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Using Statistical Control Charts to Monitor Building Water Consumption: A Case Study on the Replacement of Toilets

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Abstract: This manuscript proposes the usage of Statistical Control Charts (SCC) to monitor water consumption in buildings. The charts were employed to study the impact of replacing toilets, providing visual and statistical feedback to measure the efficiency gain resulting from the replacement of outdated flushing equipment with newer devices. The case study was conducted in a building from a university in the South of Brazil. The building has four restrooms, from which a total of 41,554 readings were collected during a 15-month period using digital water meters. After the toilets were replaced, a reduction averaging 30.22% in water consumption was observed (from 7.51 L/flush/day to 5.24 L/flush/day). Additionally, the control charts were able to pinpoint dates when unique events happened during the water-consumption monitoring process.

Keywords: water consumption; statistical control charts; water monitoring; toilets

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1. Introduction

Locally available water sources are limited, and droughts impact several regions of the world, contributing to the water resource crisis, which represents an obstacle that restricts the world's sustainable development [1]. An ever-growing economy resulting from the development of industrialized countries and modern technologies has raised increasing attention when considering how to efficiently manage renewable natural resources, such as water [2]. To emphasize the water scarcity problem, Rodrigues et al. [3] mentioned that, due to the current climate change events, water has become a critical resource worldwide, and the risk of hydric stress will rise significantly in the coming decades. Meireles and Sousa [4] stated that, in addition to its scarcity, water consumption in buildings is related to substantial energy consumption. According to Thornton et al. [5], water loss control is a topic of the twenty-first century, as the loss is considered a universal problem that occurs both at the end-users plumbing system and at the water supplier's distribution piping. It is essential, therefore, to monitor water consumption to avoid losses and identify effective measures to enforce water consumption reduction.

The urban environment, which includes buildings and infrastructures, heavily contributes to the consumption of water resources [6]. Regarding building water systems, toilets are responsible for considerable water consumption [7,8]. According to Anand and Apul [9], a large portion of residential per capita water consumption corresponds to toilet flushing and, in school and office environments, this percentage is even higher since toilets and lavatory taps are the main water end-uses there.

Anand and Apul [9] mentioned that alternative technologies that require less potable water and generate less wastewater could provide other environmental benefits besides water-saving. Cheng et al. [10] mentioned the existence of challenges, such as the lack of proper funding and/or weak sanitary awareness displayed by the general public, that need to be overcome so that better environmental methods and technologies for toilet flushing can be achieved. Complementarily, Lute et al. [11] concluded that targeted interventions to decrease the stigma involving toilets and increase pro-environmental motivation might help meet water conservation goals. According to Akiyama et al. [12], many countries have established regulations regarding the volume of water that should be used to flush toilets. In 1997, the Brazilian government established the flushing volume limit, which was gradually reduced from 12 L per flush (LPF) (allowed until 2002) to 6 LPF (after 2002) [13].

Shewhart [14] stated that an essential part of understanding the variability of a process takes place through monitoring. According to the author, the variability of a process can be either random or attributed to a special cause. A process is under statistical control when only process-inherent random variability is present. In addition, the process can be improved through the detection and elimination of attributable causes. In this sense, monitoring water consumption through Statistical Control Charts (SCC) is a viable alternative to identify the variability resulting from changes or improvements in the system. In addition, control charts are easy-to-implement tools with visual feedback, which can quickly detect changes and special causes and signal the need for intervention. According to Thomann et al. [15], SCCs are a powerful tool for data analysis as the control chart technique allows for statistical and fast graphical analysis of the measurement process.

Considering the wide range of applications that control charts display, SCCs have already been used to monitor water parameters. For instance, Iglesias et al. [16] found that a Shewhart SCC could be employed in searching and removing abnormal figures in water quality analysis based on global indicators. In addition, Shewhart, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA) SCCs were used to observe the quality control of physical-chemical and biological aspects of two Brazilian rivers [17]. Hashim et al. [18] proposed the application of multivariate control charts in monitoring water quality in a water-treatment plant in Kota Kinabalu, Malaysia. Thomann et al. [15] proposed the use of online sensors to monitor wastewater treatment plants to detect 'out of control' situations using statistical control charts.

In addition, other control chart applications can be mentioned, such as monitoring and identifying patterns and changes in energy consumption time series in buildings [19,20]. Vivancos et al. [19] used control charts to study eventual appliance changes motivated by ordinary events in a residential building, and Horrigan et al. [20] used control charts for environmental and energy management in buildings. Quality control charts were proven effective in detecting changes in consumption patterns and a potential method to provide constant feedback on the impact of domestic routines in energy consumption [19].

