A Comparative Study of Electronic Voting and Paper Ballot Systems in Modern Elections

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2 June 2023

Abstract

Paper ballots have long dominated the voting system in the United States. In the wave of new technology, the limitations of conventional systems have become more apparent. To address this further, five states introduced electronic voting systems as their primary collection system for the 2020 presidential election, including Georgia, which announced its switch to ballot-marking devices in 2019. An electronic voting system is commonly adopted when attempting to reduce waiting times at polling locations, decrease long-term costs, increase voter confidence, and deliver election results faster. As states continue to implement various versions of electronic voting systems, many studies have demonstrated improvements in their processes and security. Yet, long waiting lines continue to impact voters and consequently decrease voter turnout. To address this issue and support local election officials in future elections, this study defines processing times for the electronic voting process through statistical methods and applies discrete event simulation to compare results to a conventional paper process. Simulation models will utilize observed time studies during the 2022 midterm elections in Atlanta, GA (ballot-marking devices), and the 2018 midterm elections in Rhode Island (paper ballots), and estimated voter waiting times are compared. The results of this study will aid election officials in quantifying the effects of moving from paper ballots to electronic voting and supporting election planning decisions.

1 Introduction

As election systems evolve, voting technologies, processes, and methods change. While some changes are accompanied by a lead time for process reconsideration, changes can also occur rapidly due to legislative and judicial decisions, pandemics, or technology shifts. Election administrators frequently are asked to alter their methods of election planning and resource allocation to execute more with fewer readily available resources. When not adequately accounted for, system changes can lead to longer wait times at polling locations. For example, U.S. voters in 2020 elections waited upwards of four hours to vote in some locations (e.g. Laughland and Levine, 2020; Perez, 2020; Swasey and Wise, 2020). Delays in election results reporting, ADA inaccessibility, and unclear processes. While national consistency in elections is infeasible, measuring the effects of system changes and improving elections planning is achievable.

In 2002, the Help America Vote Act (HAVA) was codified into law, reforming voting processes used across the United States in response to challenges faced in the 2000 election.[1] Efforts to improve voting processes were focused primarily on upgrading and updating voting equipment to safely and effectively serve the electorate. Since the enactment of HAVA, states have adopted or modified voting processes and systems to better serve voters and ensure that elections are verifiable. One option for HAVA compliance is the use of ballot marking devices (BMDs) in place of mechanical and fully electronic voting processes. BMDs allow a voter to utilize technology to mark ballot selections while still receiving a physical paper ballot that can be checked and verified by the voter. Figure 1 demonstrates the changes in the voting equipment used between 2014 and 2024. According to Verified Voting (2023a), in 2014, 3209 precincts reported using ballot marking devices. In 2018, 3917 precincts reported using BMDs, representing a 22.1% increase from 2014. With a significant increase in adoption by 2022, 5079 precincts reported using BMDs, a 29.7% increase from 2018 and a 58.3% increase from 2014 (Verified Voting, 2023a)(see the red bar in Figure 1). Whereas the total registered number of voters per marking method between 2014 and 2024 can be seen in Figure 2 (see the red bar for BMD). According to Verified Voting (2023a), in 2014, 133,736 voters were registered in a precinct that offered BMDs for all and 131,125,658 voters were registered in a precinct where paper-ballots were their primary voting method.[2] In 2018, 4,022,747 voters were registered in a precinct that offered BMDs for all, and 147,713,031 were registered in a precinct where paper ballots were the primary method; representing a 29.1% increase and 0.126% increase from 2014, respectively. In 2022, 51,860,277 voters were registered in a precinct that offered BMDs for all, representing an 11.9% increase from 2018 and a 386.8% increase from 2014. There is clearly a paradigm shift in the utilization of technology in elections that mirrors innovation in other fields, thus creating an opportunity for elections to explore the implementation of technology in their systems, such as BMDs.

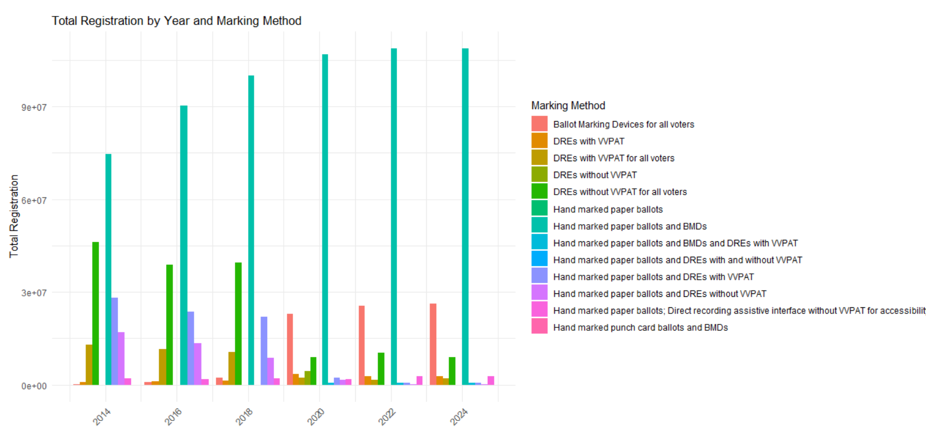

Figure 1: Total Registration per Ballot Marking Type (Verified Voting, 2023a)

In a system where manual processes have long dominated voting in U.S. elections, the initial impact

[1] H.R. 3295 (2002)

[2] BMDs, Direct Recording Equipment, and other accessible equipment may be provided for voters in need.

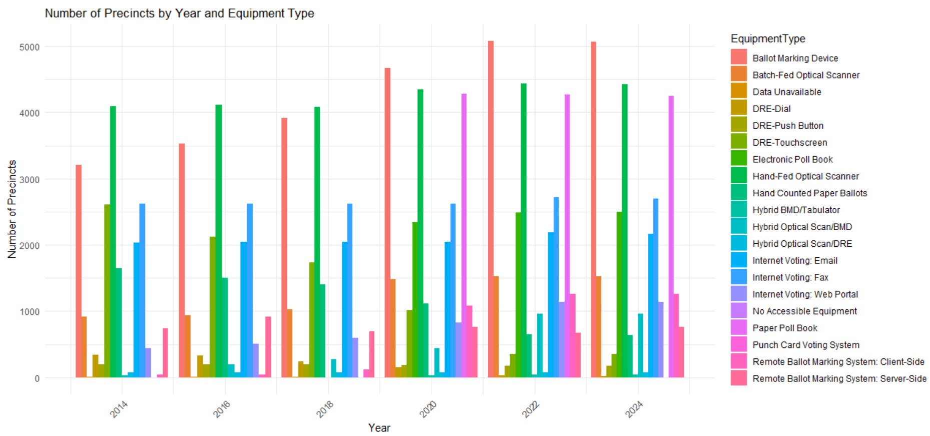

Figure 2: Total Precincts per Ballot Marking Type (Verified Voting, 2023a)

of entertaining electronic voting initiated security concerns and demonstrated some of the limitations and advantages of both alternatives (Appel et al., 2020; Bernhard et al., 2020). Electronic voting systems are commonly adopted when attempting to reduce waiting times at polling locations by limiting the number of materials (Kortum et al., 2020), decrease long-term costs (of State, 2010), and increase usability for disabled voters (Bernhard et al., 2020; Kortum et al., 2020). As a result, more states have solidified their switch to electronic voting. As of 2022, Georgia, South Carolina, and Louisiana utilize BMDs or direct recording electronic systems with voter-verified paper audit trail printers. Other states, including Rhode Island, Arizona, Michigan, and New Hampshire, utilize paper ballots and digital ballot scanning devices exclusively, with exceptions for accessible ballot marking (Verified Voting, 2023a). With the continued shift toward the use of BMDs, areas of elections research have focused on the usability, security, and perception of BMDs.

