if such behavior is not codified or written down [264]. Risk management culture and practices can be a powerful technique for identifying biases across the AI lifecycle and from a socio-technical system perspective.

[22] Bd. Governors Fed. Rsrv. Sys., *supra* note 20.

Effective challenge The principal of effective challenge is a central component of model risk management frameworks. This practice is heavily relied on by the financial sector to mitigate algorithmic risk, and mandates that important model design and implementation decisions be questioned by experts with the authority and stature to make changes in design and implementation.[23] Fostering a culture of effective challenge encourages actively challenging and questioning steps in the development of AI systems, and can help to raise issues of AI bias before they materialize in deployed systems. An organizational culture that encourages serious questioning of AI system designs will be more likely to identify problems before they turn into harmful incidents. Relatedly, while individuals who are part of the development of AI systems may be knowledgeable about the potential harmful impacts of the technology they build, impact assessments should not be exclusively developed by these teams due to increased likelihood of confirmation bias and other incentives that may cause conflicts of interest.

Three lines of defense Because culture can be difficult to map or measure directly, one way to encourage this approach is to incentivize critical thinking and review at an organizational and procedural level. Model risk management frameworks, for example, are often systematically implemented through the so-called "three lines of defense," which creates separate teams that are held accountable for different aspects of the model lifecycle. Typically, the first line of defense focuses on model development, the second on risk management, and the third on auditing.[24] While a traditional three-lines approach may be impractical for smaller organizations, ensuring that a culture of effective challenge is encouraged and sustained can help organizations to anticipate, and therefore to effectively mitigate, risks of bias before they materialize.

Risk Mitigation, Risk Tiering & Incentive Structures
Some applications of AI are high-risk.[25] A central cultural component of effective risk management for AI bias lies in a clear acknowledgment that risk mitigation, rather than risk avoidance, is often the most effective factor in managing such risks.[26] Developing a risk mitigation mindset, meaning a clear acceptance that incidents can and will occur, and emphasizing practical detection and mitigation once they do, can help ensure that any risks of bias are quickly mitigated in practice. This acknowledgement enables a clear triaging of risks which can enable organizations to focus finite resources on the risks of bias that are most material, and therefore most likely to cause real-world harm. An additional component of effective organizational culture includes aligning pay and promotion incentives across teams to AI risk mitigation efforts, such that participants in the risk mitigation

[23] *Id.*
[24] Off. Superintendent Fin. Inst. Canada, Enterprise-Wide Model Risk Management for Deposit-Taking Institutions, E-23 (Sept. 2017).
[25] Eur. Comm'n, Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts (proposed Apr. 21, 2021), https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206.
[26] Bd. Governors Fed. Rsrv. Sys., *supra* note 20

mechanisms—like the three lines of defense—are truly motivated to use sound development approaches, test rigorously and audit thoroughly.[27]

Information Sharing
As described in a NIST special publication [265], sharing cyber threat information helps organizations improve both their own security postures, and those of other organizations. Identifying internal mechanisms for teams to share information about bias incidents or other harmful impacts from AI helps to elevate the importance of AI risks and provides information for teams to avoid past failed designs. Some initial efforts are already underway [266]. As teams begin to create norms for tracking such incidents, it can potentially transform AI practices and the organizational culture. Improving awareness of how bias presents in deployed AI and its related impacts can enhance knowledge and capabilities, and prevent incidents. Fostering a culture of information sharing can also serve as a new area for community engagement.

4. Conclusions

This document has provided a broad overview of the complex challenge of addressing and managing risks associated with AI bias. It is clear that developing detailed technical guidance to address this challenging area will take time and input from diverse stakeholders, within and beyond those groups who design, develop, and deploy AI applications, and including members of communities that may be impacted by the deployment of AI systems.

Since AI is neither built nor deployed in a vacuum, we approach AI as a socio-technical system, acknowledging that AI systems and associated bias extend beyond the computational level. Bias can be introduced purposefully or inadvertently, or it can emerge as the AI system is used, impacting society at large through perpetuating and amplifying biased and discriminatory outcomes. Adopting a socio-technical perspective brings new requirements, many of which are contextual in nature, to the processes that comprise the AI lifecycle. It is important to gain understanding in how computational and statistical factors interact with systemic and human biases.

NIST has provided an initial socio-technical framing for AI bias in this document, including key context and terminology, highlights of the main challenges, and foundational directions for future guidance. This information is classified and discussed through the document according to three key areas:

1. dataset availability, representativeness, and suitability in socio-technical contexts;
2. TEVV considerations for measurement and metrics to support testing and evaluation;
3. human factors, including societal and historic biases within individuals and organizations, participatory approaches such as human-centered design, and human–in–the–loop practices.

[27] *Id.*

Identifying the key requirements for improving our knowledge in this area is a necessary first step. To ensure broad input, engagement, and consensus, NIST will carry out supporting standards development activities such as workshops and public comment periods for draft documents.

NIST intends to develop further consensus socio-technical guidance in collaboration with the research community and a broad set of other stakeholders, including those who are directly impacted by AI bias. The intent is for this guidance to be of specific assistance for organizations who commission, design, develop, deploy, use, or evaluate AI for a variety of use cases. By providing these entities with clear, explicit, and technically valid guidance NIST intends to improve the state of practice for AI bias and assure system trustworthiness.

5. Glossary

activity bias A type of selection bias that occurs when systems/platforms get their training data from their most active users, rather than those less active (or inactive) [131]. 8

aleatoric uncertainty Aleatoric uncertainty, also known as statistical uncertainty, refers to unknowns that differ each time we run the same experiment. It refers to the variability in the outcome of an experiment which is due to inherently random effects. For example, in machine learning context, the data-generating process may have a stochastic component that cannot be reduced by any additional source of information. Consequently, even the best model trained on this data will not be able to provide a definite answer. 9, 20, 21

amplification bias Arises when the distribution over prediction outputs is skewed in comparison to the prior distribution of the prediction target [267]. 8

anchoring bias A cognitive bias, the influence of a particular reference point or anchor on people's decisions. Often more fully referred to as anchoring-and-adjustment, or anchoring-and-adjusting: after an anchor is set, people adjust insufficiently from that anchor point to arrive at a final answer. Decision makers are biased towards an initially presented value [79]. 8, 9

annotator reporting bias When users rely on automation as a heuristic replacement for their own information seeking and processing [268]. A form of individual bias but often discussed as a group bias, or the larger effects on natural language processing models. 8

automation complacency When humans over-rely on automated systems or have their skills attenuated by such over-reliance (e.g., spelling and autocorrect or spellcheckers). 8

availability heuristic Also referred to as availability bias. A mental shortcut whereby people tend to overweight what comes easily or quickly to mind, meaning that what is easier to recall—e.g., more "available"—receives greater emphasis in judgement and decision-making. 8

behavioral bias Systematic distortions in user behavior across platforms or contexts, or across users represented in different datasets [144, 269]. 8

cognitive bias A broad term referring generally to a systematic pattern of deviation from rational judgement and decision-making. A large variety of cognitive biases have been identified over many decades of research in judgement and decision-making, some of which are adaptive mental shortcuts known as heuristics. 8

concept drift Use of a system outside the planned domain of application, and a common cause of performance gaps between laboratory settings and the real world. 8

confirmation bias also called confirmatory bias, a cognitive bias where people tend to prefer information that aligns with, or confirms, their existing beliefs. People can exhibit confirmation bias in the search for, interpretation of, and recall of information. In the famous Wason selection task experiments, participants repeatedly showed a preference for confirmation over falsification. They were tasked with identifying an underlying rule that applied to number triples they were shown, and they overwhelmingly tested triples that confirmed rather than falsified their hypothesized rule [270]. 8, 9, 27

construct validity A form of validation that seeks to answer whether a test measures what it intends to measure. [271]. 15

consumer bias Arises when an algorithm or platform provides users with a new venue within which to express their biases, and may occur from either side, or party, in a digital interaction [272]. 8

content production bias Arises from structural, lexical, semantic, and syntactic differences in the contents generated by users [144]. 8

data dredging A statistical bias in which testing huge numbers of hypotheses of a dataset may appear to yield statistical significance even when the results are statistically nonsignificant. 8, 27

data generation bias Arises from the addition of synthetic or redundant data samples to a dataset [273]. 8

deployment bias Arises when systems are used as decision aids for humans, since the human intermediary may act on predictions in ways that are typically not modeled in the system [90]. However, it is still individuals using the deployed system. 8, 26

detection bias Systematic differences between groups in how outcomes are determined and may cause an over- or underestimation of the size of the effect [274]. 8

Dunning–Kruger effect A cognitive bias, the tendency of people with low ability in a given area or task to overestimate their self-assessed ability. Typically measured by comparing self-assessment with objective performance, often called subjective ability and objective ability, respectively [275]. 8, 26

ecological fallacy Occurs when an inference is made about an individual based on their membership within a group. 8, 23

emergent bias Use of a system outside the planned domain of application, and a common cause of performance gaps between laboratory settings and the real world. 8

epistemic uncertainty An epistemic uncertainty, also known as systematic uncertainty, refers to deficiencies by a lack of knowledge or information. This may be because the methodology on which a model is built neglects certain effects or because particular data have been deliberately hidden. 9, 20–22

error propagation Arises when applications that are built with machine learning are used to generate inputs for other machine learning algorithms. If the output is biased in any way, this bias may be inherited by systems using the output as input to learn other models [82]. 8

evaluation bias Arises when the testing or external benchmark populations do not equally represent the various parts of the user population or from the use of performance metrics that are not appropriate for the way in which the model will be used [90]. 8

exclusion bias When specific groups of user populations are excluded from testing and subsequent analyses [276]. 8

feedback loop bias Effects that may occur when an algorithm learns from user behavior and feeds that behavior back into the model [272]. 8

funding bias Arises when biased results are reported in order to support or satisfy the funding agency or financial supporter of the research study [85], but it can also be the individual researcher. 8

governance a framework of policies, rules, and processes for ensuring direction, management and accountability. ii

groupthink A psychological phenomenon that occurs when people in a group tend to make non-optimal decisions based on their desire to conform to the group, or fear of dissenting with the group. In groupthink, individuals often refrain from expressing their personal disagreement with the group, hesitating to voice opinions that do not align with the group. 8

heuristics in the context of human decision making, often referred to as "mental shortcuts," a term that encompasses many methods that may be less than fully rational or optimal, yet are often sufficient for an approximate solution. Although heuristics can reduce cognitive load and aid people when making decisions, such heuristics also result in systematic errors and cognitive biases [79]. 34

historical bias referring to the long-standing biases encoded in society over time. Related to, but distinct from, biases in historical description, or the interpretation, analysis, and explanation of history. A common example of historical bias is the tendency to view the larger world from a Western or European view. 8

human reporting bias When users rely on automation as a heuristic replacement for their own information seeking and processing [268]. 8

implicit bias An unconscious belief, attitude, feeling, association, or stereotype that can affect the way in which humans process information, make decisions, and take actions. 8

inherited bias Arises when applications that are built with machine learning are used to generate inputs for other machine learning algorithms. If the output is biased in any way, this bias may be inherited by systems using the output as input to learn other models [82]. 8

institutional bias In contrast to biases exhibited at the level of individual persons, institutional bias refers to a tendency exhibited at the level of entire institutions, where practices or norms result in the favoring or disadvantaging of certain social groups. Common examples include institutional racism and institutional sexism [91]. 8

interpretation bias A form of information processing bias that can occur when users interpret algorithmic outputs according to their internalized biases and views [272]. 8

language model A computational model that has been trained using statistical methods to find patterns in written and/or spoken language, in order to predict or classify words, text, or speech. 21

linking bias Arises when network attributes obtained from user connections, activities, or interactions differ and misrepresent the true behavior of the users [144]. 8

loss of situational awareness bias When automation leads to humans being unaware of their situation such that, when control of a system is given back to them in a situation where humans and machines cooperate, they are unprepared to assume their duties. This can be a loss of awareness over what automation is and isn't taking care of. 8