The evaluation of water consumption in buildings is crucial for the establishment of water efficiency strategies in the urban environment. Water consumption in toilets is quite significant, leading several countries to establish limitations regarding the maximum consumption of water for this plumbing fixture. The objective of this article is the use of the monitoring capabilities of the control charts to analyze changes in the water consumption pattern originated by the replacement of toilets in a case study. The main contribution of this research is the evaluation of the water savings accomplished by the replacement of toilets through statistical process control, providing subsidies, both for the use of control charts for the continuous monitoring of the water usage in buildings and for the replacement of ordinary plumbing fixtures by water-saving ones. This paper is organized as follows: Section 2 exposes some recent studies in water consumption monitoring, Section 3 introduces the main concepts of the Statistical Control Charts employed in this paper; Section 4 describes the methodological procedures; the results and discussion are presented in Section 5; and, finally, conclusions are drawn in Section 6.

2. Water Consumption Monitoring

Fuentes and Mauricio [21] proposed the implementation of a smart water consumption measurement system for real-time household water consumption monitoring with a leak-detection algorithm. The algorithm is based on rules, historical context, and user location to cover 10 possible water consumption scenarios between normal and anomalous consumption. Patabendige et al. [22] presented an algorithm and a web-based software system to detect anomalous water consumption for non-residential consumers by calculating a daily anomaly score based on 10 features of daily water demand and its historical context. In a case study conducted in Gorino Ferrarese, Italy, Luciani et al. [23] used a real-time household water consumption monitoring and processing system. The system was based on an algorithm that analyses hourly water consumption patterns and searches for zero-flow values in order to detect water leakages. Schultz et al. [24] evaluated the use of an online platform where households could access their domestic water consumption and be alerted about the possibility of a leak. The authors used a leak-detection algorithm in which households with a continuous water flow of at least 7.5 g/h in a 24 h period were flagged as a potential leak.

Regarding the use of SCCs to monitor urban water consumption, Romano et al. [25] proposed the use of a statistical control-based system to determine the approximate location of a leak/burst within a District Metered Area in water distribution systems. Gove et al. [26] examined the use of X-bar and CUSUM control charts to evaluate water catchment data from the water supply system of the city of Perth, Western Australia, in order to detect changes due to long-term decline in rainfall. Nam et al. [27] proposed a hybrid principal component analysis and standardized exponential weighted moving average system for burst detection in water distribution networks. Regarding the use of SCCs to monitor water consumption in buildings, in another publication within the same research project, Freitas et al. [28] proposed the use of Shewhart, EWMA, and combined Shewhart-EWMA control charts to analyze dual-flush devices in a case study conducted in Southern Brazil.

3. Statistical Control Charts

Essentially, control charts are made up of three lines: a central line (CL), a lower control limit (LCL), and an upper control limit (UCL) plotted as a graphical tool [29]. According to Montgomery [29], the CL represents the mean of the process, whereas the LCL and UCL, positioned, respectively, below and above the CL, are the control limits. A point within the control limits indicates that the process is under control and no action is required, and a point outside indicates that the process is out of control and corrective actions are required to find and eliminate assignable causes [29]. Variable control charts are responsible for plotting numerical quality characteristics, while attributes control charts are used in situations in which the quality characteristics are not numerical, such as classifications (e.g., defective or non-defective) [29].

Considering variable control charts, there are two main types: for subgroup-collected data and for individual measurements. For sub-grouped data, the plotted observations represent statistics of subgroups, such as the mean, range, or standard deviation [29]. For individual measurements, the sample size used for process control is n = 1; that is, each point represents an individual observation or a statistic [29].

The SCC operationalization process can normally be divided into two phases: the first (Phase 1) defines the control limits; and the second (Phase 2) is the process control itself. Since at the beginning of Phase 1, little is known about the process, the statistical analysis is exploratory. The main goal then is to adjust the process for stability appropriately and, as such, one of the most relevant results during this phase is the control limits' estimation [30,31].

Phase 2 then utilizes the sample mean and the control limits calculated in Phase 1 for further and continuous monitoring of the sample data, collected sequentially over time. If the mean of a newly collected sample falls outside the corresponding control limits, then the process is called out of control [30]. To ensure process reliability, any emerging changes must be analyzed [31].