As states continuously implement versions of electronic voting systems, many studies have demonstrated theoretical improvements in the voting process with a focus on security and accessibility (e.g., Feng et al., 2010; Jafar et al., 2021).[3] However, limited information explores the performance of voting processes using BMDs with respect to voter wait times, and fewer compare the performance of differing voting processes. Understanding the performance of voting processes (i.e., voter wait times) is critical in election planning. Depending on the performance of a voting system, decisions on staffing, voting equipment allocation, and voter information, among others, must be adjusted to ensure that voters do not face significant delays in voting. Voter wait times are often directly affected by administrative decision-making, impacting how voters experience the voting process (e.g., Bernardo et al., 2022a; Bernardo and Macht, 2022; Bernardo et al., 2022b; Samuelson et al., 2007). Generally, more resources, like increased allocation of voting machines and poll workers, improve the resulting voter experience, while fewer resources lead to longer queue times and decreased confidence (Alvarez et al., 2008; Bernardo et al., 2022b; Bracken et al., 2020; Chen et al., 2020; Claassen et al., 2013; King, 2019; Pettigrew, 2017; Stewart III). Increased wait times and technical difficulties have also demonstrated an increase in the likelihood of reneging (i.e., leaving prior to voting) on voting as the wait time increases (Bernardo et al., 2022b; Stein et al., 2020).

While current research on voting efficiency is limited with respect to BMDs, the goal of decreasing queue times on Election Day is not. Opportunity costs due to long waiting times at polling stations, such as lost productivity and disenfranchisement, emphasize the urgency to explore more efficient voting systems. The "time tax," or the cost of waiting in line to vote as described in Mukherjee (2009-2010), can be negligible if only a few seconds pass prior to initiating the process or can be extensive if the delay time is significantly long (Cottrell et al., 2021). The impact of long queue times extends beyond individual voters. Overburdened polling stations may result in overcrowded polling locations, leading to logistical challenges and potential health and safety risks. Additionally, excessive wait times disproportionately affect marginalized communities (Cottrell et al., 2021; Stein et al., 2020). As the urgency to explore more efficient voting systems

[3] Also see the Help America Vote Act, H.R. 3295 (2002)

is highlighted by disenfranchisement and long wait times, it becomes necessary to address these concerns through research and analysis. There have been additional operations research applications for elections, including forecasting on voter's time-in-system (Samuelson et al., 2007). This approach aims to maximize the efficiency and effectiveness of the electoral process by employing data-driven methods and simulations to inform decision-making (Bernardo et al., 2022a; Bernardo and Macht, 2022; Stewart III; Yang et al., 2013). By leveraging operations research techniques, election administrators can make informed choices regarding resource allocation, resulting in reduced queue times and improved overall voter experience. Addressing these issues requires a comprehensive examination of electronic voting systems, their implementation, and the necessary safeguards to ensure the security, privacy, and integrity of such systems to maintain public trust and confidence in our democratic processes.

Scholarship has begun to explore the benefits and capabilities of BMDs with respect to security, usability, and voter perception; however, an exploration into the operational differences between BMDs and alternative voting systems is limited. Scholarship that has focused on voting processes utilizing BMDs investigates voters' abilities to identify mistakes on the ballot and exhibit varying success rates. Some studies suggest a low success rate (Bernhard et al., 2020), while others indicate a higher success rate (Kortum et al., 2020). The crux of the problem lies not in voters casting their ballot but rather in their capacity to identify and address issues with their ballot after it has been printed (Appel et al., 2020). The issue of verifying ballots can be approached as a two-part question: will voters check their ballot, and if they do, are voters scrutinizing its contents? The aforementioned studies tested sample sizes of approximately 108 and 241 participants, respectively, and tested if the participants were (a) observed examining their ballot, (b) if they reported the error on the exit survey, or (c) if they reported the error to a poll workers (Bernhard et al., 2020; Kortum et al., 2020). These studies reveal that a portion of voters uncover errors without or with interventions to prompt voters to check their ballots. One of the studies showed an increase after proper signage, poll workers prompting participants, and additional materials (i.e., scripts similar to sample ballots that could be filled out prior to voting) (Bernhard et al., 2020). The other study employed differing levels of errors, lengths of the ballots, ballot design, and between-subjects design (Kortum et al., 2020) and saw an increase in shorter Voting Solutions for All People (VSAP) style ballots. Overall, there presents a gap in the literature on comparative operational differences between BMDs and other voting systems, and with the potential to exercise operation research methods in order to do so.

With a focus on polling location operations, a substantial body of work has investigated election preparation and resource allocation for in-person elections either generally or focusing on a single polling location. Allen and Bernshteyn (2006) and Stewart III apply queuing theory as a method for allocating voting equipment to polling locations. Allen and Bernshteyn (2006) utilized data from the 2004 presidential election in Franklin County, Ohio to generate queuing models and subsequently allocate voting machines and estimate voter wait times for the 2008 presidential election. Developing on the applications of queuing models for elections, additional scholarship has applied discrete event simulation (DES) to model voting processes in the U.S. (Allen, 2011; Allen et al., 2020; Yang et al., 2013) and Nigeria (Ganiyu et al., 2016; Olabisi, 2012). Continuing their study of Franklin County, Ohio, Allen (2011) conducted a case study using DES to assess various system scenarios, including new voting machines, differing resource allocation, early voting, paper ballots, and specific direct recording electronic voting machine allocations. Yang et al. (2013) utilized DES to assess several resource allocation methods for the same Franklin County election, demonstrating the effects of election settings and resource allocation strategies on voter wait times. Allen et al. (2020) applied DES to generate voter wait time estimates at different resource allocations and applied an optimization method to identify the ideal combination of voting resources (i.e., poll books and voting machines) for a given in-person polling location. McCool-Guglielmo et al. (2022) utilized DES to assess the effect of equipment layout on polling location performance. Olabisi (2012) presented a methodology for simulating Nigerian elections and optimizing resource allocation to provide election administrators with tools for election preparation. Building on the methods employed in Olabisi (2012) for Nigerian elections, Ganiyu et al. (2016) used an adapted DES system to simulate voting processes allowing for specific programming of individual processes within the system (e.g., voter arrivals, ballot marking). Ganiyu et al. (2016) used this adapted form of DES to measure the effect of voter turnout and poll staffing on system performance (e.g., voter wait time, line length). While each of these works contributes to the broader field of knowledge regarding voting process performance, few focus on the use of BMDs or compare alternative voting processes to those using BMDs. (Bernardo et al., 2022a) similarly apply DES to investigate a polling location and compare its performance under several

COVID-19 scenarios. This study demonstrates that necessary changes to the voting process to mitigate the spread of COVID-19 affect voter wait times and require additional considerations when planning elections (Bernardo et al., 2022a, p. 12-13).

To address the shift to an increasingly electronic world, five states introduced electronic voting systems as their primary collection system for the 2020 presidential election, including Georgia, which announced its switch to BMD's in 2019 for implementation in the 2020 election, as reported by Fowler (2019); Verified Voting (2023a). This study explores voting processes observed in Georgia during the 2022 midterm election and defines processing times for the BMD-based ballot marking process through statistical methods. To further investigate the performance of BMD-based voting processes, simulations are performed utilizing real data observed from elections in 2018 and 2022 to compare wait times between the Georgia, BMD-based voting process and the Rhode Island, hand-marked paper ballot-based voting process. Outcomes from these simulations report estimated voter waiting times, which are compared through statistical analysis of the two voting processes. The results of this study may assist election officials in quantifying the effects of moving from hand-marked ballots to electronically-marked ballots and support election planning decisions for future applications.

2 Methodology

This paper utilizes discrete event simulation to establish computational mirrors of election systems for comparison between the midterm elections in Georgia (2022) and Rhode Island (2018). Through a detailed statistical analysis, processing times, rates, and distributions for each observed in-person voting process step are determined. Once these processing times were established, they were placed into the computational simulation models as inputs, then underwent a circular verification and validation process, and, finally, the outcome performance metrics were reviewed.

2.1 Processing Steps for In-Person Voting

Processing steps to check-in, vote, and tabulate in-person ballots can differ between states and counties based on available resources, voting methods, legislation, and a variety of other factors.