McNamara fallacy The belief that quantitative information is more valuable than other information. 12

measurement bias Arises when features and labels are proxies for desired quantities, potentially leaving out important factors or introducing group or input-dependent noise that leads to differential performance [90]. 8

mode confusion bias When modal interfaces confuse human operators, who misunderstand which mode the system is using, taking actions which are correct for a different mode but incorrect for their current situation. This is the cause of many deadly accidents, but also a source of confusion in everyday life. 8

model A conceptual, mathematical, or physical representation of phenomenon observed in a system of ideas, events, or processes. In computationally-based models used in AI, phenomenon are often abstracted for mathematical representation, which means that characteristics that can not be represented mathematically may not be captured in the model. i, v

model selection bias The bias introduced while using the data to select a single seemingly "best" model from a large set of models employing many predictor variables. Model selection bias also occurs when an explanatory variable has a weak relationship with the response variable [277]. 8

popularity bias A form of selection bias that occurs when items that are more popular are more exposed and less popular items are under-represented [130]. 8

population bias Systematic distortions in demographics or other user characteristics between a population of users represented in a dataset or on a platform and some target population [144]. 8

presentation bias Biases arising from how information is presented on the Web, via a user interface, due to rating or ranking of output, or through users' own self-selected, biased interaction [131]. 8

proxy A variable that can stand in for another, usually not directly observable or measurable, variable. 20

ranking bias A form of anchoring bias. The idea that top-ranked results are the most relevant and important and will result in more clicks than other results [131, 278]. 8

Rashomon effect or principle Refers to differences in perspective, memory and recall, interpretation, and reporting on the same event from multiple persons or witnesses. 8

representation bias Arises due to non-random sampling of subgroups, causing trends estimated for one population to not be generalizable to data collected from a new population [85]. 8

selective adherence Decision-makers' inclination to selectively adopt algorithmic advice when it matches their pre-existing beliefs and stereotypes [215]. 8

Simpson's Paradox A statistical phenomenon where the marginal association between two categorical variables is qualitatively different from the partial association between the same two variables after controlling for one or more other variables. For example, the statistical association or correlation that has been detected between two variables for an entire population disappears or reverses when the population is divided into subgroups. 8, 17

societal bias often referred to as social bias. Can be positive or negative, and take a number of different forms, but is typically characterized as being for or against groups or individuals based on social identities, demographic factors, or immutable physical characteristics. Societal or social biases are often stereotypes. Common examples of societal or social biases are based on concepts like race, ethnicity, gender, sexual orientation, socioeconomic status, education, and more. Societal bias is often recognized and discussed in the context of NLP (Natural Language Processing) models. 8

socio-technical A term used to describe how humans interact with technology within the broader societal context. ii

streetlight effect A bias whereby people tend to search only where it is easiest to look [279]. 8

sunk cost fallacy A human tendency where people opt to continue with an endeavor or behavior due to previously spent or invested resources, such as money, time, and effort, regardless of whether costs outweigh benefits. For example, in AI, the sunk cost fallacy could lead development teams and organizations to feel that because they have already invested so much time and money into a particular AI application, they must pursue it to market rather than deciding to end the effort, even in the face of significant technical debt and/or ethical debt. 8

survivorship bias tendency for people to focus on the items, observations, or people that "survive" or make it past a selection process, while overlooking those that did not. 8

technochauvinism The belief that technology is always the solution [35]. 12

temporal bias Bias that arises from differences in populations and behaviors over time [144, 280]. 8

uncertainty bias Arises when predictive algorithms favor groups that are better represented in the training data, since there will be less uncertainty associated with those predictions [281]. 8

user interaction bias Arises when a user imposes their own self-selected biases and behavior during interaction with data, output, results, etc [131]. 8

References

[1] NIST, "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools," National Institute of Standards and Technology, Tech. Rep., 2019. [Online]. Available: https://www.nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf

[2] I. Ajunwa, S. A. Friedler, C. Scheidegger, and S. Venkatasubramanian, "Hiring by Algorithm: Predicting and Preventing Disparate Impact," *undefined*, 2016. [Online]. Available: /paper/Hiring-by-Algorithm%3A-Predicting-and-Preventing-Ajunwa-Friedler/bd31ad5e998629998f35db9a10d858b36e603248

[3] S. Barocas, A. Biega, B. Fish, J. Niklas, and L. Stark, "When not to design, build, or deploy," in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, ser. FAT* '20. New York, NY, USA: Association for Computing Machinery, Jan. 2020, p. 695. [Online]. Available: https://doi.org/10.1145/3351095.3375691

[4] M. Bogen, "All the Ways Hiring Algorithms Can Introduce Bias," *Harvard Business Review*, May 2019, section: Hiring. [Online]. Available: https://hbr.org/2019/05/all-the-ways-hiring-algorithms-can-introduce-bias

[5] J. Dastin, "Amazon scraps secret AI recruiting tool that showed bias against women," *Reuters*, Oct. 2018. [Online]. Available: https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

[6] E. Harlen and O. Schnuck, "Objective or Biased," 2021. [Online]. Available: https://web.br.de/interaktiv/ki-bewerbung/en

[7] J. Sanchez-Monedero, L. Dencik, and L. Edwards, "What does it mean to solve the problem of discrimination in hiring? Social, technical and legal perspectives from the UK on automated hiring systems," *arXiv:1910.06144 [cs]*, Jan. 2020, arXiv: 1910.06144. [Online]. Available: http://arxiv.org/abs/1910.06144

[8] M. Evans and A. W. Mathews, "New York Regulator Probes UnitedHealth Algorithm for Racial Bias," *Wall Street Journal*, Oct. 2019. [Online]. Available: https://www.wsj.com/articles/new-york-regulator-probes-unitedhealth-algorithm-for-racial-bias-11572087601

[9] H. Fry, *Hello world: being human in the age of algorithms*. WW Norton & Company, 2018.

[10] M. A. Gianfrancesco, S. Tamang, J. Yazdany, and G. Schmajuk, "Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data," *JAMA Intern Med*, vol. 178, no. 11, p. 1544, Nov. 2018. [Online]. Available: http://archinte.jamanetwork.com/article.aspx?doi=10.1001/jamainternmed.2018.3763

[11] E. Guo and K. Hao, "This is the Stanford vaccine algorithm that left out frontline doctors," 2020. [Online]. Available: https://www.technologyreview.com/2020/12/21/1015303/stanford-vaccine-algorithm/

[12] H. Ledford, "Millions of black people affected by racial bias in health-care algorithms," *Nature*, vol. 574, no. 7780, pp. 608–609, Oct. 2019,

number: 7780 Publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/d41586-019-03228-6

[13] T. M. Maddox, J. S. Rumsfeld, and P. R. O. Payne, "Questions for Artificial Intelligence in Health Care," *JAMA*, vol. 321, no. 1, p. 31, Jan. 2019. [Online]. Available: http://jama.jamanetwork.com/article.aspx?doi=10.1001/jama.2018.18932

[14] Z. Obermeyer, B. Powers, C. Vogeli, and S. Mullainathan, "Dissecting racial bias in an algorithm used to manage the health of populations," *Science*, vol. 366, no. 6464, pp. 447–453, Oct. 2019. [Online]. Available: https://www.sciencemag.org/lookup/doi/10.1126/science.aax2342

[15] T. Simonite, "How an Algorithm Blocked Kidney Transplants to Black Patients | WIRED," *Wired*, 2020. [Online]. Available: https://www.wired.com/story/how-algorithm-blocked-kidney-transplants-black-patients/

[16] M. Singh and K. N. Ramamurthy, "Understanding racial bias in health using the Medical Expenditure Panel Survey data," *arXiv:1911.01509 [cs, stat]*, Nov. 2019, arXiv: 1911.01509. [Online]. Available: http://arxiv.org/abs/1911.01509

[17] T. M. Cruz, "Perils of data-driven equity: Safety-net care and big data's elusive grasp on health inequality," *Big Data & Society*, vol. 7, no. 1, p. 205395172092809, Jan. 2020. [Online]. Available: http://journals.sagepub.com/doi/10.1177/2053951720928097

[18] J. Angwin, J. Larson, S. Mattu, L. Kirchner, and ProPublica, "Machine Bias: There's software used across the country to predict future criminals. And it's biased against blacks." *ProPublica*, 2016.

[19] L. Dormehl, "Algorithms Are Great and All, But They Can Also Ruin Lives," *Wired*, 2014. [Online]. Available: https://www.wired.com/2014/11/algorithms-great-can-also-ruin-lives/

[20] S. Goel, R. Shroff, J. L. Skeem, and C. Slobogin, "The Accuracy, Equity, and Jurisprudence of Criminal Risk Assessment," *SSRN Journal*, 2018. [Online]. Available: https://www.ssrn.com/abstract=3306723

[21] S. Brayne, "Enter the Dragnet," 2020. [Online]. Available: https://logicmag.io/commons/enter-the-dragnet/

[22] A. Chouldechova, "Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments," *Big Data*, vol. 5, no. 2, pp. 153–163, Jun. 2017. [Online]. Available: http://www.liebertpub.com/doi/10.1089/big.2016.0047

[23] EPIC, "Algorithms in the Criminal Justice System Risk Assessment Tools," Electronic Privacy Information Center (EPIC), Tech. Rep., 2020. [Online]. Available: https://epic.org/algorithmic-transparency/crim-justice/

[24] K. Hill, "Flawed Facial Recognition Leads To Arrest and Jail for New Jersey Man," 2020. [Online]. Available: https://www.nytimes.com/2020/12/29/technology/facial-recognition-misidentify-jail.html

[25] J. E. Johndrow and K. Lum, "An algorithm for removing sensitive information: Application to race-independent recidivism prediction," *Ann. Appl. Stat.*, vol. 13,

no. 1, pp. 189–220, Mar. 2019. [Online]. Available: https://projecteuclid.org/euclid.aoas/1554861646
[26] F. Kamiran, A. Karim, S. Verwer, and H. Goudriaan, "Classifying Socially Sensitive Data Without Discrimination: An Analysis of a Crime Suspect Dataset," in *2012 IEEE 12th International Conference on Data Mining Workshops*. Brussels, Belgium: IEEE, Dec. 2012, pp. 370–377. [Online]. Available: http://ieeexplore.ieee.org/document/6406464/
[27] J. Kleinberg, H. Lakkaraju, J. Leskovec, J. Ludwig, and S. Mullainathan, "Human decisions and machine predictions," *The quarterly journal of economics*, vol. 133, no. 1, pp. 237–293, 2018.
[28] A. Liptak, "Sent to Prison by a Software Program's Secret Algorithms," *The New York Times*, May 2017. [Online]. Available: https://www.nytimes.com/2017/05/01/us/politics/sent-to-prison-by-a-software-programs-secret-algorithms.html
[29] R. Wexler, "When a Computer Program Keeps You in Jail," *The New York Times*, p. 2, 2017. [Online]. Available: https://www.nytimes.com/2017/06/13/opinion/how-computers-are-harming-criminal-justice.html
[30] "State v. Loomis," 2016.
[31] M. Aitken, E. Toreini, P. Carmichael, K. Coopamootoo, K. Elliott, and A. van Moorsel, "Establishing a social licence for Financial Technology: Reflections on the role of the private sector in pursuing ethical data practices," *Big Data & Society*, vol. 7, no. 1, p. 205395172090889, Jan. 2020. [Online]. Available: http://journals.sagepub.com/doi/10.1177/2053951720908892
[32] J. P. Bajorek, "Voice Recognition Still Has Significant Race and Gender Biases," *Harvard Business Review*, 2019, section: Technology. [Online]. Available: https://hbr.org/2019/05/voice-recognition-still-has-significant-race-and-gender-biases
[33] E. Bary, "How artificial intelligence could replace credit scores and reshape how we get loans," 2018. [Online]. Available: https://www.marketwatch.com/story/ai-based-credit-scores-will-soon-give-one-billion-people-access-to-banking-services-2018-10-09
[34] R. Benjamin, *Race after technology: Abolitionist tools for the new jim code*. John Wiley & Sons, 2019.
[35] M. Broussard, *Artificial Unintelligence: How Computers Misunderstand the World*. MIT Press, 2018.
[36] J. Boulamwini and T. Gebru, "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification," in *Proceedings of Machine Learning Research*, 2018, pp. 77–91.
[37] C. Criado-Perez, *Invisible Women: Data Bias in a World Designed for Men*. Abrams Press, 2019.
[38] C. Dwork, M. Hardt, T. Pitassi, O. Reingold, and R. Zemel, "Fairness Through Awareness," *arXiv:1104.3913 [cs]*, Nov. 2011, arXiv: 1104.3913. [Online]. Available: http://arxiv.org/abs/1104.3913
[39] V. Eubanks, *Automating inequality: How high-tech tools profile, police, and punish*

the poor. St. Martin's Press, 2018.