A control chart performance is measured by how fast it can detect variation in a process. For such evaluation, the Average Run Length (ARL) parameter is used. The

ARL corresponds to the expected number of samples or observations that are needed to generate an out-of-control signal, that is when a point falls outside the control limits [29]. An efficient chart has a small probability of generating false alarms and will rapidly detect a legitimate change [29].

3.1. Shewhart Control Chart

Shewhart are the most widely used control charts, especially in the industrial production process, due to their relative ease of implementation and interpretation [32]. The main decision rule is based on the analysis of the last observation plotted in the chart. The process is out of statistical control when the last observation is not within the control limits [29]. Shewhart SCCs usually operate under certain rules called Western Electric Rules or run rules, which are four rules based on chart analysis that determine if a certain process is under control considering features such as random fluctuations in variables, therefore, being able to distinguish between unnatural and natural patterns [29,33]. The four Western Electric Rules can indicate that a process is out of control if [30]: (i) one point is outside the three-sigma limit (LCL or UCL) (rule 1); (ii) two out of three consecutive points are outside the two-sigma control limit (rule 2); (iii) four out of five consecutive points are at least one sigma away from the center line (rule 3); (iv) eight consecutive points are located on one side of the center line (rule 4). The first run rule (i) is the standard procedure for Shewhart Charts. The others are used to increase the sensitivity of the chart to assignable causes and sometimes are called warning limits [29].

Walter A. Shewhart, the creator of statistical quality control charts [34], stated that the limits should be defined to avoid wasting time and effort looking for trouble in a process [14,34]. Therefore, a symmetrical range characterized by limits $\mu \pm t\sigma$ is usually attributed, whereas μ is the mean and sigma (σ) the standard deviation of the process. As for t, Shewhart [14] mentions that experience indicates that t = 3 seems to be an acceptable economic value. Wheeler [35] mentions that the 3σ are not probability limits since Shewhart made some considerations when selecting this criterion and, as such, the strongest justification is the empirical evidence that the three-sigma limits work well in practice.

In this study, variables control charts were applied for individual data. This control chart uses the moving range ($\overline{MR}$) of two successive observations to estimate process variability. Equations (1)–(3) correspond, respectively, to the Lower Control Limit (LCL), the Central Line (CL), and the Upper Control Limit (UCL) present in a Shewhart Control Chart [18].

$$LCL = \overline{X} - \left(3\frac{\overline{MR}}{d_2}\right) = \overline{X} - E_2\overline{MR} \quad (1)$$

$$CL = \overline{X} \quad (2)$$

$$UCL = \overline{X} + \left(3\frac{\overline{MR}}{d_2}\right) = \overline{X} + E_2\overline{MR} \quad (3)$$

where $\overline{X}$ represents the process mean; the moving range is defined as $\overline{MR}_i = |x_i - x_{i-1}|$; $\overline{MR} = (1/m)\sum_{i=1}^{m}\overline{MR}_i$; for i = 1, 2, … , m and $E_2 = 3/d_2$ is a variable that is dependent on the number of samples m. The standard deviation σ can be estimated from either the standard deviation or the range (R) of the observations within each sample. Since R is a random variable, the quantity W = R/σ, is also a random variable. The parameters of the probabilistic distribution of W have been determined for any sample size. The mean of the distribution of W is called d_2, which can be found in the literature [29].

In order to use the Shewhart control charts for data analysis, some criteria must be satisfied first. The data must follow a normal distribution and cannot have any signs of autocorrelation. These rules are verified in Phase 1 [29]. The Shewhart chart with three-sigma limits, as in Equations (1)–(3), has an ARL_0 = 370, meaning that, if the process is in control, a signal will be given every 370 samples, on average, and the probability that a single point falls outside the control limits when the process is in control is $\alpha = 0.0027$ [29].

3.2. Exponentially Weighted Moving Average Control Chart

As previously stated, Shewhart control charts are popular due to their relative easiness to operate and to interpret the results. The main decision rule is based on the analysis of the last observation plotted in the chart, which can also be an issue because, as such, the chart ignores any extra information from the historical data, meaning that all observations, regardless of their age, are assigned the same weight when the control chart limits are calculated [29]. Therefore, one can say that Shewhart control charts do not have any "memory of past events", which makes it relatively insensitive for detecting small changes in the process in the order of 1.5 standard deviations or less [29].

To address this limitation, newer and more sophisticated types of control charts, which take into consideration past observations and their age, were developed, resulting in control charts with better responsiveness to small and persistent changes in the process average. In this scenario, CUSUM and EWMA are alternatives to the Shewhart control charts. Both can detect small changes in the process before the Shewhart control charts does [29].