Rhode Island's voting process relies on paper ballots as the primary method of conducting elections. This approach provides election officials with the ability to perform a manual recount or audit if necessary. The process entails check-in, where voters verify their identity and receive a paper ballot, followed by marking the ballot by hand, and feeding it into a ballot scanner once the ballot is marked. The use of scanners ensures transparency as voters can witness their votes being processed and confirm their acceptance. In compliance with HAVA, BMD's are also available for voters who require accessible equipment in Rhode Island.

Georgia's voting process, as observed in the 2022 midterm election, consists of checking in with a poll worker on an electronic poll book with a government-issued identification card, after which the voter receives a voter access card. Then the voter travels to a ballot marking device where they are prompted to insert their card into the machine. Voters then digitally mark their ballot on the screen and, when they are complete, are prompted to verify their selections. The ballot is then printed, and the voter removes their voter access card and proceeds to a ballot scanner. The voter can then input their ballot into the scanner and confirm that it has been scanned and counted, and places their voter access in the designated bin. The printed ballot allows voters to confirm their selection on paper prior to recording their votes and can be preserved and used in the event of an audit or a recount (Verified Voting, 2023b).

Georgia's system is of particular interest for this research since its voting process mirrors the voting process in Rhode Island, even using the same check-in equipment. The primary difference between these voting processes is the method of marking ballots, which provides an opportunity to compare the performance of digital ballot marking to hand-marking paper ballots.

2.2 Data Acquisition

The University of Rhode Island Voter OperaTions and Election Systems (URI VOTES) performed data collection in Rhode Island during the 2018 midterm election and in Georgia during the 2022 midterm election. Data collectors were trained prior to observing the voting processes with identical instructions on how to track individual processing steps.

2.2.1 2018 Midterm Election Rhode Island

In conjunction with the Rhode Island Board of Elections and the Rhode Island Sectary of State's office, sixteen data collectors observed elections and performed time studies at seven polling locations across Rhode Island during the 2018 midterm election. To perform observations in these polling locations, teams of two data collectors remained in designated areas for observers with a view of all voting processes. Each collector tracked two processes, with one recording voter arrival times and check-in processing times and the other recording ballot marking times and ballot scanning times. When possible, each data collector would track an individual voter throughout the entire voting process to determine total throughput time. Data collectors were instructed to count arrivals when voters entered the primary entrance to the voting area or when they joined the queue to check in. To track processing times, collectors began tracking when a voter occupied the space at the station and ended tracking when the voter began to exit the station. Timers used for tracking were equipped with a function to undo a previous observation to minimize inaccurate data.

The total sample size for all of the locations observed on Election Day is 3065 observations with the following breakdown by station: 1) voting booth: 685 observations, 2) check-in: 1144 observations, 3) ballot scanning: 1138 observations, and 4) throughput: 98 observations. For the location analyzed in this study, the total sample size is 960 observations, with 320 observations for the voting booth station, 320 for check-in, and 320 for ballot scanning.

2.2.2 2022 Midterm Election Georgia

In conjunction with the Carter Center, located in Atlanta, Georgia, a team of six individuals collected data at five polling locations across Fulton County.[4] Upon arriving at the polling location, the team sat in a designated area for observers and turned off all electronic devices. Due to restrictions on the use of electronics within Georgia polling locations, teams manually timed voting processes using pen, paper, and stopwatches. The processing steps recorded were check-in, ballot marking, and scanning. Due to the use of pen and paper for data collection as well as limited visibility to the polling location entrance, voter arrivals were difficult to track and were not recorded for all observed locations. At all locations, there were instances of voters arriving at an incorrect voting location and being offered a provisional ballot. These check-ins were recorded with a start time but with no ending time. Two main collection methods were used, including recording from a continuous clock and recording the discrete start and ending times. Exact specifications on when the recorder started and ended the clock were user-specific, but in general, the time began when the voter occupied a station and ended when the voter was leaving the station after service. A total sample size of 1513 observations were recorded with the following breakdown by the station for all of the polling location observed: 1) BMD: 543 observations, 2) check-in: 627 observations, 3) check-in provisional: 2 observations, and 4) ballot scanning: 312 observations. For the location analyzed in this study, the total sample size is 738 observations, with 433 for check-in, 183 observations for the BMD, 2 for provisional check-in, and 120 for ballot scanning.

2.3 Data Cleaning

To ensure consistency and accuracy in the data obtained in the two data sets, some data cleaning was performed. Data collected from Westerly, RI, were cleaned by removing observations that were missing starting or ending times or recorded processing times of zero. The data collected from Atlanta, GA, originated from multiple observers who employed different methods of data collection, such as marking start and end times on a continuous clock or recording exact duration. When start and end times were available, they were recorded in their respective columns and were subtracted to calculate the duration. The data was further cleaned by eliminating instances where the total duration equaled zero or contained no response. Similarly, entries with a start time of zero or no response were removed from the data set. Additionally, provisional

[4]The Carter Center is a nonpartisan organization focused on human rights, alleviating suffering, and promoting democracy. The Center actively collaborates with a wide range of organizations, from governmental bodies to grassroots organizations, and has aided in adopting methodologies for observing elections across the globe (The Carter Center, 2007, 2023).

ballot check-ins were removed from the Atlanta, GA, data because they are outside the bounds of this study and have a small sample size (n=2).

The resulting sample sizes after data cleaning did not have an effect on the sample sizes of the data set from Rhode Island; thus, all remained the same as previously reported.

The total sample size for Atlanta, GA, decreased from 1513 to 1483 observations (98.02% data retained). For the location to be analyzed in this study, the total sample size decreased to 731 observations (99.05% data retained) with the following break down by station after the data were cleaned: 432 observations from check-in (99.77% data retained), 179 observations from BMD (97.81% data retained), and 120 observations from ballot scanning (100% data retained).

2.4 Descriptive Statistics

To explore the processing times observed in each state, Table 1 presents descriptive statistics and corresponding probability distributions to describe the data. It is important to note that there are inherent differences in the ballot marking times due to the differences in ballot length and style, which often differs between elections and polling locations. During the 2018 midterm election, the ballot length for the Westerly, RI precinct in this study was 18 total questions (Bernardo et al., 2022b). The ballot length for the Atlanta, Georgia precinct in 2022 was 22 total questions. The processing times generated from the respective data sets represent the total time to mark the ballot and cannot be broken down per item on the ballot. Future work could quantify the percentage of time spent on each question type, allowing for the study to be scaled down by question. However, the difference between the three questions, in this case, does not raise particular concerns for further comparison. Figure 3 is an example of histograms that were developed.

Table 1: *Descriptive Statistics for Sample Data Sets (minutes)*

Year	State	Type	n	Mean	SD	Min	Q1	Q2	Q3	Max
2018	RI	Check-in	320	0.71	0.35	0.07	0.52	0.63	0.80	4.57
2018	RI	Ballot Marking	320	3.80	1.88	0.02	2.62	3.43	4.51	17.2
2018	RI	Ballot Scanning	320	0.28	0.17	0.07	0.18	0.25	0.32	1.45
2022	GA	Check-in	432	1.10	0.58	0.13	0.85	0.98	1.21	5.87
2022	GA	BMD	179	5.19	2.09	1.30	3.84	4.90	6.00	14.47
2022	GA	Ballot Scanning	120	0.39	0.60	0.07	0.25	0.30	0.37	6.42

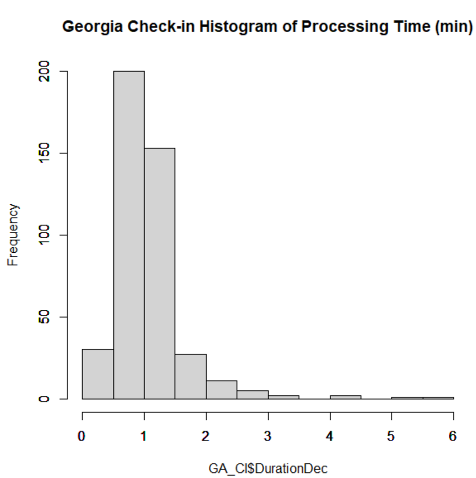

Figure 3: GA Check-in Processing Times Histogram (minutes)

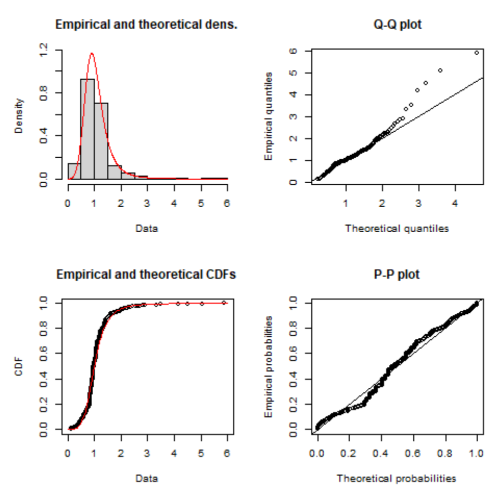

Figure 4: GA Check-In Processing Times Fitting Distribution - LogLogistic

2.5 Comparison of Data

Prior to utilizing the observed data in simulation analysis, a statistical comparison of data within each location is performed. This test is conducted to determine if observations from different polling locations within each state may be combined into a larger data set to develop more robust statistics.