[40] M. Hardt, E. Price, and N. Srebro, "Equality of Opportunity in Supervised Learning," *arXiv:1610.02413 [cs]*, Oct. 2016, arXiv: 1610.02413. [Online]. Available: http://arxiv.org/abs/1610.02413

[41] S. Noble, *Algorithms of oppression: How search engines reinforce racism*. NYU Press, 2018.

[42] C. O'Neil, *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Broadway Books, 2017.

[43] A. Pandey and A. Caliskan, "Iterative Effect-Size Bias in Ridehailing: Measuring Social Bias in Dynamic Pricing of 100 Million Rides," *arXiv:2006.04599 [cs]*, Jun. 2020, arXiv: 2006.04599. [Online]. Available: http://arxiv.org/abs/2006.04599

[44] J. Redden, "The Harm That Data Do," *Scientific American*, 2018. [Online]. Available: https://www.scientificamerican.com/article/the-harm-that-data-do/

[45] M. Specia, "Siri and Alexa Reinforce Gender Bias, U.N. Finds," *The New York Times*, May 2019. [Online]. Available: https://www.nytimes.com/2019/05/22/world/siri-alexa-ai-gender-bias.html

[46] D. M. West, "Brookings survey finds worries over AI impact on jobs and personal privacy, concern U.S. will fall behind China," Brookings, Tech. Rep., 2018.

[47] S. Furman and J. Haney, "Is My Home Smart or Just Connected?" in *International Conference on Human-Computer Interaction*. Cham: Springer, 2020, pp. 273–287.

[48] A. Kerr, M. Barry, and J. D. Kelleher, "Expectations of artificial intelligence and the performativity of ethics: Implications for communication governance," *Big Data & Society*, vol. 7, no. 1, p. 205395172091593, Jan. 2020. [Online]. Available: http://journals.sagepub.com/doi/10.1177/2053951720915939

[49] E. Fast and E. Horvitz, "Long-Term Trends in the Public Perception of Artificial Intelligence," *Thirty-First AAAI Conference on Artificial Intelligence*, p. 7, 2017.

[50] A. Smith and M. Anderson, "Automation in Everyday Life," Pew Research Center, Tech. Rep., 2017.

[51] W. H. Ware, "Records, Computers and the Rights of Citizens," RAND Corporation, Santa Monica, CA, Tech. Rep., 1973. [Online]. Available: https://www.rand.org/pubs/papers/P5077.html.Alsoavailableinprintform.

[52] T. Feathers, "Major Universities Are Using Race as a "High Impact Predictor" of Student Success – The Markup," 2021, section: News. [Online]. Available: https://themarkup.org/news/2021/03/02/major-universities-are-using-race-as-a-high-impact-predictor-of-student-success

[53] L. Kirchner and M. Goldstein, "Access Denied: Faulty Automated Background Checks Freeze Out Renters – The Markup," 2020, section: Locked Out. [Online]. Available: https://themarkup.org/locked-out/2020/05/28/access-denied-faulty-automated-background-checks-freeze-out-renters

[54] I. Ajunwa, "The Paradox of Automation as Anti-Bias Intervention," *Cardozo L. Rev.*, vol. 41, p. 1671, 2020. [Online]. Available: https://heinonline.org/HOL/Page?handle=hein.journals/cdozo41&id=1711&div=&collection=

[55] M. Bogen and A. Rieke, “Help Wanted: An Examination of Hiring Algorithms, Equity, and Bias,” 2019. [Online]. Available: https://www.upturn.org/reports/2018/hiring-algorithms
[56] H. Schellmann, “Auditors are testing hiring algorithms for bias, but big questions remain,” 2021. [Online]. Available: https://www.technologyreview.com/2021/02/11/1017955/auditors-testing-ai-hiring-algorithms-bias-big-questions-remain/
[57] R. Bartlett, A. Morse, R. Stanton, and N. Wallace, “Consumer-Lending Discrimination in the FinTech Era,” National Bureau of Economic Research, Tech. Rep. w25943, Jun. 2019. [Online]. Available: https://www.nber.org/papers/w25943
[58] M. Henry-Nickie, “How artificial intelligence affects financial consumers,” 2019. [Online]. Available: https://www.brookings.edu/research/how-artificial-intelligence-affects-financial-consumers/
[59] M. Weber, M. Yurochkin, S. Botros, and V. Markov, “Black Loans Matter: Distributionally Robust Fairness for Fighting Subgroup Discrimination,” *arXiv:2012.01193 [cs]*, Nov. 2020, arXiv: 2012.01193. [Online]. Available: http://arxiv.org/abs/2012.01193
[60] H. Suresh and J. V. Guttag, “A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle,” *arXiv:1901.10002 [cs, stat]*, Jun. 2021, arXiv: 1901.10002. [Online]. Available: http://arxiv.org/abs/1901.10002
[61] S. Barocas, M. Hardt, and A. Narayanan, *Fairness and Machine Learning*. fairmlbook.org, 2019.
[62] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Online edition, 2021, 4th US edition, http://aima.cs.berkeley.edu/index.html.
[63] A. L. Samuel, “Some Studies in Machine Learning Using the Game of Checkers,” *IBM Journal of Research and Development*, vol. 3, no. 3, pp. 210–229, 1959.
[64] S. Milano, M. Taddeo, and L. Floridi, “Recommender systems and their ethical challenges,” *AI & SOCIETY*, vol. 35, 12 2020.
[65] K. De Vries, “Identity, Profiling Algorithms and a World of Ambient Intelligence,” *Ethics and Information Technology*, vol. 12, pp. 71–85, 03 2010.
[66] R. Richardson, J. M. Schultz, and K. Crawford, “Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, And Justice,” *New York University Law Review*, vol. 94, p. 42, 2018.
[67] D. Elliott, R. G. Lowitz, and W. C. NFP, “What Is the Cost of Poor Credit?” *Washington, DC: Urban Institute*, 2018.
[68] W. Haven, “Bias Isn’t the Only Problem with Credit Scores - and, No, AI Can’t Help,” MIT Technology Review, June 2021, https://www.technologyreview.com/2021/06/17/1026519/racial-bias-noisy-data-credit-scores-mortgage-loans-fairness-machine-learning/.
[69] L. Sarkesian and S. Singh, “HUD’s New Rule Paves the Way for Rampant Algorithmic Discrimination in Housing Decisions,” New America, Oct. 2020, https://www.newamerica.org/oti/blog/huds-new-rule-paves-the-way-for-rampant-algorithmic-discrimination-in-housing-decisions/.

[70] OECD, "Glossary of statistical terms," OECD Online Resource, July 2007, https://stats.oecd.org/glossary/detail.asp?ID=3605.

[71] ISO, "Statistics — Vocabulary and symbols — Part 1: General statistical terms and terms used in probability," ISO, Tech. Rep. ISO 3534-1:2006, 2006. [Online]. Available: https://www.iso.org/cms/render/live/en/sites/isoorg/contents/data/standard/04/01/40145.html

[72] B. Cowgill, F. Dell'Acqua, S. Deng, D. Hsu, N. Verma, and A. Chaintreau, "Biased Programmers? Or Biased Data? A Field Experiment in Operationalizing AI Ethics," *arXiv:2012.02394 [cs, econ, q-fin]*, Dec. 2020, arXiv: 2012.02394. [Online]. Available: http://arxiv.org/abs/2012.02394

[73] S. Barocas and A. D. Selbst, "Big Data's Disparate Impact," *California Law Review*, vol. 104, no. 3, pp. 671–732, 2016, publisher: California Law Review, Inc. [Online]. Available: https://www.jstor.org/stable/24758720

[74] S. Costanza-Chock, "Design Justice, A.I., and Escape from the Matrix of Domination," *Journal of Design and Science*, Jul. 2018. [Online]. Available: https://jods.mitpress.mit.edu/pub/costanza-chock

[75] M. Elish, S. Barocas, A. Plasek, and K. Ferryman, "The social & economic implications of artificial intelligence technologies in the near-term," AI Now, New York, Tech. Rep., 2016. [Online]. Available: https://ainowinstitute.org/AI_Now_2016_Primers.pdf

[76] A. Jacobs and H. Wallach, "Measurement and Fairness," *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 375–385, Mar. 2021, arXiv: 1912.05511. [Online]. Available: http://arxiv.org/abs/1912.05511

[77] S. Passi and S. Barocas, "Problem Formulation and Fairness," *Proceedings of the Conference on Fairness, Accountability, and Transparency*, pp. 39–48, Jan. 2019, arXiv: 1901.02547. [Online]. Available: http://arxiv.org/abs/1901.02547

[78] A. D. Selbst, D. Boyd, S. A. Friedler, S. Venkatasubramanian, and J. Vertesi, "Fairness and Abstraction in Sociotechnical Systems," in *Proceedings of the Conference on Fairness, Accountability, and Transparency - FAT* '19*. Atlanta, GA, USA: ACM Press, 2019, pp. 59–68. [Online]. Available: http://dl.acm.org/citation.cfm?doid=3287560.3287598

[79] A. Tversky and D. Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Science*, vol. 185, no. 4157, pp. 1124–1131, 1974, publisher: American Association for the Advancement of Science. [Online]. Available: https://www.jstor.org/stable/1738360

[80] A. Caliskan, J. J. Bryson, and A. Narayanan, "Semantics derived automatically from language corpora contain human-like biases," *Science*, vol. 356, no. 6334, pp. 183–186, Apr. 2017. [Online]. Available: https://www.sciencemag.org/lookup/doi/10.1126/science.aal4230

[81] D. Danks and A. J. London, "Algorithmic Bias in Autonomous Systems," in *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence*. Melbourne, Australia: International Joint Conferences on Artificial

Intelligence Organization, Aug. 2017, pp. 4691–4697. [Online]. Available: https://www.ijcai.org/proceedings/2017/654

[82] T. Hellström, V. Dignum, and S. Bensch, "Bias in Machine Learning – What is it Good for?" *arXiv:2004.00686 [cs]*, Sep. 2020, arXiv: 2004.00686. [Online]. Available: http://arxiv.org/abs/2004.00686

[83] ISO/IEC, "ISO/IEC 2382:2015, Information technology — Vocabulary," International Organization for Standardization, Geneva, Switzerland, Tech. Rep., 2015. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso-iec:2382:ed-1:v1:en

[84] ——, "ISO/IEC 20546:2019, Information technology — Big data — Overview and vocabulary," International Organization for Standardization, Geneva, Switzerland, Tech. Rep., 2019. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso-iec:20546:ed-1:v1:en

[85] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, "A Survey on Bias and Fairness in Machine Learning," *arXiv:1908.09635 [cs]*, Sep. 2019, arXiv: 1908.09635. [Online]. Available: http://arxiv.org/abs/1908.09635

[86] M. Mitchell, *Artificial Intelligence: A Guide for Thinking Human*. Farrar, Straus, and Giroux, 2019.