The main distinction, as well as the greatest strength of the EWMA chart, is its ability to assign a weight parameter to the analyzed data. Because of that, the EWMA chart is much more sensitive to smaller shifts relative to the process average [29]. Additionally, the EWMA control chart can identify trends (increase or decrease) in the data series, which allows it to identify whether a process changed positively or negatively, depending on the process details. For example: in a water consumption process, it can be used to observe if the consumption decreased or increased after any intervention. Baldewijns et al. [36] found that EWMA charts were effective in detecting positive and negative trends in health data. Vasconcellos et al. [37] applied an EWMA chart to study the flow history in small hydroelectric plants.

The EWMA control chart is similar to the Shewhart control chart in many aspects. Similar to the latter, the former is composed of the same three plot lines: CL, LCL, and UCL. In addition, in the EWMA chart, the method employed to verify if a given process is under control is based on parameters such as points above the UCL or below the LCL, which represent an out-of-control process [29]. The EWMA control chart is developed by plotting Z_i and the number of samples i (or time), defined in Equation (4) [29].

$$Z_i = \lambda X_i + (1 - \lambda) Z_{i-1} \tag{4}$$

where X_i is the most recent observed value and λ is the weight constant that controls the amount of influence of the previous observations, $0 < \lambda < 1$. Values near one (1) put almost all weight on the current observation and, for values near zero (0), a small weight is applied to the past observations. Smaller λ values allow changes of lesser magnitude to be detected. Usually, a value of λ = 0.1 or λ = 0.2 is utilized [29]. The initial value is the process target value with $Z_0 = \mu_0$, and μ_0 is also used as the reference value (or central line) in the chart. When the target value is unknown, the μ_0 parameter can be replaced by the average of a large number of observations that are under statistical control. Supposing that the observations x_{i} are a random independent variable with variance σ^2, then the variance of z_i is given by Equation (5) [29].

$$\sigma_i^2 = \sigma^2 \left(\frac{\lambda}{2 - \lambda} \right) \left(1 - (1 - \lambda)^{2i} \right) \tag{5}$$

In order to calculate the control limits, Equations (6)–(8) [18] are employed.

$$LCL = \mu_0 - L\sigma \sqrt{\frac{\lambda}{2 - \lambda} \left(1 - (1 - \lambda)^{2i} \right)} \tag{6}$$

$$CL = \mu_0 \tag{7}$$

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{2-\lambda}\left(1-(1-\lambda)^{2i}\right)} \tag{8}$$

where L is the control limits amplitude, to which the value of three σ is frequently attributed [29].

4. Materials and Methods

The toilet flushing water consumption data were gathered using digital water meters, which were installed in the toilets' water supply pipes, collecting data 24 h a day and registering each individual flush. The restrooms are part of a building located on the Santa Catarina State University campus in the city of Joinville (Southern Brazil). The campus provides education for up to 3100 students, and the building in which the study is conducted is mainly used for weekday classes and other university extracurricular activities. The total water consumption difference between the men's and women's restrooms could be biased due to the presence of urinals in the men's restrooms. In this study, the water consumption in 4 restrooms was analyzed (2 men's and 2 women's restrooms). The student's gender distribution in the campus, as informed by the campus administration, was around 67% men and 33% women. In order to better understand the daily toilet water consumption, 3 key variables were selected for analysis:

- Total volume of water per day: total volume of water, measured in liters/day, consumed by the toilets in a day.
- Average volume of water per flush per day, measured in liters/flush/day.
- Number of flushes: total amount of toilet flushes in a day.

The water consumption analysis is performed using the SCCs for each key variable in order to obtain a complete analysis of the water consumption process. Initially, data were collected from 7 August 2017 to 1 July 2018, a period that corresponds to Phase 1 of the SCCs. Because of the nature of Phase 1, this period was rigorously statistically analyzed, so that an optimal stabilization could be achieved, therefore, accurately defining the control limits [38]. For instance, the months of December 2017 and January 2018 were removed from the data pool as the summer-break period was ongoing during these months. Weekends, holidays, and days when leakages or shortages were registered were also removed from the data pool to obtain a more stable and reliable Phase 1. Water consumption in universities can be affected by periodicity and seasonality. Thus, in order to ensure that the process was stationary, weekends and holidays were removed from the analysis.