The Kruskal-Wallis test was first performed on the sample data from Georgia. The data were compared per voting station with respect to the polling location, which allowed the testing of whether data from the polling locations statistically differed from any other. A similar approach was taken for the Rhode Island sample data set, comparing data collected from several polling locations in 2018. The results of the Kruskal-Wallis tests indicate that observations from at least one polling location differed from the observations of another polling location.

To further determine if data could be combined, a Mann-Whitney U-Test was performed for each pair-wise comparison of polling location observations. The results of the Mann-Whitney U-Test indicate that data from no other polling location can be added to the Atlanta, GA data or the Westerly, RI data.

2.6 Fitting Distribution

The voting processing time data were fit to probability distributions to be used in later analysis. Using the *fitdistrplus* package in *R*, this analysis fits the sample data to either the log-logistic, log-normal, gamma, or Weibull distribution. The best fit was determined visually (e.g., see Figure 4) as well as by comparing the Kolmogorov-Smirnov test statistic for the considered distributions. Figure 2 displays the probability distributions that were fit to each step of the two observed polling locations.

Table 2: *Processing Times for Sample Data from Georgia in 2022 and Rhode Island in 2018*

Location	Process	n	Mean Time (minutes)	Maximum Time (minutes)	Probability Distribution
GA	Check-in	432	1.10	5.87	Loglogistic(4.415, 0.997)
GA	Ballot-Marking	179	5.19	14.47	Loglogistic(4.674, 4.842)
GA	Ballot-Scanning	120	0.39	6.42	Loglogistic(4.038, 0.299)
RI	Check-in	320	0.71	4.57	Loglogistic(4.888, 0.646)
RI	Ballot-Marking	320	3.80	17.20	Loglogistic(4.082, 3.437)
RI	Ballot-Scanning	320	0.28	1.45	Loglogistic(4.106, 0.244)

Note. Probability distributions were determined by comparing the best fit of the distribution based on the Kolmogorov-Smirnov statistic. Distribution parameters are presented as distribution(shape, scale).

2.7 Discrete Event Simulation

The Simio™ simulation software is used to create the discrete event simulation (DES) model to describe the voting processes. As discussed in the literature, employing simulations enables researchers to gain valuable insights into optimizing the voter experience and addressing potential disparities in wait times (Herron and Smith, 2016). A simulation approach is, therefore, employed to act as a proxy for the investigated polling locations. Through this proxy, factors that may have differed between the specific elections and polling locations may be controlled for, narrowing the focus on the comparison of ballot marking methods and the corresponding performance of the voting processes.

For the simulation modeling and analysis, several assumptions are made. First, unlike the common practice in elections where voters are held at the check-in queue when a location is at capacity, the simulated system allows voters to wait between stations. This ensures that wait times may be attributed to specific process steps rather than the system as a whole. Second, it is assumed that voters do not balk (i.e., decide not to enter), jockey (i.e., switch lines), or renege (i.e., leave prior to voting), and voters are served on a first-in, first-out basis. Each of the simulated voting processes requires seven data inputs: voter gait speed, voter turnout, voter arrival behavior, station processing times, path lengths between stations, station capacities, and method of ballot marking. In order to ensure that the simulated voter behavior mimics the observed behavior, simulation logic is included in the model. This logic includes that the polling locations are simulated for a 13-hour Election Day, where voters who enter the system prior to close are permitted to complete the process after scheduled operation hours, while voters who arrive after the closing time will be turned away. Non-standard voting processes, such as casting a provisional ballot, discarding and reissuing ballots with errors, and exiting prior to completing the voting process, are not considered in this analysis, and only voters who enter and complete every step are simulated. Paths between processes are assigned values based on the approximate facility size of the polling location in Atlanta, Georgia. This ensures that all simulated voters will be traveling the same distance regardless of which experimental model is being run. The path lengths are as follows: 1) enter to check-in: 9.47 ft., 2) check-in to ballot marking: 11.33 ft., 3) ballot marking to scanner: 12.04 ft., 4) scanner to exit: 15.01 ft. These pathways can be visualized in Figure 5.

The capacities of the processing steps in the simulation model are determined from the observed capacities of the polling location observed in Atlanta, Georgia. The resource allocation for both the Rhode Island and Georgia polling locations are assumed to be as follows: 4 check-in devices, 12 ballot marking stations (i.e., privacy booths in Rhode Island or BMDs in Georgia), and 2 ballot scanners. The layout of the voting area and the distances between stations are also estimated from the Georgia polling location, as depicted in Figure 5. The turnout rate, arrival rate, and capacities are assumed to be the same for both Rhode Island and Georgia, enabling the processing times to be the only factors affecting the total time-in-system, wait times, and total number in the system.

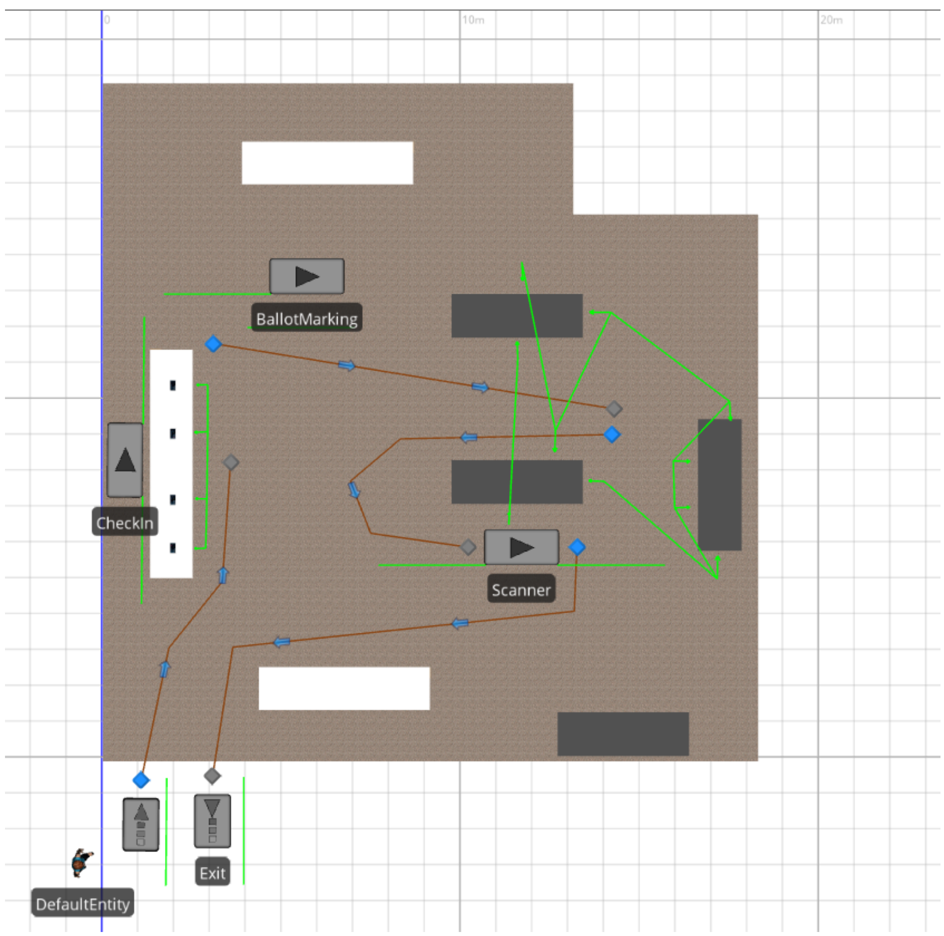

Figure 5: Floor Plan of Simulated Site

In the model, voter turnout refers to the number of voters who arrive and participate at the polling location. The total number of voter arrivals is 1076 voters and is determined from reported turnout rates from Fulton County, GA, for the polling location simulated (Fulton County, GA, 2022). The voter arrival pattern is simulated with a standard arrival pattern, shown in Figure 6, representing commonly observed peaks during the morning and afternoon on Election Day (Bernardo and Macht, 2022; Edelstein, 2006; Yang et al., 2013). The voter gait speed, shown in Table 3, is estimated for the U.S. population and is separated by age and sex (Bernardo and Macht, 2022; Bohannon and Andrews, 2011; US Census Bureau, 2019).