[87] S. Mitchell and J. Shadlen, "Mirror mirror: Reflections on quantitative fairness. Shira Mitchell: Statistician," Dec 2020. [Online]. Available: https://shiraamitchell.github.io/fairness/

[88] D. K. Mulligan, J. A. Kroll, N. Kohli, and R. Y. Wong, "This Thing Called Fairness: Disciplinary Confusion Realizing a Value in Technology," *Proc. ACM Hum.-Comput. Interact.*, vol. 3, no. CSCW, pp. 1–36, Nov. 2019, arXiv: 1909.11869. [Online]. Available: http://arxiv.org/abs/1909.11869

[89] Organisation for Economic Co-operation and Development, "Recommendation of the Council on Artificial Inteliigence," 2019. [Online]. Available: https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449

[90] H. Suresh and J. Guttag, "A Framework for Understanding Unintended Consequences of Machine Learning," *arXiv:1901.10002 [cs, stat]*, Feb. 2020, arXiv: 1901.10002. [Online]. Available: http://arxiv.org/abs/1901.10002

[91] D. Chandler and R. Munday, *A Dictionary of Media and Communication*. Oxford University Press, Jan. 2011, publication Title: A Dictionary of Media and Communication. [Online]. Available: https://www.oxfordreference.com/view/10.1093/acref/9780199568758.001.0001/acref-9780199568758

[92] M. Ngan, P. J. Grother, and M. Ngan, *Face recognition vendor test (FRVT) performance of automated gender classification algorithms*. US Department of Commerce, National Institute of Standards and Technology, 2015.

[93] D. I. Perrett, K. J. Lee, I. Penton-Voak, D. Rowland, S. Yoshikawa, D. M. Burt, S. Henzi, D. L. Castles, and S. Akamatsu, "Effects of sexual dimorphism on facial attractiveness," *Nature*, vol. 394, no. 6696, pp. 884–887, 1998.

[94] I. M. Scott, A. P. Clark, S. C. Josephson, A. H. Boyette, I. C. Cuthill, R. L. Fried, M. A. Gibson, B. S. Hewlett, M. Jamieson, W. Jankowiak *et al.*, "Human prefer-

ences for sexually dimorphic faces may be evolutionarily novel," *Proceedings of the National Academy of Sciences*, vol. 111, no. 40, pp. 14 388–14 393, 2014.

[95] K. Kleisner, P. Tureček, S. C. Roberts, J. Havlíček, J. V. Valentova, R. M. Akoko, J. D. Leongómez, S. Apostol, M. A. Varella, and S. A. Saribay, "How and why patterns of sexual dimorphism in human faces vary across the world," *Scientific reports*, vol. 11, no. 1, pp. 1–14, 2021.

[96] O. Keyes, "The misgendering machines: Trans/hci implications of automatic gender recognition," *Proceedings of the ACM on Human-Computer Interaction*, vol. 2, no. CSCW, 2018. [Online]. Available: https://doi.org/10.1145/3274357

[97] Organization of Scientific Area Committees for Forensic Science, "OSAC Preferred Terms," 2021. [Online]. Available: https://www.nist.gov/system/files/documents/2021/04/28/OSAC%20Preferred%20Terms_April%202021.pdf

[98] D. Kahneman, S. P. Slovic, P. Slovic, and A. Tversky, *Judgment under uncertainty: Heuristics and biases*. Cambridge university press, 1982.

[99] A. I. Al-Alawi, M. Naureen, E. I. AlAlawi, and A. A. N. Al-Hadad, "The Role of Artificial Intelligence in Recruitment Process Decision-Making," in *2021 International Conference on Decision Aid Sciences and Application (DASA)*. IEEE, 2021, pp. 197–203.

[100] A. Rieke, U. Janardan, M. Hsu, and N. Duarte, "Essential Work: Analyzing the Hiring Technologies of Large Hourly Employers," Upturn, July 2021, https://www.upturn.org/reports/2021/essential-work/.

[101] L. X. Z. Brown and M. Richardson, "Algorithm-driven Hiring Tools: Innovative Recruitment or Expedited Disability Discrimination?" Ctr. for Democracy & Tech., Dec. 2020, https://cdt.org/insights/report-algorithm-driven-hiring-tools-innovative-recruitment-or-expedited-disability-discrimination.

[102] A. D'Amour, K. Heller, D. Moldovan, B. Adlam, B. Alipanahi, A. Beutel, C. Chen, J. Deaton, J. Eisenstein, M. D. Hoffman, F. Hormozdiari, N. Houlsby, S. Hou, G. Jerfel, A. Karthikesalingam, M. Lucic, Y. Ma, C. McLean, D. Mincu, A. Mitani, A. Montanari, Z. Nado, V. Natarajan, C. Nielson, T. F. Osborne, R. Raman, K. Ramasamy, R. Sayres, J. Schrouff, M. Seneviratne, S. Sequeira, H. Suresh, V. Veitch, M. Vladymyrov, X. Wang, K. Webster, S. Yadlowsky, T. Yun, X. Zhai, and D. Sculley, "Underspecification Presents Challenges for Credibility in Modern Machine Learning," *arXiv:2011.03395 [cs, stat]*, Nov. 2020, arXiv: 2011.03395. [Online]. Available: http://arxiv.org/abs/2011.03395

[103] R. Bommasani, D. A. Hudson, E. Adeli, R. Altman, S. Arora, S. von Arx, M. S. Bernstein, J. Bohg, A. Bosselut, E. Brunskill, E. Brynjolfsson, S. Buch, D. Card, R. Castellon, N. Chatterji, A. Chen, K. Creel, J. Q. Davis, D. Demszky, C. Donahue, M. Doumbouya, E. Durmus, S. Ermon, J. Etchemendy, K. Ethayarajh, L. Fei-Fei, C. Finn, T. Gale, L. Gillespie, K. Goel, N. Goodman, S. Grossman, N. Guha, T. Hashimoto, P. Henderson, J. Hewitt, D. E. Ho, J. Hong, K. Hsu, J. Huang, T. Icard, S. Jain, D. Jurafsky, P. Kalluri, S. Karamcheti, G. Keeling, F. Khani, O. Khattab, P. W. Kohd, M. Krass, R. Krishna, R. Kuditipudi, A. Kumar,

F. Ladhak, M. Lee, T. Lee, J. Leskovec, I. Levent, X. L. Li, X. Li, T. Ma, A. Malik, C. D. Manning, S. Mirchandani, E. Mitchell, Z. Munyikwa, S. Nair, A. Narayan, D. Narayanan, B. Newman, A. Nie, J. C. Niebles, H. Nilforoshan, J. Nyarko, G. Ogut, L. Orr, I. Papadimitriou, J. S. Park, C. Piech, E. Portelance, C. Potts, A. Raghunathan, R. Reich, H. Ren, F. Rong, Y. Roohani, C. Ruiz, J. Ryan, C. Ré, D. Sadigh, S. Sagawa, K. Santhanam, A. Shih, K. Srinivasan, A. Tamkin, R. Taori, A. W. Thomas, F. Tramèr, R. E. Wang, W. Wang, B. Wu, J. Wu, Y. Wu, S. M. Xie, M. Yasunaga, J. You, M. Zaharia, M. Zhang, T. Zhang, X. Zhang, Y. Zhang, L. Zheng, K. Zhou, and P. Liang, "On the Opportunities and Risks of Foundation Models," *arXiv:2108.07258 [cs]*, Aug. 2021, arXiv: 2108.07258. [Online]. Available: http://arxiv.org/abs/2108.07258

[104] D. Schiff, A. Ayesh, L. Musikanski, and J. C. Havens, "IEEE 7010: A new standard for assessing the well-being implications of artificial intelligence," *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Oct 2020. [Online]. Available: http://dx.doi.org/10.1109/SMC42975.2020.9283454

[105] A. Birhane, P. Kalluri, D. Card, W. Agnew, R. Dotan, and M. Bao, "The Values Encoded in Machine Learning Research," *arXiv:2106.15590 [cs]*, Jun. 2021, arXiv: 2106.15590. [Online]. Available: http://arxiv.org/abs/2106.15590

[106] N. Schmidt and B. Stephens, "An Introduction to Artificial Intelligence and Solutions to the Problems of Algorithmic Discrimination," *arXiv preprint arXiv:1911.05755*, 2019.

[107] C. Barabas, C. Doyle, J. Rubinovitz, and K. Dinakar, "Studying Up: Reorienting the Study of Algorithmic Fairness Around Issues of Power," in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 2020, pp. 167–176.

[108] B. Fish and L. Stark, "Reflexive Design for Fairness and Other Human Values in Formal Models," *arXiv:2010.05084 [cs]*, Oct. 2020, arXiv: 2010.05084. [Online]. Available: http://arxiv.org/abs/2010.05084

[109] K. Robertson, C. Khoo, and Y. Song, "To Surveil and Predict: A Human Rights Analysis of Algorithmic Policing in Canada," Citizen Lab & Int'l Hum. Rts. Prog., U. Toronto, Sept. 2020, https://citizenlab.ca/wp-content/uploads/2020/09/To-Surveil-and-Predict.pdf.

[110] S. C. Slota, K. R. Fleischmann, S. Greenberg, N. Verma, B. Cummings, L. Li, and C. Shenefiel, "Many hands make many fingers to point: challenges in creating accountable AI," *AI & Soc*, Nov. 2021. [Online]. Available: https://link.springer.com/10.1007/s00146-021-01302-0

[111] S. Mitchell, E. Potash, S. Barocas, A. D'Amour, and K. Lum, "Prediction-Based Decisions and Fairness: A Catalogue of Choices, Assumptions, and Definitions," *Annu. Rev. Stat. Appl.*, vol. 8, no. 1, pp. 141–163, Mar. 2021, arXiv: 1811.07867. [Online]. Available: http://arxiv.org/abs/1811.07867

[112] B. Green, "The Flaws of Policies Requiring Human Oversight of Government Algorithms," *SSRN Journal*, 2021. [Online]. Available: https://www.ssrn.com/abstract=3921216

[113] B. Green and A. Kak, “The false comfort of human oversight as an antidote to A.I. harm.” [Online]. Available: https://slate.com/technology/2021/06/human-oversight-artificial-intelligence-laws.html
[114] M. Boyarskaya, A. Olteanu, and K. Crawford, “Overcoming Failures of Imagination in AI Infused System Development and Deployment,” *arXiv:2011.13416 [cs]*, Dec. 2020, arXiv: 2011.13416. [Online]. Available: http://arxiv.org/abs/2011.13416
[115] D. Boyd and K. Crawford, “CRITICAL QUESTIONS FOR BIG DATA: Provocations for a cultural, technological, and scholarly phenomenon,” *Information, Communication & Society*, vol. 15, no. 5, pp. 662–679, Jun. 2012. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/1369118X.2012.678878
[116] C. D’Ignazio and L. Klein, *Data Feminism*. MIT Press, 2020. [Online]. Available: https://data-feminism.mitpress.mit.edu/
[117] A. Jacobs, S. L. Blodgett, S. Barocas, H. Daumé, and H. Wallach, “The meaning and measurement of bias: lessons from natural language processing,” in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, ser. FAT* ’20. New York, NY, USA: Association for Computing Machinery, Jan. 2020, p. 706. [Online]. Available: https://doi.org/10.1145/3351095.3375671
[118] E. Moss and J. Metcalf, “High Tech, High Risk: Tech Ethics Lessons for the COVID-19 Pandemic Response,” *Patterns*, vol. 1, no. 7, p. 100102, Oct. 2020. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2666389920301367
[119] A. L. Washington and R. Kuo, “Whose side are ethics codes on?: power, responsibility and the social good,” in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Barcelona Spain: ACM, Jan. 2020, pp. 230–240. [Online]. Available: https://dl.acm.org/doi/10.1145/3351095.3372844
[120] E. Morozov, *To save everything, click here: The folly of technological solutionism*. Penn State University Press, 2013.
[121] B. Aguera y Arcas, M. Mitchell, and A. Todorov, “Physiognomy’s new clothes,” May 2017. [Online]. Available: https://medium.com/@blaisea/physiognomys-new-clothes-f2d4b59fdd6a
[122] J. A. Kroll, “Outlining Traceability: A Principle for Operationalizing Accountability in Computing Systems,” *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 758–771, Mar. 2021, arXiv: 2101.09385. [Online]. Available: http://arxiv.org/abs/2101.09385
[123] R. Berk, H. Heidari, S. Jabbari, M. Joseph, M. Kearns, J. Morgenstern, S. Neel, and A. Roth, “A convex framework for fair regression,” 2017.
[124] R. Tromble, “Where Have All the Data Gone? A Critical Reflection on Academic Digital Research in the Post-API Age,” *Social Media + Society*, vol. 7, no. 1, p. 2056305121988929, Jan. 2021, publisher: SAGE Publications Ltd. [Online]. Available: https://doi.org/10.1177/2056305121988929
[125] A. Cobham, *The Uncounted*. John Wiley & Sons, 2020.
[126] D. Stone, *Counting: How We Use Numbers to Decide What Matters*. Liveright Publishing, 2020.