Outliers were flagged and removed using the median and interquartile deviation method [39]. Autocorrelation function (ACF) charts, the Box-Pierce independence test [40], and the Shapiro–Wilk Normality test [41] were applied to address autocorrelation and adherence to normal distribution. This period is marked by the fact that the monitored toilets were outdated according to the Brazilian Standard NBR 16727-1 [42].

During the second semester of 2018, from 1 August 2018 to 14 December 2018, the restrooms were remodeled, and all fixtures were replaced by newer equipment, thus data collection was interrupted during this period. The new toilets were in compliance with NBR 16727-1 [42] requirements, which state that the nominal full flush volume of the toilet must be 6 LPF. When the remodeling finished in early 2019, data collection resumed from 25 April 2019 to 28 June 2019, the period that represents the SCCs Phase 2 data. The toilets were equipped with dual flush systems in both Phases 1 and 2.

The final control charts consist of the stabilized Phase 1, which represents the old equipment data, followed by Phase 2, representing the new equipment data. In Phase 1, the data needed to be stabilized to allow for reliable control over the process. This step is not applied to Phase 2 because this is the process control stage of the chart, which is compared to the calibrated stage (Phase 1). Weekends and holidays, though, were also removed from Phase 2.

R software [43] was used for statistical analysis. QCC R package [44] was used to calculate the control limits and to plot the control charts. The Shewhart Chart function in the QCC package was modified to clarify the interpretation of the supplementary rules. The selected control chart models, Shewhart and EWMA, were chosen based on their ability to detect, respectively, large and small shifts in the key variables [45,46]. The goal of employing the SCCs combined with the key variables was to monitor the water consumption process, observe and analyze data variance, pinpoint and explain irregularities. The SCCs also provided good visual feedback for the overall process.

5. Results

To monitor the toilets' water consumption, data were initially collected from 7 August 2017 to 1 July 2018, a period corresponding to Phase 1. The data were compiled into the key variables (Table 1) for both phases that were analyzed within the control charts. To stabilize Phase 1, as described in the Materials and Methods Section, the control charts were primarily used to flag and, therefore, remove out-of-control days from the data pool, resulting in 85 days of stabilized data. Phase 2 occurred after the remodeling of the University's restrooms, corresponding to the period from 25 April 2019 to 28 June 2019.

Table 1. Summary of Phases 1 and 2.

		Total Volume Per Day (L/Day)	**Average Volume Per Flush Per Day (L/Flush/Day)**	**Number of Flushes**
Phase 1	Minimum	1024	6.55	120
	Maximum	2359	9.02	318
	Average	1606	7.51	215
	Standard Deviation	288.61	0.59	39.65
Phase 2	Minimum	474.1	2.83	99
	Maximum	2364.50	6.72	364
	Average	936.8	5.24	179.20
	Standard Deviation	314.20	0.68	54.38

Regarding the assumptions, Phase 1 data showed adherence to the normal distribution: total volume per day (p-value = 0.9561); average volume per flush per day (p-value = 0.1225), and number of flushes (p-value = 0.8401). Furthermore, the data did not show autocorrelation: total volume per day (p-value = 0.1748); average volume per flush per day (p-value = 0.8176) and number of flushes (p-value = 0.5851). Figure 1 presents a Shewhart Control Chart detailing the total water consumption per day. The LCL and UCL in Figure 1 were calculated using Equations (1) and (3), respectively. In all the following charts, Phase 1 and 2 are separated by a single vertical dashed line.

Figure 1 shows that, as soon as Phase 2 starts, the overall water consumption process starts to destabilize according to the Western Electric Rules (mentioned in Section 3.1). A decrease in the process average can be observed, as highlighted by the out-of-control points identified by the Western Electric Rules, providing a clear visualization of the phenomenon. Complementarily, Figure 2 presents an EWMA Control Chart detailing the total water consumption per day. The LCL and UCL in Figure 2 were obtained using Equations (6) and (8), respectively. Figure 3 presents the number of flushes per day in a Shewhart Control Chart. The LCL and UCL in Figure 3 were calculated using Equations (1) and (3), respectively.