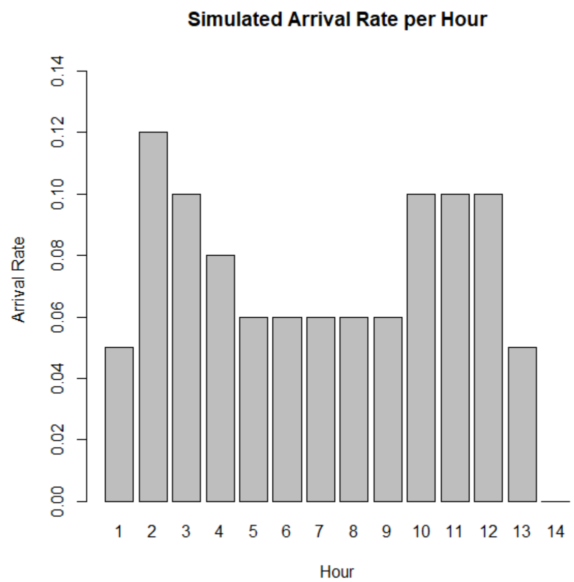

Figure 6: Simulated Arrival Rate per Hour[1]

Note.[1](Bernardo and Macht, 2022; Edelstein, 2006; Yang et al., 2013)

Processing times for voting steps are simulated using the probability distributions presented in Table 2 from the collected data. Randomly generated values are set with a random seed of 13 to allow for repeatability and comparability.

Simulation models are verified by observing the behavior of voters within the system, witnessing where they queue, examining preliminary results, and ensuring that the logic within the code accurately represents what occurred during observation (Bernardo et al., 2022a). After gaining feedback from other URI VOTES members who were present at the time of observation, the model is adjusted and improved so that it best represents the observed system. Simulation scenarios are replicated 20 times [5].

2.8 Voting Process Performance

To evaluate the performance of each model scenario, 95% confidence intervals were calculated for the mean and maximum wait times for each voting station (i.e., check-in, ballot marking, and ballot scanning), the percent utilization of each station, the overall voter wait times, the number of voters in the system, and the time-in-system. This interval is derived by averaging the wait times across multiple replications of each model scenario resulting in a mean of means. When comparing different models, confidence intervals are examined to determine if there are significant differences between them. To assess the general performance of a system, the established guidelines such as the the recommendation put forth by the Presidential Commission on Election Administration in 2014 (U.S. Election Assistance Commission, 2022). According to this recommendation, and similar standards adopted by certain jurisdictions (Cummings et al.), it is expected that no voter should wait longer than 30-minutes to vote. This is the benchmark is utilized to gauge whether a system meets

[5]The required number of replications for each model is estimated as defined in Banks et al. (2010), using an α of 0.05 and a deviation of 5% on the sample mean.

Table 3: *Voter Gait Speed by Age and Sex*

Sex	Age	Gait Speed (m/s)[1]	Percent of Voting-age Population[2]
Female	18-29	1.342	8.65%
Female	30-39	1.337	8.37%
Female	40-49	1.39	7.88%
Female	50-59	1.313	9.18%
Female	60-69	1.241	9.57%
Female	70-79	1.132	6.43%
Female	80+	0.943	3.05%
Male	18-29	1.358	7.81%
Male	30-39	1.433	7.46%
Male	40-49	1.434	7.07%
Male	50-59	1.433	8.30%
Male	60-69	1.339	8.48%
Male	70-79	1.262	5.48%
Male	80+	0.968	2.26%

Note. [1] Bohannon and Andrews (2011); [2] US Census Bureau (2019).

the satisfactory wait time criteria. After individual process performances are determined, the performance differences between the Georgia and Rhode Island polling locations are quantified by comparing the wait times at each of the processing steps and the overall queue time throughout the system.

3 Results and Discussion

3.1 Voting Process Performance

To assess the performance of each model scenario (i.e., voting process), 95% confidence intervals were used for the mean and maximum voter wait times. These confidence intervals are compared against a 30-minute maximum allowable wait. This benchmark was utilized to assess whether a system meets the acceptable wait time criterion. After determining voter wait times for each voting process, the disparities are quantified between the two systems by analyzing the wait times at each station, the overall wait time within each system, the number of voters in the system, the time-in-system, and the percent utilization per station.

Table 4 and Figures 7 and 8 display the confidence intervals for the mean and maximum time waiting at each station. Investigating the confidence intervals per station, there is no individual voting step that exhibits a wait time greater than 30 minutes. In fact, wait times remain under two minutes for all stations in both voting processes. Confidence intervals on the mean and maximum overall voter wait times are displayed per voting process in Table 5 and Figure 9. From this table, the absolute longest time that a voter waited in either simulated system is 9.286 minutes, observed in the Georgia location, which is below the 30-minute voter wait time threshold and indicates that both simulated polling locations meet wait time criteria.

After assessing each voting processes performance with respect to the voter wait time, further analysis is conducted on the simulation results. Additional metrics considered are the number of voters in the system and the total time spent in the system. Table 6 and Figures 10 and 11 display the 95% confidence interval on the mean number of voters in the system per hour and the mean time-in-system (minutes) for the mean and maximum values across replications. On average, there are approximately ten voters within the system, with a maximum of 31 voters for the Georgia location. The Rhode Island location displayed a smaller number in the system, with a mean of 8 voters and a maximum of 22 voters. These findings corroborate the findings on voter wait times in each system. If voters spend less time in queues, then more voters can move through the system.

Rhode Island voters spend about 5.439 minutes in the simulated polls, with a maximum time-in-system of 27.832 minutes. Georgia voters spend 7.740 minutes in the simulated polls with a maximum time-in-system of 27.832 minutes. From these models, the percent of time spent in queues for each system is shown

Table 4: *95% Confidence Interval on the Simulated Voter Wait Times per Station (minutes)*

Location	Station	Metric	Mean	95% Confidence Interval
GA	Check-in	Mean	0.168	(0.155, 0.167)
GA	Check-in	Maximum	1.475	(1.232, 1.718)
GA	BMD	Mean	0.564	(0.430, 0.698)
GA	BMD	Maximum	5.576	(4.529, 6.622)
GA	Ballot Scanning	Mean	0.1686	(0.167,0.170)
GA	Ballot Scanning	Maximum	0.797	(0.673, 0.920)
RI	Check-in	Mean	0.126	(0.125, 0.127)
RI	Check-in	Maximum	0.663	(0.602, 0.724)
RI	Ballot Marking	Mean	0.1727	(0.162, 0.183)
RI	Ballot Marking	Maximum	1.795	(1.483, 2.106)
RI	Ballot Scanning	Mean	0.162	(0.161, 0.163)
RI	Ballot Scanning	Maximum	0.571	(0.522, 0.620)