[127] B. Plank, “What to do about non-standard (or non-canonical) language in NLP,” *arXiv:1608.07836 [cs]*, Aug. 2016, arXiv: 1608.07836. [Online]. Available: http://arxiv.org/abs/1608.07836

[128] Y. Tan and L. E. Celis, “Assessing Social and Intersectional Biases in Contextualized Word Representations,” *arXiv:1911.01485 [cs, stat]*, Nov. 2019, arXiv: 1911.01485. [Online]. Available: http://arxiv.org/abs/1911.01485

[129] A. Paullada, I. D. Raji, E. M. Bender, E. Denton, and A. Hanna, “Data and its (dis)contents: A survey of dataset development and use in machine learning research,” *arXiv:2012.05345 [cs]*, Dec. 2020, arXiv: 2012.05345. [Online]. Available: http://arxiv.org/abs/2012.05345

[130] H. Abdollahpouri, M. Mansoury, R. Burke, and B. Mobasher, “The Unfairness of Popularity Bias in Recommendation,” *arXiv:1907.13286 [cs]*, Sep. 2019, arXiv: 1907.13286. [Online]. Available: http://arxiv.org/abs/1907.13286

[131] R. Baeza-Yates, “Bias on the web,” *Commun. ACM*, vol. 61, no. 6, pp. 54–61, 2018. [Online]. Available: https://dl.acm.org/doi/10.1145/3209581

[132] A. Lambrecht and C. E. Tucker, “Algorithmic Bias? An Empirical Study into Apparent Gender-Based Discrimination in the Display of STEM Career Ads,” *SSRN Journal*, 2016. [Online]. Available: http://www.ssrn.com/abstract=2852260

[133] M. Miceli, J. Posada, and T. Yang, “Studying Up Machine Learning Data: Why Talk About Bias When We Mean Power?” *arXiv:2109.08131 [cs]*, Sep. 2021, arXiv: 2109.08131. [Online]. Available: http://arxiv.org/abs/2109.08131

[134] E. H. Simpson, “The interpretation of interaction in contingency tables,” *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 13, no. 2, pp. 238–241, 1951. [Online]. Available: http://www.jstor.org/stable/2984065

[135] F. P. Calmon, D. Wei, K. N. Ramamurthy, and K. R. Varshney, “Optimized data pre-processing for discrimination prevention,” 2017.

[136] F. Kamiran and T. Calders, “Data preprocessing techniques for classification without discrimination,” *Knowledge and Information Systems*, vol. 33, no. 1, pp. 1–33, 2012. [Online]. Available: https://doi.org/10.1007/s10115-011-0463-8

[137] M. Feldman, S. Friedler, J. Moeller, C. Scheidegger, and S. Venkatasubramanian, “Certifying and removing disparate impact,” 2015. [Online]. Available: https://arxiv.org/abs/1412.3756

[138] K. Peng, A. Mathur, and A. Narayanan, “Mitigating dataset harms requires stewardship: Lessons from 1000 papers,” *arXiv:2108.02922 [cs]*, Aug. 2021, arXiv: 2108.02922. [Online]. Available: http://arxiv.org/abs/2108.02922

[139] R. K. E. Bellamy, K. Dey, M. Hind, S. C. Hoffman, S. Houde, K. Kannan, P. Lohia, J. Martino, S. Mehta, A. Mojsilovic, S. Nagar, K. N. Ramamurthy, J. Richards, D. Saha, P. Sattigeri, M. Singh, K. R. Varshney, and Y. Zhang, “AI Fairness 360: An Extensible Toolkit for Detecting, Understanding, and Mitigating Unwanted Algorithmic Bias,” *arXiv:1810.01943 [cs]*, Oct. 2018, arXiv: 1810.01943. [Online]. Available: http://arxiv.org/abs/1810.01943

[140] C. G. Northcutt, A. Athalye, and J. Mueller, “Pervasive label errors in test sets desta-

bilize machine learning benchmarks," 2021.

[141] T. Bolukbasi, K.-W. Chang, J. Zou, V. Saligrama, and A. Kalai, "Quantifying and Reducing Stereotypes in Word Embeddings," *arXiv:1606.06121*, vol. 1, p. 5, 2016.

[142] P. Parasurama and J. Sedoc, "Gendered Language in Resumes and its Implications for Algorithmic Bias in Hiring," *arXiv:2112.08910 [cs]*, Dec. 2021, arXiv: 2112.08910. [Online]. Available: http://arxiv.org/abs/2112.08910

[143] A. L. Hoffmann, "Where fairness fails: data, algorithms, and the limits of antidiscrimination discourse," *Information, Communication & Society*, vol. 22, no. 7, pp. 900–915, 2019.

[144] A. Olteanu, C. Castillo, F. Diaz, and E. Kıcıman, "Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries," *Front. Big Data*, vol. 2, p. 13, Jul. 2019. [Online]. Available: https://www.frontiersin.org/article/10.3389/fdata.2019.00013/full

[145] T. N. Bond and K. Lang, "The sad truth about happiness scales," *Journal of Political Economy*, vol. 127, no. 4, pp. 1629–1640, 2019.

[146] D. Kahneman, A. M. Rosenfield, L. Gandhi, and T. Blaser, "Noise: How to Overcome the High, Hidden Cost of Inconsistent Decision Making," *Harvard Business Review*, Oct. 2016, section: Decision making and problem solving. [Online]. Available: https://hbr.org/2016/10/noise

[147] M. M. Malik, "A Hierarchy of Limitations in Machine Learning," *arXiv:2002.05193 [cs, econ, math, stat]*, Feb. 2020, arXiv: 2002.05193. [Online]. Available: http://arxiv.org/abs/2002.05193

[148] G. Friedman and T. McCarthy, "Employment Law Red Flags in the Use of Artificial Intelligence in Hiring," 2019. [Online]. Available: https://www.americanbar.org/groups/business_law/publications/blt/2020/10/ai-in-hiring/

[149] E. Hüllermeier and W. Waegeman, "Aleatoric and epistemic uncertainty in machine learning: an introduction to concepts and methods," *Machine Learning*, vol. 110, no. 3, p. 457–506, Mar 2021. [Online]. Available: http://dx.doi.org/10.1007/s10994-021-05946-3

[150] Y. Nesterov, *Introductory lectures on convex optimization*, 2004th ed., ser. Applied Optimization. New York, NY: Springer, Dec. 2003.

[151] M. J. Kochenderfer and T. A. Wheeler, *Algorithms for Optimization*. London, England: MIT Press, Mar. 2019.

[152] L. Breiman, "Statistical modeling: The two cultures (with comments and a rejoinder by the author)," *Statistical science*, vol. 16, no. 3, pp. 199–231, 2001.

[153] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, "An image is worth 16x16 words: Transformers for image recognition at scale," *ArXiv*, vol. abs/2010.11929, 2021.

[154] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, "On the dangers of stochastic parrots: Can language models be too big?" in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, ser. FAccT '21.

New York, NY, USA: Association for Computing Machinery, 2021, p. 610–623. [Online]. Available: https://doi.org/10.1145/3442188.3445922

[155] C. Wagner, D. Garcia, M. Jadidi, and M. Strohmaier, "It's a man's Wikipedia? Assessing gender inequality in an online encyclopedia," in *Proceedings of the international AAAI conference on web and social media*, vol. 9, no. 1, 2015, pp. 454–463.

[156] A. Choromanska, M. Henaff, M. Mathieu, G. B. Arous, and Y. LeCun, "The loss surfaces of multilayer networks," in *Artificial intelligence and statistics*. PMLR, 2015, pp. 192–204.

[157] IEEE, "IEEE Standard for Floating-Point Arithmetic," *IEEE Std 754-2008*, pp. 1–70, 2008.

[158] K. Novak, *Numerical Methods for Scientific Computing: The Definitive Manual for Math Geeks*, 2nd ed. Equal Share Press, 2022.

[159] M. J. Wolf, K. W. Miller, and F. S. Grodzinsky, "Why we should have seen that coming: comments on Microsoft's Tay "experiment," and wider implications," *The ORBIT Journal*, vol. 1, no. 2, pp. 1–12, 2017.

[160] J. W. Rae, S. Borgeaud, T. Cai, K. Millican, J. Hoffmann, F. Song, J. Aslanides, S. Henderson, R. Ring, S. Young, E. Rutherford, T. Hennigan, J. Menick, A. Cassirer, R. Powell, G. van den Driessche, L. A. Hendricks, M. Rauh, P.-S. Huang, A. Glaese, J. Welbl, S. Dathathri, S. Huang, J. Uesato, J. Mellor, I. Higgins, A. Creswell, N. McAleese, A. Wu, E. Elsen, S. Jayakumar, E. Buchatskaya, D. Budden, E. Sutherland, K. Simonyan, M. Paganini, L. Sifre, L. Martens, X. L. Li, A. Kuncoro, A. Nematzadeh, E. Gribovskaya, D. Donato, A. Lazaridou, A. Mensch, J.-B. Lespiau, M. Tsimpoukelli, N. Grigorev, D. Fritz, T. Sottiaux, M. Pajarskas, T. Pohlen, Z. Gong, D. Toyama, C. de Masson d'Autume, Y. Li, T. Terzi, V. Mikulik, I. Babuschkin, A. Clark, D. de Las Casas, A. Guy, C. Jones, J. Bradbury, M. Johnson, B. Hechtman, L. Weidinger, I. Gabriel, W. Isaac, E. Lockhart, S. Osindero, L. Rimell, C. Dyer, O. Vinyals, K. Ayoub, J. Stanway, L. Bennett, D. Hassabis, K. Kavukcuoglu, and G. Irving, "Scaling language models: Methods, analysis & insights from training gopher," 2022.

[161] A. Tamkin, M. Brundage, J. Clark, and D. Ganguli, "Understanding the capabilities, limitations, and societal impact of large language models," 2021.

[162] A. F. Ansari, M. L. Ang, and H. Soh, "Refining deep generative models via discriminator gradient flow," 2021.

[163] J. Z. Forde, A. F. Cooper, K. Kwegyir-Aggrey, C. De Sa, and M. Littman, "Model Selection's Disparate Impact in Real-World Deep Learning Applications," *arXiv:2104.00606 [cs]*, Apr. 2021, arXiv: 2104.00606. [Online]. Available: http://arxiv.org/abs/2104.00606

[164] S. L. Blodgett, S. Barocas, H. Daumé III, and H. Wallach, "Language (Technology) is Power: A Critical Survey of "Bias" in NLP," *arXiv:2005.14050 [cs]*, May 2020, arXiv: 2005.14050. [Online]. Available: http://arxiv.org/abs/2005.14050

[165] G. Neff and P. Nagy, "Automation, Algorithms, and Politics| Talking to Bots: Symbiotic Agency and the Case of Tay," *International Journal of*

Communication, vol. 10, no. 0, p. 17, Oct. 2016, number: 0. [Online]. Available: https://ijoc.org/index.php/ijoc/article/view/6277

[166] D. Hovy and S. Prabhumoye, "Five sources of bias in natural language processing," *Language and Linguistics Compass*, vol. 15, no. 8, p. e12432, 2021, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/lnc3.12432. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/lnc3.12432

[167] R. Geirhos, J.-H. Jacobsen, C. Michaelis, R. Zemel, W. Brendel, M. Bethge, and F. A. Wichmann, "Shortcut Learning in Deep Neural Networks," *Nature Machine Intelligence*, vol. 2, no. 11, pp. 665–673, 2020.