Note. The confidence intervals are calculated with an α of 0.05

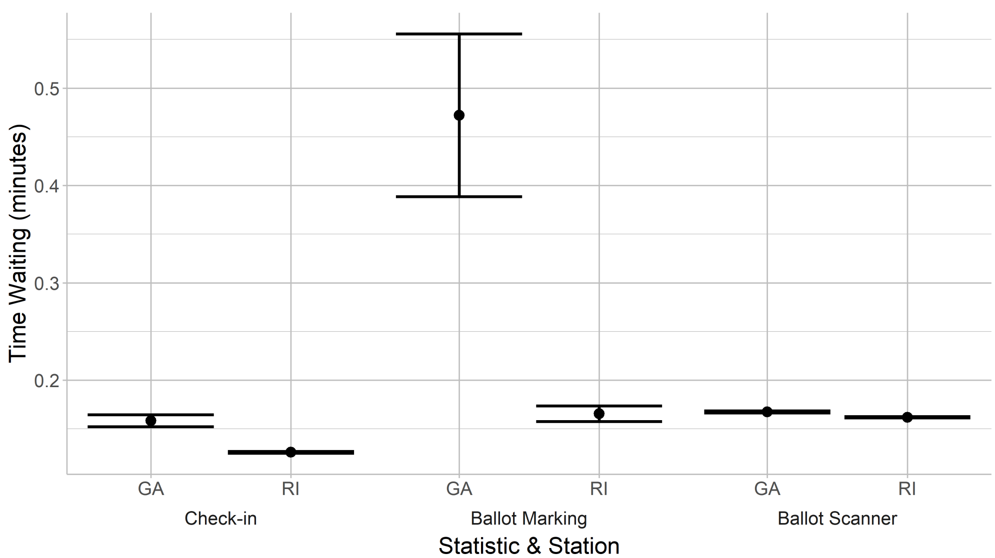

Figure 7: 95% Confidence Interval on Mean Wait Time by Voting Station

in Table 7. These values indicate that voters spend more time waiting, on average, in the Georgia polling location than in the Rhode Island polling location. This may indicate that ballot marking is the bottleneck of the Georgia voting process, as the ballot marking station experienced the longest mean and maximum wait times. Shorter wait times contribute to increased throughput and productivity within the voting system. When voters spend less time in queue, they can move through the process more quickly, allowing for a larger number of voters to be served within a given time frame. This can help prevent congestion and overcrowding, ensuring a steady flow of voters and reducing the likelihood of bottlenecks. Reducing the time in line also minimizes the potential for voters to renege or balk. By creating a system with shorter wait times, the likelihood of voter reneging is reduced, preserving the integrity of the electoral system and ensuring that voters have the opportunity to cast their votes. Furthermore, shorter wait times can lead to improved operational efficiency and resource utilization. When voters spend less time in line, the overall demand for resources such as voting machines, staff, and facilities is better distributed. This allows for more effective planning and allocation of resources, reducing idle time and optimizing resource utilization. It also enables the system to handle higher volumes of voters without straining the available resources.

An additional measure of process performance and efficiency is the percent utilization of resources. High

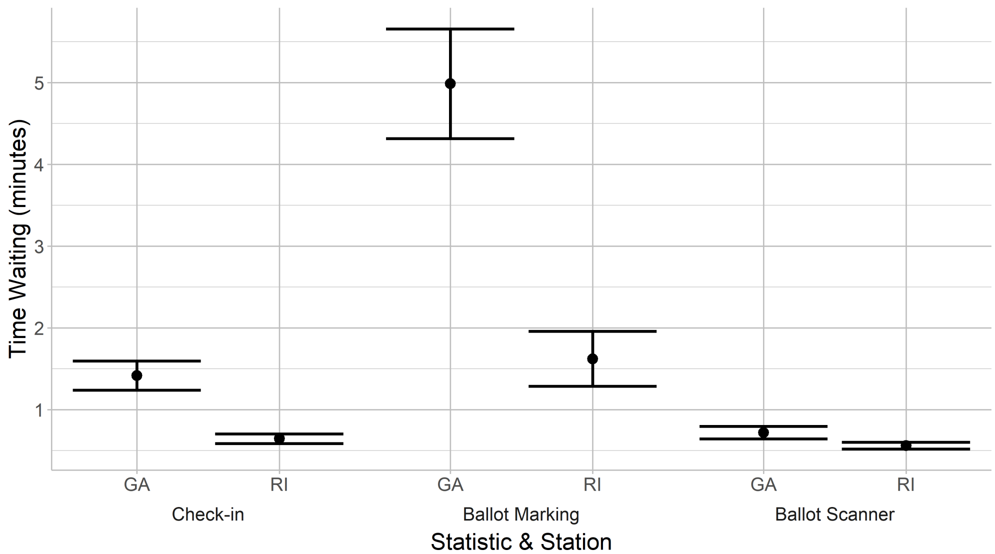

Figure 8: 95% Confidence Interval on Maximum Wait Time by Voting Station

Table 5: *95% Confidence Interval on the Total Wait Time*

Location	Metric	Mean	95% Confidence Interval
GA	Mean	1.086	(0.955, 1.216)
GA	Maximum	8.113	(6.940, 9.286)
RI	Mean	0.653	(0.643, 0.663)
RI	Maximum	3.294	(3.001, 3.587)

utilization percentages indicate efficient resource utilization but may indicate the need for increased resources, especially when quantifying human-operated processes (e.g., check-ins). Monitoring and analyzing utilization percentages helps identify areas for improvement, enhance resource allocation models, and better overall operational efficiency. Table 8 and Figure 12 display the average percent utilization for each station within each voting process. The values for all stations across processes are low compared to the theoretically desirable 80% utilization. Ballot Scanning is the station that is the least active throughout the duration of the simulation, while Georgia BMDs and Rhode Island ballot marking experience the highest utilization. It's important to note that resource allocation adjustments have limitations, particularly in the case of Georgia's non-modular Ballot Marking devices compared to the modular privacy booths in Rhode Island. One Georgia BMD unit contains four BMDs. Therefore, when adjusting resource allocations, it's crucial to take into account that the need for one additional BMD in Georgia may lead to a total of four BMDs being added to the system, and adding an additional scanner will lead to a total of one scanner and two BMDs being added to the system.[6] In this case, lower utilization is beneficial because having too few resources could potentially risk an increase in the time in a queue past the 30-minute allowable max and potential reneging, which could negatively impact voter enfranchisement.

In summary, based on the results from the 95% confidence interval of the time spent in the queue for each of the stations and the resulting analysis of the total wait time, simulated voters wait less than 30 minutes. Voter wait times in the simulated Rhode Island voting process tend to be shorter, with respect to maximum wait time being approximately 4.819 minutes less than those observed in the simulated voting process for Georgia. On average, simulated Rhode Island voters spend 12% of their voting experience in line compared to 14.03% for simulated Georgia voters. A high percentage of time spent in line can indicate an increased risk of causing a bottleneck. Visually and quantitatively, all but one confidence interval appear to

[6]BMDs and ballot scanners in Georgia are distributed in large metal units that contain multiple devices. Georgia's BMD units contain four BMDs, while scanner units contain one ballot scanner and two BMDs.

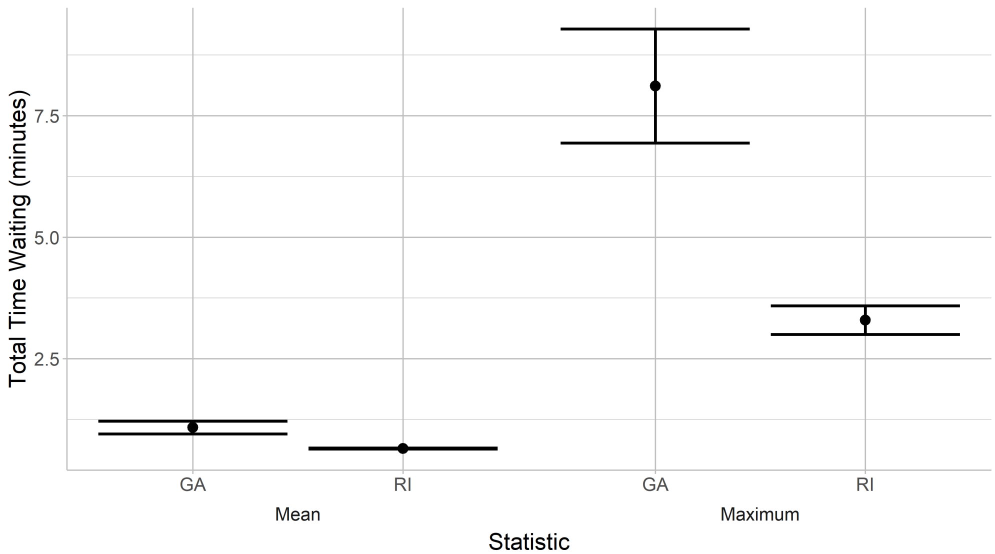

Figure 9: 95% Confidence Interval on Overall Wait Times

Table 6: *95% Confidence Interval of Number and Time-in-System*

Location	Metric	Type	Mean	Confidence Interval
GA	Voters In System	Mean	9.968	(9.681, 10.254)
GA	Voters In System	Maximum	30.050	(27.755, 32.345)
GA	Time-In-System	Mean	7.740	(7.586, 7.893)
GA	Time-In-System	Maximum	29.063	(26.368, 31.758)
RI	Voters In System	Mean	7.001	(6.888, 7.115)
RI	Voters In System	Maximum	21.350	(20.191, 22.509)
RI	Time-In-System	Mean	5.439	(5.412, 5.465)
RI	Time-In-System	Maximum	27.832	(24.190, 31.474)

Note. The confidence intervals are calculated with an α of 0.05

not overlap, indicating the need for statistical testing to determine if performance differences are significant.

3.2 Comparing Voting Process Results

To compare the Georgia voting process and the Rhode Island voting process, *t-tests* are performed for each performance metric (i.e., wait time per station, overall wait time, number of voters in the system, time-in-system, and resource utilization). Results of these comparisons are presented in Tables 9, 10, 11, 12, and 13.

Comparing these voting processes indicates that there are significant differences in several performance metrics between the Georgia voting process and the Rhode Island voting process. In fact, all performance metrics but maximum time-in-system differ significantly between the voting processes. Voter wait times per station are longer for the simulated Georgia voting process by between 7.740 and 29.063 minutes on average and between 5.439 and 27.832 minutes for maximums wait times. The average overall voter wait time is longer in the Georgia voting process by 0.433 minutes, and maximum wait times are longer by 4.819 minutes. Even though the maximum time in the system is statistically the same for Georgia and Rhode Island, what occurs during the voting process is not. At the extreme for the two locations, voters spend their time differently, as Georgia voters have an increased time in the queue compared to Rhode Island. The time in queue, which is characterized as non-value-added time, could potentially lead to increased frustration among voters and a decrease in voter confidence.

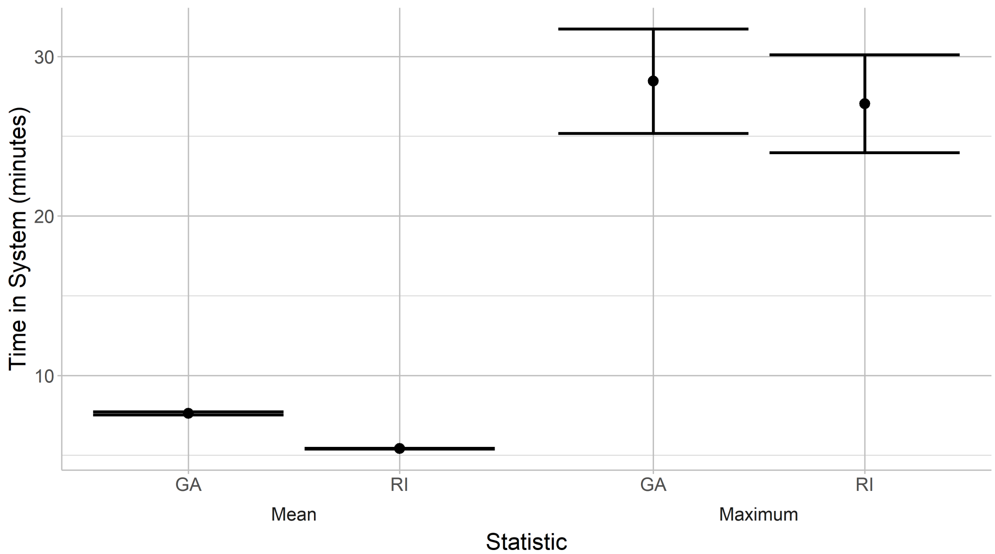

Figure 10: 95% Confidence Interval on Time-in-System

Table 7: *Percentage of Time Spent in the Queue*

Location	Metric	Mean
GA	Mean	14.03%
GA	Maximum	27.00%
RI	Mean	12.00%
RI	Maximum	11.84%

Note. The confidence intervals are calculated with an α of 0.05

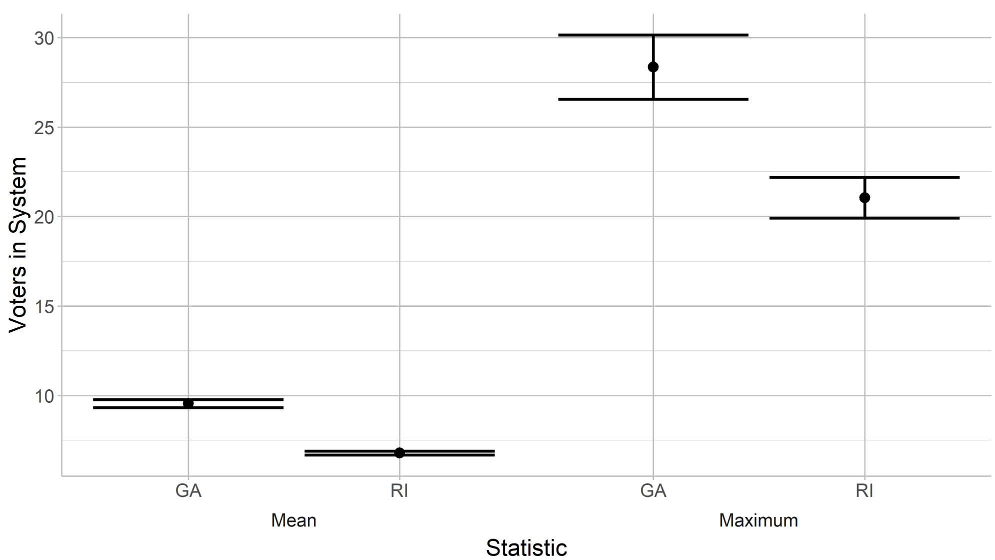

Figure 11: 95% Confidence Interval on Number in System

Table 8: *95% Confidence Interval for the Scheduled Utilization*

Location	Station	Mean	Confidence Interval
GA	Check-in	34.843	(34.289, 35.398)
GA	BMD	56.203	(55.340, 57.066)
GA	Ballot Scanning	21.369	(21.024, 21.715)
RI	Check-in	22.286	(21.950, 22.621)
RI	Ballot Marking	41.031	(40.362, 41.699)
RI	Ballot Scanning	17.257	(16.987, 17.527)