[168] M. Hashemi and M. Hall, "RETRACTED ARTICLE: Criminal Tendency Detection from Facial Images and the Gender Bias Effect," *Journal of Big Data*, vol. 7, no. 1, pp. 1–16, 2020.

[169] BBC, "Facial recognition to 'predict criminals' sparks row over AI bias," BBC Online News, June 2020, https://www.bbc.com/news/technology-53165286.

[170] S. Levin, "New AI can guess whether you're gay or straight from a photograph," The Guardian, Sept. 2017, https://www.theguardian.com/technology/2017/sep/07/new-artificial-intelligence-can-tell-whether-youre-gay-or-straight-from-a-photograph.

[171] J. D. West and C. T. Bergstrom, "Misinformation In and About Science," *Proceedings of the National Academy of Sciences*, vol. 118, no. 15, 2021.

[172] A. E. Miller, "Searching for gaydar: Blind spots in the study of sexual orientation perception," *Psychology & Sexuality*, vol. 9, no. 3, pp. 188–203, 2018.

[173] L. F. Barrett, R. Adolphs, S. Marsella, A. M. Martinez, and S. D. Pollak, "Emotional Expressions Reconsidered: Challenges to Inferring Emotion from Human Facial Movements," *Psychological science in the public interest*, vol. 20, no. 1, pp. 1–68, 2019.

[174] B. M. Booth, L. Hickman, S. K. Subburaj, L. Tay, S. E. Woo, and S. K. D'Mello, "Bias and Fairness in Multimodal Machine Learning: A Case Study of Automated Video Interviews," in *Proceedings of the 2021 International Conference on Multimodal Interaction*. Montréal QC Canada: ACM, Oct. 2021, pp. 268–277. [Online]. Available: https://dl.acm.org/doi/10.1145/3462244.3479897

[175] A. Narayanan, "How to recognize AI snake oil," CITP (Princeton U.), Feb. 2022, https://www.cs.princeton.edu/~arvindn/talks/MIT-STS-AI-snakeoil.pdf.

[176] T. H. Davenport and J. G. Harris, *Competing on analytics*. Boston, MA: Harvard Business Review Press, Feb. 2007.

[177] J. Kleinberg, J. Ludwig, S. Mullainathan, and C. R. Sunstein, "Algorithms as discrimination detectors," *Proc Natl Acad Sci USA*, vol. 117, no. 48, pp. 30 096–30 100, Dec. 2020. [Online]. Available: http://www.pnas.org/lookup/doi/10.1073/pnas.1912790117

[178] M. H. Jarrahi, G. Newlands, M. K. Lee, C. T. Wolf, E. Kinder, and W. Sutherland, "Algorithmic management in a work context," *Big Data & Society*, vol. 8, no. 2, p. 20539517211020332, 2021.

[179] S. Brayne, *Predict and surveil*. New York, NY: Oxford University Press, Jan. 2021.

[180] B. Cowgill, "Bias and Productivity in Humans and Algorithms: Theory and Evidence from Resume Screening," *Columbia Business School, Columbia University*, p. 35, 2020.

[181] C. Thompson, "Who's homeless enough for housing? in san francisco an algorithm decides," Nov 2021. [Online]. Available: https://www.codastory.com/authoritarian-tech/san-francisco-homeless-algorithm/

[182] Office of Inspector General, "Advisory concerning the Chicago police department's predictive risk models," City of Chicago, Tech. Rep., Jan. 2020, https://igchicago.org/wp-content/uploads/2020/01/OIG-Advisory-Concerning-CPDs-Predictive-Risk-Models-.pdf.

[183] D. Hunter and N. Evans, "Facebook emotional contagion experiment controversy," *Research Ethics*, vol. 12, no. 1, pp. 2–3, 2016.

[184] Y. Wang and M. Kosinski, "Deep neural networks are more accurate than humans at detecting sexual orientation from facial images," *Journal of Personality and Social Psychology*, vol. 114, p. 246–257, 2018.

[185] M. Roberts, D. Driggs, M. Thorpe, J. D. Gilbey, M. Yeung, S. Ursprung, A. I. Avilés-Rivero, C. Etmann, C. McCague, L. Beer, J. R. Weir-McCall, Z. Teng, E. Gkrania-Klotsas, J. H. F. Rudd, E. Sala, and C.-B. Schönlieb, "Common pitfalls and recommendations for using machine learning to detect and prognosticate for covid-19 using chest radiographs and ct scans," *Nat. Mach. Intell.*, vol. 3, pp. 199–217, 2021.

[186] L. Wynants, B. Calster, G. Collins, R. Riley, G. Heinze, E. Schuit, M. Bonten, D. Dahly, J. Damen, T. Debray, V. Jong, M. Vos, P. Dhiman, M. Haller, M. Harhay, L. Henckaerts, P. Heus, M. Kammer, N. Kreuzberger, A. Lohmann, K. Luijken, J. Ma, G. Martin, D. McLernon, C. Navarro, J. Reitsma, J. Sergeant, C. Shi, N. Skoetz, L. Smits, K. Snell, M. Sperrin, R. Spijker, E. Steyerberg, T. Takada, I. Tzoulaki, S. Kuijk, B. Bussel, I. Horst, F. Royen, J. Verbakel, C. Wallisch, J. Wilkinson, R. Wolff, L. Hooft, K. Moons, and M. Smeden, "Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal," *BMJ*, vol. 369, p. m1328, Apr. 2020, publisher: British Medical Journal Publishing Group Section: Research. [Online]. Available: https://www.bmj.com/content/369/bmj.m1328

[187] M. Hutson, *Has artificial intelligence become alchemy?* American Association for the Advancement of Science, 2018.

[188] R. Dijkgraaf, Quanta Magazine, Oct 2021. [Online]. Available: https://www.quantamagazine.org/science-has-entered-a-new-era-of-alchemy-good-20211020/

[189] L. Wynants, B. Van Calster, G. S. Collins, R. D. Riley, G. Heinze, E. Schuit, M. M. Bonten, D. L. Dahly, J. A. Damen, T. P. Debray *et al.*, "Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal," *bmj*, vol. 369, 2020.

[190] M. Sap, D. Card, S. Gabriel, Y. Choi, and N. A. Smith, "The risk of racial bias in hate speech detection," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Florence, Italy: Association

for Computational Linguistics, Jul. 2019, pp. 1668–1678. [Online]. Available: https://aclanthology.org/P19-1163

[191] E. Ntoutsi, P. Fafalios, U. Gadiraju, V. Iosifidis, W. Nejdl, M.-E. Vidal, S. Ruggieri, F. Turini, S. Papadopoulos, E. Krasanakis, I. Kompatsiaris, K. Kinder-Kurlanda, C. Wagner, F. Karimi, H. Alani, B. Berendt, T. Kruegel, C. Heinze, K. Broelemann, G. Kasneci, T. Tiropanis, and S. Staab, "Bias in Data-driven AI Systems - An Introductory Survey," *arXiv:2001.09762v1 [cs.CY]*, p. 19, 2020.

[192] "Leveraging responsible AI to counteract bias in health care," Aug. 2021. [Online]. Available: https://www.statnews.com/2021/08/06/leverage-responsible-ai-counteract-bias-health-care/

[193] A. Słowik and L. Bottou, "Algorithmic Bias and Data Bias: Understanding the Relation between Distributionally Robust Optimization and Data Curation," *arXiv:2106.09467 [cs, stat]*, Jun. 2021, arXiv: 2106.09467. [Online]. Available: http://arxiv.org/abs/2106.09467

[194] K. R. Varshney, *Trustworthy Machine Learning*. Chappaqua, NY, USA: Independently Published, 2022.

[195] CFPB, "Using publicly available information to proxy for unidentified race and ethnicity," Consumer Financial Protection Bureau, 2014, https://files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf.

[196] N. Gill, P. Hall, K. Montgomery, and N. Schmidt, "A Responsible Machine Learning Workflow with Focus on Interpretable Models, Post-hoc Explanation, and Discrimination Testing," *Information*, vol. 11, no. 3, p. 137, 2020.

[197] S. Venkatasubramanian, C. Scheidegger, S. Friedler, and A. Clauset, *Fairness in Networks: Social Capital, Information Access, and Interventions*. New York, NY, USA: Association for Computing Machinery, 2021, p. 4078–4079. [Online]. Available: https://doi.org/10.1145/3447548.3470821

[198] S. A. Friedler, C. Scheidegger, and S. Venkatasubramanian, "The (im)possibility of fairness: Different value systems require different mechanisms for fair decision making," *Commun. ACM*, vol. 64, no. 4, p. 136–143, mar 2021. [Online]. Available: https://doi.org/10.1145/3433949

[199] M. J. Kusner, J. R. Loftus, C. Russell, and R. Silva, "Counterfactual Fairness," *arXiv:1703.06856 [cs, stat]*, Mar. 2018, arXiv: 1703.06856. [Online]. Available: http://arxiv.org/abs/1703.06856

[200] L. Wang, "Race as proxy: Situational racism and self-fulfilling stereotypes," *DePaul Law Review*, vol. 53, p. 1013, 2004.

[201] A. Agan and S. Starr, "Ban the Box, Criminal Records, and Racial Discrimination: A Field Experiment*," *The Quarterly Journal of Economics*, vol. 133, no. 1, pp. 191–235, 08 2017. [Online]. Available: https://doi.org/10.1093/qje/qjx028

[202] K. Fiscella and A. M. Fremont, "Use of geocoding and surname analysis to estimate race and ethnicity," *Health services research*, vol. 41, pp. 1482–500, 2006.

[203] S. Jabbari, M. Joseph, M. Kearns, J. Morgenstern, and A. Roth, "Fairness in Reinforcement Learning," *arXiv:1611.03071 [cs]*, Aug. 2017, arXiv: 1611.03071.

[Online]. Available: http://arxiv.org/abs/1611.03071

[204] A. D'Amour, H. Srinivasan, J. Atwood, P. Baljekar, D. Sculley, and Y. Halpern, "Fairness is not static: Deeper understanding of long term fairness via simulation studies," in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, ser. FAT* '20. New York, NY, USA: Association for Computing Machinery, 2020, p. 525–534. [Online]. Available: https://doi.org/10.1145/3351095.3372878

[205] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, "Language models are few-shot learners," 2020.

[206] N. Kilbertus, M. Rojas-Carulla, G. Parascandolo, M. Hardt, D. Janzing, and B. Schölkopf, "Avoiding discrimination through causal reasoning," 2018.

[207] J. Kleinberg, S. Mullainathan, and M. Raghavan, "Inherent trade-offs in the fair determination of risk scores," 2016.

[208] K. T. Rodolfa, H. Lamba, and R. Ghani, "Empirical observation of negligible fairness–accuracy trade-offs in machine learning for public policy," *Nature Machine Intelligence*, vol. 3, no. 10, pp. 896–904, 2021.

[209] R. Richardson, "Defining and demystifying automated decision systems," March 2021, forthcoming. [Online]. Available: https://ssrn.com/abstract=3D3811708

[210] R. Binns, M. Van Kleek, M. Veale, U. Lyngs, J. Zhao, and N. Shadbolt, "'It's Reducing a Human Being to a Percentage'; Perceptions of Justice in Algorithmic Decisions," Montreal QC, Canada, Jan. 2018. [Online]. Available: https://osf.io/9wqxr

[211] C. M. Scaparrotti, *Joint Publication 3-13 Information Operations*. Citeseer, 2012.