Note. The confidence intervals are calculated with an α of 0.05

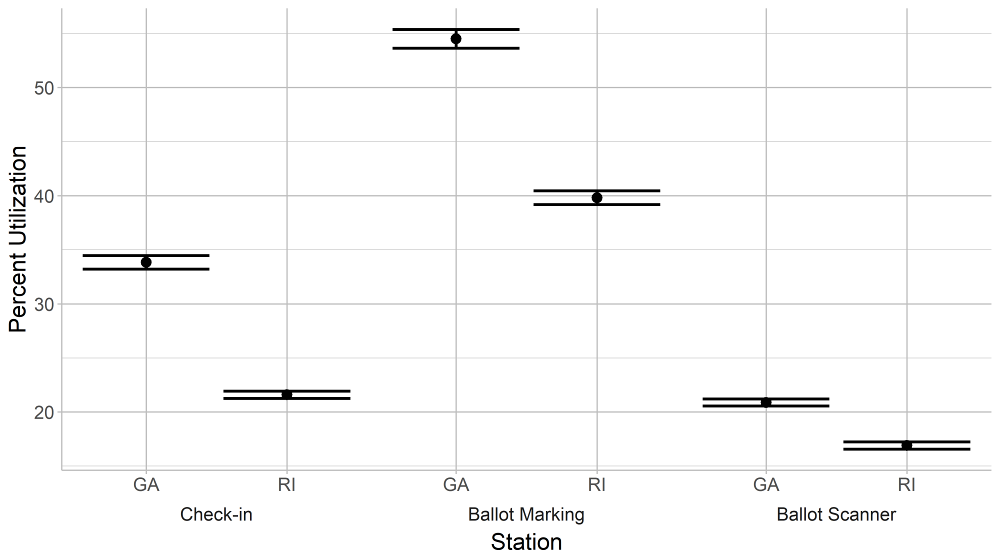

Figure 12: 95% Confidence Interval on Percent Utilization

Table 9: *Two Sample t-test on the Sample Means: Wait Time per Station*

Location1	Location2	Type	Station	P-value	Test Statistic
GA	RI	Average	Check-in	1.46E-10	12.015
GA	RI	Average	Ballot Marking	7.00E-06	6.093
GA	RI	Average	Scanner	7.76E-08	7.526
GA	RI	Max	Check-in	9.13E-07	6.802
GA	RI	Max	Ballot Marking	2.67E-07	7.246
GA	RI	Max	Scanner	1.51E-03	3.566

Table 10: *Two Sample t-test on the Sample Means: Total Wait Time*

Location1	Location2	Type	P-value	Test Statistic
GA	RI	Average	5.18E-06	6.261
GA	RI	Maximum	1.33E-07	7.723

Table 11: *Two Sample t-test on the Sample Means: Time-In-System*

Location1	Location2	Type	P-value	Test Statistic
GA	RI	Average	1.92E-18	30.836
GA	RI	Max	0.57	0.569

Table 12: *Two Sample t-test on the Sample Means: Number In System*

Location1	Location2	Type	P-Value	TestStatistic
GA	RI	Mean	6.65E-17	20.135
GA	RI	Max	1.03E-07	7.082

Table 13: *Two Sample t-test on the Sample Means: Percent Utilization*

Location1	Location2	Station	P-value	Test Statistic
GA	RI	Check-in	1.35E-28	40.563
GA	RI	Ballot Marking	1.73E-26	29.082
GA	RI	Scanner	8.61E-21	19.629

4 Conclusion

The simulation results with a turnout of 1076 voters (Fulton County, GA, 2022) demonstrated that Rhode Island voters had, on average, less time spent in the system and less time spent in the queue. The queues for both the Georgia and Rhode Island voting processes tended to form prior to ballot marking, but the effect was more drastic in Georgia, which indicates that ballot marking is the bottleneck of the Georgia voting process. Shorter wait times can also contribute to increased throughput and productivity within the system because voters can move through the process more quickly, allowing for a larger number of voters to be served during Election Day. Additionally, the results of this study indicate that there are significant performance differences between all metrics, with the exception of the maximum time-in-system. Despite the lack of statistical difference between maximum time-in-system, the distribution of where time is spent by voters differs, with Georgia voters spending more time in queue compared to Rhode Island. Despite the statistical differences in performance, the values of these differences may not be practically significant at the simulated level of turnout. However, as voter turnout increases, the effects of small voting delays propagate into significant voter wait times. With continued increases in election participation (McDonald, 2018, 2020), the findings underscore the need for further investigation and consideration of these factors when evaluating and optimizing the voting process in locations utilizing different voting equipment.

This study acknowledges several limitations that should be taken into consideration when interpreting results. It is important to acknowledge that each polling location has it's unique characteristics that could influence processing times, capacities, and other aspects of the voting process. Future work could explore varying aspects of location-specific characteristics (Bernardo and Macht, 2022). An additional limitation includes the differences in ballot lengths and styles across precincts, states, and elections. These differences introduce variations in ballot marking times that can affect overall voting times and wait times of the voting process. Another limitation is that different voting methods may have different learning curves, particularly with the introduction of new equipment and voting procedures. The amount of experience that voters and poll workers have with a voting process may affect processing times, with established processes (e.g., Rhode Island's voting process) likely taking less time for voters and poll workers than new processes (e.g., Georgia's voting process). For example, one study found that the acquisition of new touch-screen voting machines, in response to HAVA, made waiting times worse in many instances due to the increased time required to vote using these machines Samuelson et al. (2007). Similarly, the observed voting processes occurred in different years, with one occurring prior to the COVID-19 pandemic (i.e., Rhode Island in 2018) and the other occurring after the onset of the pandemic (i.e., Georgia in 2022). It is currently unclear if or how the pandemic may have influenced voter and poll worker behavior with respect to voting processes. Additionally, demographic and geographical characteristics may impact processing times and voting process performance, which may provide additional insights into potential disparities. Many studies have identified potential differences in voting resource allocation for precincts with differing socioeconomic statuses. Furthermore, given the difference in demographics between the two investigated locations, the potential of this impact is more likely than not and should be investigated further.

Despite these limitations, this analysis identifies voting process performance differences between two reasonably similar polling locations during midterm elections. From this initial investigation, there are many opportunities for future work. One possible avenue for future work is to gather additional data for both ballot marking types during the same election, which could result in more robust statistics, a better representation of a generalizable model, and a greater possibility to implement additional operations research theory. Furthermore, modeling the data with the objective of determining the ideal capacity of the resources in the model or comparing various ballot marking technologies to assess their effectiveness and usability would provide insights into the strengths and weaknesses of each option. Another aspect to consider is voter perception and satisfaction with new technological devices, which could be assessed through surveys to gauge voters' thoughts after using the device while correlating these responses with actual system performance. In a controlled environment, this study could also aid in gauging the associated learning curve when adopting new voting equipment, which could impact voter confidence and perception of the device.

Moreover, conducting a cost-effectiveness analysis that compares the expenses associated with different ballot marking methods, including initial investment, poll worker training, maintenance, operational costs, and educational voter materials, would provide valuable insights. This analysis could also consider the long-term financial implications of adopting specific voting systems and compare the non-value-added time that voters may spend waiting in queues. This analysis could provide resources on cost-effectiveness to election officials that could aid in quantifying their planning and implementation of objectives. By addressing the aspects explained above, future research could build on the findings of this paper and contribute to improving the overall electoral process.

The findings addressed in this analysis and future work provide data and information that can support election officials with election planning and equipment acquisition decisions. Additionally, several performance metrics are discussed that quantifies the percentage of time spent in the queue, the percent utilization of voting resources, and overall queue time, which may be used to track and improve operational efficiency. Through this objective, efficient voting processes may aid in increasing voter confidence, decreasing resource and equipment costs, promoting voter enfranchisement, and helping to sustain the integrity of democracy.

5 Acknowledgements

I would like to express my gratitude to the following individuals and organizations who have provided valuable support and assistance through the completion of this research:

First and foremost, I would like to extend my gratitude to the Democracy Fund for financially supporting travel and other expenses associated with this research. An additional thank you to Fulton County, the Carter Center, and the Rhode Island Board of Elections for supporting the URI VOTES team throughout this process. I am immensely grateful to the Sustainable Innovative Solutions Lab at the University of Rhode Island, specifically, Sara Nunes, Malinda Fry, and Mehrsa Khaleghikarahrodi, Ph.D, for their unwavering guidance, support, and positively. Their insightful feedback have been invaluable in shaping this work. I would also like to extend my sincere appreciation to the additional authors of this paper, Leonie Otte, Nicholas Bernardo, Ph.D. and Grethcen Macht, Ph.D., for their valuable insights and suggestions that have greatly enhanced the quality of this research. Their contributions to the field have served as a foundation for this analysis and have been instrumental in shaping my understanding of the subject matter. Finally, I would like to thank my friends and family for their unwavering support, understanding, and patience. Their encouragement and belief in my abilities have been instrumental to my success.

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