[212] G. Raman, B. AlShebli, M. Waniek, T. Rahwan, and J. C.-H. Peng, "How weaponizing disinformation can bring down a city's power grid," *PLOS ONE*, vol. 15, pp. 1–14, 08 2020. [Online]. Available: https://doi.org/10.1371/journal.pone.0236517

[213] E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini, "The rise of social bots," *Commun. ACM*, vol. 59, no. 7, p. 96–104, jun 2016. [Online]. Available: https://doi.org/10.1145/2818717

[214] W. Phillips, "The Oxygen of Amplification: Better Practices for Reporting on Extremists, Antagonists, and Manipulators Online," Data & Society, May 2018, https://datasociety.net/wp-content/uploads/2018/05/FULLREPORT_Oxygen_of_Amplification_DS.pdf.

[215] S. Alon-Barkat and M. Busuioc, "Decision-makers Processing of AI Algorithmic Advice: Automation Bias versus Selective Adherence," *arXiv:2103.02381 [cs]*, Mar. 2021, arXiv: 2103.02381. [Online]. Available: http://arxiv.org/abs/2103.02381

[216] B. J. Dietvorst, J. P. Simmons, and C. Massey, "Algorithm aversion: people erro-

neously avoid algorithms after seeing them err," *J Exp Psychol Gen*, vol. 144, no. 1, pp. 114–126, Feb. 2015.

[217] ——, "Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them," *Management Science*, vol. 64, no. 3, pp. 1155–1170, Mar. 2018. [Online]. Available: http://pubsonline.informs.org/doi/10.1287/mnsc.2016.2643

[218] M. Veale, M. Van Kleek, and R. Binns, "Fairness and Accountability Design Needs for Algorithmic Support in High-Stakes Public Sector Decision-Making," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI '18*. Montreal QC, Canada: ACM Press, 2018, pp. 1–14. [Online]. Available: http://dl.acm.org/citation.cfm?doid=3173574.3174014

[219] S. Picard, M. Watkins, M. Rempal, and A. Kerodal, "Beyond the Algorithm: Pretrial Reform, Risk Assessment, and Racial Fairness," Center for Court Innovation, Tech. Rep., 2020. [Online]. Available: https://www.courtinnovation.org/publications/beyond-algorithm

[220] B. Knowles and J. T. Richards, "The Sanction of Authority: Promoting Public Trust in AI," *arXiv:2102.04221 [cs]*, Jan. 2021, arXiv: 2102.04221. [Online]. Available: http://arxiv.org/abs/2102.04221

[221] C. Prunkl, C. Ashurst, M. Anderljung, H. Webb, J. Leike, and A. Dafoe, "Institutionalizing ethics in AI through broader impact requirements," *Nature Machine Intelligence*, vol. 3, no. 2, pp. 104–110, Feb. 2021, number: 2 Publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/s42256-021-00298-y

[222] E. Moss, E. Watkins, R. Singh, M. Elish, and J. Metcalf, "Assembling Accountability: Algorithmic Impact Assessment for the Public Interest." [Online]. Available: https://datasociety.net/library/assembling-accountability-algorithmic-impact-assessment-for-the-public-interest/

[223] G. Can., "Algorithmic Impact Assessment Tool," Gov't Can. Online Resource, Apr. 2021, https://www.canada.ca/en/government/system/digital-government/digital-government-innovations/responsible-use-ai/algorithmic-impact-assessment.html.

[224] M. Kop, "AI Impact Assessment & Code of Conduct," Futurium, May 2019, https://futurium.ec.europa.eu/en/european-ai-alliance/best-practices/ai-impact-assessment-code-conduct.

[225] D. Reisman, J. Schultz, K. Crawford, and M. Whittaker, "Algorithmic Impact Assessments: A Practical Framework For Public Agency Accountability," AI Now, Apr. 2018, https://ainowinstitute.org/aiareport2018.pdf.

[226] A. D. Selbst, "An Institutional View Of Algorithmic Impact Assessments," *Harvard Journal of Law & Technology*, vol. 35, no. 1, 2021.

[227] E. Moss and J. Metcalf, "Ethics Owners," Sep. 2020, publisher: Data & Society Research Institute. [Online]. Available: https://datasociety.net/library/ethics-owners/

[228] K. Crawford, "Artificial Intelligence's White Guy Problem," *The New York Times*,

p. 2, Jun. 2016. [Online]. Available: https://nyti.ms/28YaKg7

[229] D. Rock and H. Grant, "Why Diverse Teams Are Smarter," Nov. 2016, https://hbr.org/2016/11/why-diverse-teams-are-smarter.

[230] A. Rosen and I. Ihara, "Giving you more characters to express yourself," Twitter Blog, Sept. 2017, https://blog.twitter.com/en_us/topics/product/2017/Giving-you-more-characters-to-express-yourself.

[231] W. Knight, "Twitter's Photo-Cropping Algorithm Favors Young, Thin Females," Wired, Aug. 2021, https://www.wired.com/story/twitters-photo-cropping-algorithm-favors-young-thin-females.

[232] K. Yee and I. F. Peradejordi, "Sharing learnings from the first algorithmic bias bounty challenge," Twitter Engineering Blog, Sept. 2021, https://blog.twitter.com/engineering/en_us/topics/insights/2021/learnings-from-the-first-algorithmic-bias-bounty-challenge.

[233] C. Herring, "Does diversity pay?: Race, gender, and the business case for diversity," *American Sociological Review*, vol. 74, pp. 208 – 224, 2009.

[234] N. Ellemers and F. Rink, "Diversity in work groups," *Current opinion in psychology*, vol. 11, pp. 49–53, 2016.

[235] K. Talke, S. Salomo, and A. Kock, "Top management team diversity and strategic innovation orientation: The relationship and consequences for innovativeness and performance," *Journal of Product Innovation Management*, vol. 28, pp. 819–832, 2011.

[236] R. Lorenzo and M. Reeves, "How and Where Diversity Drives Financial Performance," Harvard Bus. Rev., Jan. 2018, https://hbr.org/2018/01/how-and-where-diversity-drives-financial-performance.

[237] S. M. West, M. Whittaker, and K. Crawford, "Discriminating Systems: Gender, Race, and Power in AI," AI Now Institute, Tech. Rep., 2019. [Online]. Available: https://ainowinstitute.org/discriminatingsystems.pdf

[238] D. Walsh, "How can human-centered ai fight bias in machines and people?" MIT Sloan Mgmt. Rev., Feb. 2021, https://mitsloan.mit.edu/ideas-made-to-matter/how-can-human-centered-ai-fight-bias-machines-and-people.

[239] M. Li, "To Build Less-Biased AI, Hire a More Diverse Team," Harvard Bus. Rev., Oct. 2020, https://hbr.org/2020/10/to-build-less-biased-ai-hire-a-more-diverse-team.

[240] P. Hall, N. Gill, and B. Cox, *Responsible machine learning: Actionable strategies for mitigating risks and driving adoption.* Sebastopol, CA: O'Reilly Media Inc., 2020.

[241] M. Mitchell, S. Wu, A. Zaldivar, P. Barnes, L. Vasserman, B. Hutchinson, E. Spitzer, I. D. Raji, and T. Gebru, "Model Cards for Model Reporting," in *Proceedings of the Conference on Fairness, Accountability, and Transparency - FAT* '19*. Atlanta, GA, USA: ACM Press, 2019, pp. 220–229. [Online]. Available: http://dl.acm.org/citation.cfm?doid=3287560.3287596

[242] T. Gebru, J. Morgenstern, B. Vecchione, J. Wortman Vaughan, H. Wallach,

H. Daumee III, and K. Crawford, "Datasheets for Datasets," *arXiv:1803.09010v6 [cs.DB]*, 2020.

[243] D. Broniatowski, "Psychological Foundations of Explainability and Interpretability in Artificial Intelligence," NIST, Tech. Rep., 2021.

[244] S. Gaube, H. Suresh, M. Raue, A. Merritt, S. J. Berkowitz, E. Lermer, J. F. Coughlin, J. V. Guttag, E. Colak, and M. Ghassemi, "Do as AI say: susceptibility in deployment of clinical decision-aids," *npj Digit. Med.*, vol. 4, no. 1, pp. 1–8, Feb. 2021. [Online]. Available: https://www.nature.com/articles/s41746-021-00385-9

[245] J. Zerilli, A. Knott, J. MacLaurin, and C. Gavaghan, "Algorithmic decision-making and the control problem," *Minds and Machines*, vol. 29, pp. 555 – 578, 2019.

[246] NIST, "Usability and Biometrics: Ensuring Successful Biometric Systems," NIST Online Resource, June 2008, https://www.nist.gov/system/files/usability_and_biometrics_final2.pdf.

[247] M. Theofanos *et al.*, "Usability Handbook for Public Safety Communications: Ensuring Successful Systems for First Responders," NIST (Handbook 161), May 2017, https://nvlpubs.nist.gov/nistpubs/hb/2017/NIST.HB.161.pdf.

[248] ISO, "Ergonomics of human-system interaction — Part 210: Human-centered design for interactive systems," ISO 9241-210:2019 (2nd ed.), July 2019, https://www.iso.org/standard/77520.html.

[249] E. A. Vogels, "Some digital divides persist between rural, urban and suburban America," Pew Research Center, Aug. 2021, https://www.pewresearch.org/fact-tank/2021/08/19/some-digital-divides-persist-between-rural-urban-and-suburban-america/.

[250] ——, "Digital divide persists even as americans with lower incomes make gains in tech adoption," Pew Research Center, June 2021, https://www.pewresearch.org/fact-tank/2021/06/22/digital-divide-persists-even-as-americans-with-lower-incomes-make-gains-in-tech-adoption/.

[251] X. Ferrer, T. van Nuenen, J. M. Such, M. Coté, and N. Criado, "Bias and Discrimination in AI: a cross-disciplinary perspective," *IEEE Technol. Soc. Mag.*, vol. 40, no. 2, pp. 72–80, Jun. 2021, arXiv: 2008.07309. [Online]. Available: http://arxiv.org/abs/2008.07309

[252] S. Russell, D. Dewey, and M. Tegmark, "Research priorities for robust and beneficial artificial intelligence," *AI Magazine*, vol. 36, no. 4, pp. 105–114, Dec. 2015. [Online]. Available: https://ojs.aaai.org/index.php/aimagazine/article/view/2577

[253] G. Margetis, S. Ntoa, M. Antona, and C. Stephanidis, *HUMAN-CENTERED DESIGN OF ARTIFICIAL INTELLIGENCE*. John Wiley & Sons, Ltd, 2021, ch. 42, pp. 1085–1106. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119636113.ch42

[254] B. Shneiderman, *Human-Centered AI*. London, England: Oxford University Press, Jan. 2022.

[255] S. Ejaz, "A Broken System: How the Credit Reporting System Fails Consumers and What To Do About It," Consumer Reports, June 2021, https://advocacy.consumerreports.org/wp-content/uploads/2021/06/A-Broken-System-How-the-Credit-Repor

ting-System-Fails-Consumers-and-What-to-Do-About-It.pdf.
[256] S. Ammermann, “Adverse Action Notice Requirements Under the ECOA and the FCRA,” Consumer Compliance Outlook, 2nd Q. 2013, https://consumercomplianceoutlook.org/2013/second-quarter/adverse-action-notice-requirements-under-ecoa-fcra.
[257] A. Smith, “Using Artificial Intelligence and Algorithms,” FTC, Apr. 2020, https://www.ftc.gov/news-events/blogs/business-blog/2020/04/using-artificial-intelligence-algorithms.
[258] J. A. Kroll, J. Huey, S. Barocas, E. W. Felten, J. R. Reidenberg, D. G. Robinson, and H. Yu, “Accountable Algorithms,” *University of Pennsylvania Law Review*, vol. 165, no. 633, p. 74, 2017.
[259] GAO, “Artificial Intelligence: An Accountability Framework for Federal Agencies and Other Entities,” GAO@100 (GAO-21-519SP), June 2021, https://www.gao.gov/assets/gao-21-519sp.pdf.
[260] I. D. Raji, A. Smart, R. N. White, M. Mitchell, T. Gebru, B. Hutchinson, J. Smith-Loud, D. Theron, and P. Barnes, “Closing the AI Accountability Gap: Defining an End-to-End Framework for Internal Algorithmic Auditing,” in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, ser. FAT* ’20. New York, NY, USA: Association for Computing Machinery, 2020, p. 33–44. [Online]. Available: https://doi.org/10.1145/3351095.3372873
[261] R. Carrier and S. Brown, “Taxonomy: AI Audit, Assurance, and Assessment,” ForHumanity, Feb. 2021, https://forhumanity.center/web/wp-content/uploads/2021/09/ForHumanity.center_Taxonomy_AI_Audit_Assurance_Assessment.pdf.
[262] E. Mulvaney, “NYC Targets Artificial Intelligence Bias in Hiring Under New Law,” Bloomberg Law, 2021, https://news.bloomberglaw.com/daily-labor-report/nyc-targets-artificial-intelligence-bias-in-hiring-under-new-law.
[263] R. N. Landers and T. S. Behrend, “Auditing the AI auditors: A framework for evaluating fairness and bias in high stakes ai predictive models,” 2022.
[264] D. Sull, S. Turconi, and C. Sull, “When It Comes to Culture, Does Your Company Walk the Talk?” MIT Sloan Mgmt. Rev., July 2020, https://sloanreview.mit.edu/article/when-it-comes-to-culture-does-your-company-walk-the-talk.
[265] C. Johnson, M. Badger, D. Waltermire, J. Snyder, and C. Skorupka, “Guide to cyber threat information sharing,” National Institute of Standards and Technology, NIST Special Publication 800-150, Nov 2016. [Online]. Available: https://doi.org/10.6028/NIST.SP.800-150
[266] S. McGregor, “Preventing Repeated Real World AI Failures by Cataloging Incidents: The AI Incident Database,” *arXiv:2011.08512 [cs]*, Nov. 2020, arXiv: 2011.08512. [Online]. Available: http://arxiv.org/abs/2011.08512
[267] K. Leino, E. Black, M. Fredrikson, S. Sen, and A. Datta, “Feature-Wise Bias Amplification,” *arXiv:1812.08999 [cs, stat]*, Oct. 2019, arXiv: 1812.08999. [Online]. Available: http://arxiv.org/abs/1812.08999
[268] I. Misra, C. L. Zitnick, M. Mitchell, and R. Girshick, “Seeing through the

Human Reporting Bias: Visual Classifiers from Noisy Human-Centric Labels," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Las Vegas, NV, USA: IEEE, Jun. 2016, pp. 2930–2939. [Online]. Available: http://ieeexplore.ieee.org/document/7780689/

[269] H. Miller, J. Thebault-Spieker, S. Chang, I. Johnson, L. Terveen, and B. Hecht, ""blissfully happy" or "ready to fight": Varying interpretations of emoji," in *Proceedings of the 10th International Conference on Web and Social Media, ICWSM 2016*. AAAI press, Jan. 2016, pp. 259–268. [Online]. Available: https://experts.umn.edu/en/publications/blissfully-happy-or-ready-to-fight-varying-interpretations-of-emo

[270] P. C. Wason, "Reasoning about a rule," *Quarterly Journal of Experimental Psychology*, vol. 20, no. 3, pp. 273–281, 1968. [Online]. Available: https://doi.org/10.1080/14640746808400161

[271] L. J. Cronbach and P. E. Meehl, "Construct validity in psychological tests." *Psychological bulletin*, vol. 52 4, pp. 281–302, 1955.

[272] S. Silva and M. Kenney, "Algorithms, platforms, and ethnic bias," *Commun. ACM*, vol. 62, no. 11, pp. 37–39, Oct. 2019. [Online]. Available: https://dl.acm.org/doi/10.1145/3318157

[273] E. Jeong, S. Oh, H. Kim, J. Park, M. Bennis, and S.-L. Kim, "Communication-Efficient On-Device Machine Learning: Federated Distillation and Augmentation under Non-IID Private Data," *arXiv:1811.11479 [cs, stat]*, Nov. 2018, arXiv: 1811.11479. [Online]. Available: http://arxiv.org/abs/1811.11479

[274] Centre for Evidence-Based Medicine, "Catalogue of Bias," Mar. 2017. [Online]. Available: https://catalogofbias.org/

[275] J. Kruger and D. Dunning, "Unskilled and unaware of it: how difficulties in recognizing one's own incompetence lead to inflated self-assessments." *Journal of personality and social psychology*, vol. 77 6, pp. 1121–34, 1999.

[276] M. Delgado-Rodriguez, "Bias," *Journal of Epidemiology & Community Health*, vol. 58, no. 8, pp. 635–641, Aug. 2004. [Online]. Available: https://jech.bmj.com/lookup/doi/10.1136/jech.2003.008466

[277] P. M. Lukacs, K. P. Burnham, and D. R. Anderson, "Model selection bias and freedman's paradox," *Annals of the Institute of Statistical Mathematics*, vol. 62, pp. 117–125, 2009.

[278] K. Lerman and T. Hogg, "Leveraging Position Bias to Improve Peer Recommendation," *PLOS ONE*, vol. 9, no. 6, p. e98914, Jun. 2014, publisher: Public Library of Science. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0098914

[279] A. Kaplan, *The conduct of inquiry*, A. Kaplan, Ed. Somerset, NJ: Transaction, Apr. 1998.

[280] Z. Tufekci, "Big questions for social media big data: Representativeness, validity and other methodological pitfalls," *arXiv:1403.7400 [cs.SI]*, 2014.

[281] B. Goodman and S. Flaxman, "European Union regulations on algorithmic

decision-making and a ”right to explanation”,” *AIMag*, vol. 38, no. 3, pp. 50–57, Oct. 2017, arXiv: 1606.08813. [Online]. Available: http://arxiv.org/abs/1606.08813

Exhibit__(SCSP-5)

Staff's Proposed
Outreach & Education Budget Template

BUDGET INFORMATION

KEDNY's Estimated Outreach & Education Budget for January – December:

Provide a budget breakdown of the FY'XX Estimated Budget for Outreach and Education Expenditures. Please make it clear whether your winter budget is part of your overall budget. Spending details should be included in the topic-specific pages found in Section 4.

Total .... $

Gas: Total .... $

Breakdown by Categories: note-breakdown can be modified to reflect the Utility's unique budget tracking categories.

[Insert Program Name]…………………………..……… $

	Gas
Bill Inserts	**$**
Print materials	**$**
Brochures/Flyers	**$**
Direct Mail	**$**
Educational Videos	**$**
Email	**$**
Social media	**$**
Media advertisement	**$**
Newsletters	**$**
Web and digital media	**$**
Outbound Heap calls	**$**
Administration of Care	**$**
Share and Neighborhood Heating	**$**
Other (indicate each category on a separate timeline)	**$**

BUDGET INFORMATION

KEDLI's Estimated Outreach & Education Budget for January – December:

Provide a budget breakdown of the FY'XX Estimated Budget for Outreach and Education Expenditures. Please make it clear whether your winter budget is part of your overall budget. Spending details should be included in the topic-specific pages found in Section 4.

Total .... $

Gas: Total .... $

Breakdown by Categories: note-breakdown can be modified to reflect the Utility's unique budget tracking categories.

[Insert Program Name]…………………………..……… $

	Gas
Bill Inserts	**$**
Print materials	**$**
Brochures/Flyers	**$**
Direct Mail	**$**
Educational Videos	**$**
Email	**$**
Social media	**$**
Media advertisement	**$**
Newsletters	**$**
Web and digital media	**$**
Outbound Heap calls	**$**
Administration of Care	**$**
Share and Neighborhood Heating	**$**
Other (indicate each category on a separate timeline)	**$**

BUDGET INFORMATION

NMPC's Estimated Outreach & Education Budget for January – December:

Provide a budget breakdown of the FY'XX Estimated Budget for Outreach and Education Expenditures. Please make it clear whether your winter budget is part of your overall budget. Spending details should be included in the topic-specific pages found in Section 4.

Total .... **$**

Electric: Total .... **$**
Gas: Total .... **$**

Breakdown by Categories: note-breakdown can be modified to reflect the Utility's unique budget tracking categories.

[Insert Program Name]...**$**

	Electric	Gas
Bill Inserts	$	$
Print materials	$	$
Brochures/Flyers	$	$
Direct Mail	$	$
Educational Videos	$	$
Email	$	$
Social media	$	$
Media advertisement	$	$
Newsletters	$	$
Web and digital media	$	$
Outbound Heap calls	$	$
Administration of Care	$	$
Share and Neighborhood Heating	$	$
Other (indicate each category on a separate timeline)	$	$

BUDGET INFORMATION

KEDNY's Planned and Actual Outreach & Education Expenditures for January – December XXXX:

Provide Outreach and Education expenditures for the previous year. Indicate the total proposed budget for XXXX and the total and actual expenditures. Each category table should include actual (not proposed) spending by outreach method/tool for the year.

[Insert Program Name]

Breakdown by Categories:

	Planned	Spent
Total	$	$
Gas: Total	$	$

	Gas Planned	Gas Spent
Bill Inserts	$	$
Print materials	$	$
Brochures/Flyers	$	$
Direct Mail	$	$
Educational Videos	$	$
Email	$	$
Social media	$	$
Media advertisement	$	$
Newsletters	$	$
Web and digital media	$	$
Outbound Heap calls	$	$
Administration of Care	$	$
Share and Neighborhood Heating	$	$
Other (indicate each category on a separate timeline)	$	$

BUDGET INFORMATION

KEDLI's Planned and Actual Outreach & Education Expenditures for January – December XXXX:

Provide Outreach and Education expenditures for the previous year. Indicate the total proposed budget for XXXX and the total and actual expenditures. Each category table should include actual (not proposed) spending by outreach method/tool for the year.

[Insert Program Name]

Breakdown by Categories:

	Planned	Spent
Total	$	$
Gas: Total	$	$

	Gas Planned	Gas Spent
Bill Inserts	$	$
Print materials	$	$
Brochures/Flyers	$	$
Direct Mail	$	$
Educational Videos	$	$
Email	$	$
Social media	$	$
Media advertisement	$	$
Newsletters	$	$
Web and digital media	$	$
Outbound Heap calls	$	$
Administration of Care	$	$
Share and Neighborhood Heating	$	$
Other (indicate each category on a separate timeline)	$	$

BUDGET INFORMATION

NMPC's Actual Outreach & Education Expenditures for January – December XXXX:

Provide Outreach and Education expenditures for the previous year. Indicate the total proposed budget for XXXX and the total actual expenditures. Each category table should include actual (not proposed) spending by outreach method/tool for the year.

[Insert Program Name]

Breakdown by Categories:

	Planned	Spent
Total	$	$
Electric: Total	$	$
Gas: Total	$	$

	Electric Planned	Electric Spent	Gas Planned	Gas Spent
Bill Inserts	$	$	$	$
Print materials	$	$	$	$
Brochures/Flyers	$	$	$	$
Direct Mail	$	$	$	$
Educational Videos	$	$	$	$
Email	$	$	$	$
Social media	$	$	$	$
Media advertisement	$	$	$	$
Newsletters	$	$	$	$
Web and digital media	$	$	$	$
Outbound Heap calls	$	$	$	$
Administration of Care	$	$	$	$
Share and Neighborhood Heating	$	$	$	$
Other (indicate each category on a separate timeline)	$	$	$	$