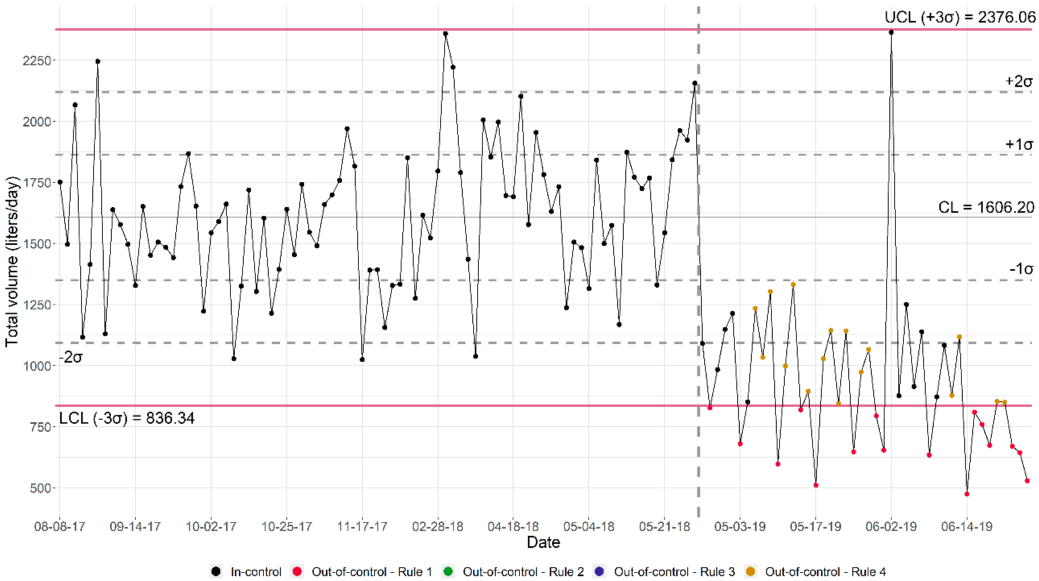

Figure 1. Shewhart Control Chart—Total volume per day.

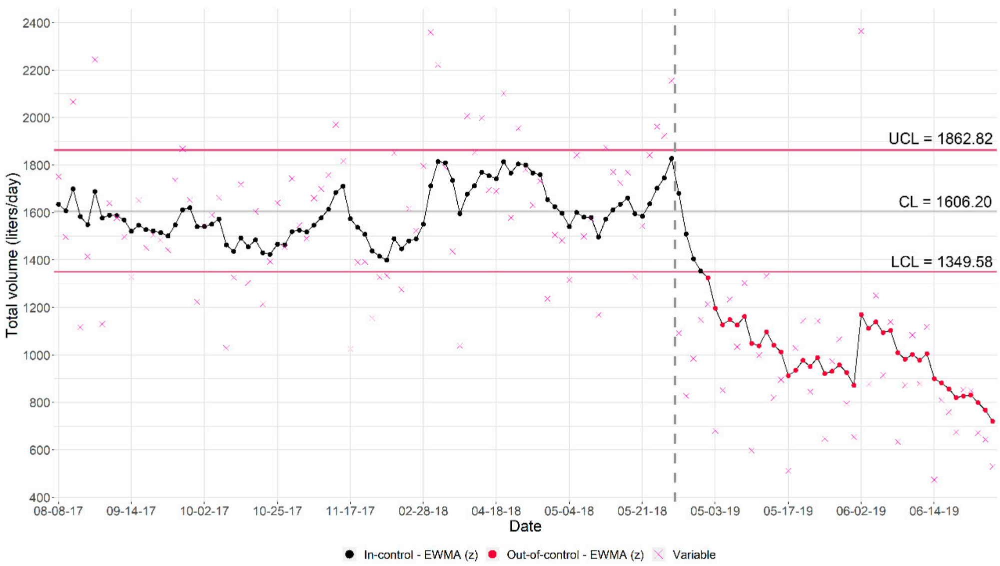

Figure 2. EWMA Control Chart—Total volume per day.

Figure 3 indicates that, with the exception of two out-of-control observations (first Western Electric Rule) and the rule 4 warning in the last two days, the process seems stable, indicating that the number of uses in the restrooms did not vary considerably. The rule 4 warning by the end of Phase 2 can be explained by the end of the school term when class attendance is reduced after some students drop out and others are approved earlier. The graph shows that the number of flushes did not change significantly after the remodeling, with no change in the pattern of toilet use. Figure 4 shows the EWMA chart for the number of flushes per day. The LCL and UCL in Figure 4 were obtained using Equations (6) and (8), respectively. It shows that the reduction pattern, pointed out by rule 4 in the Shewhart control chart (Figure 3), appears in the EWMA chart as points flagged as out of statistical control. As of mid-June, the last month before the holidays, there were fewer students attending campus.

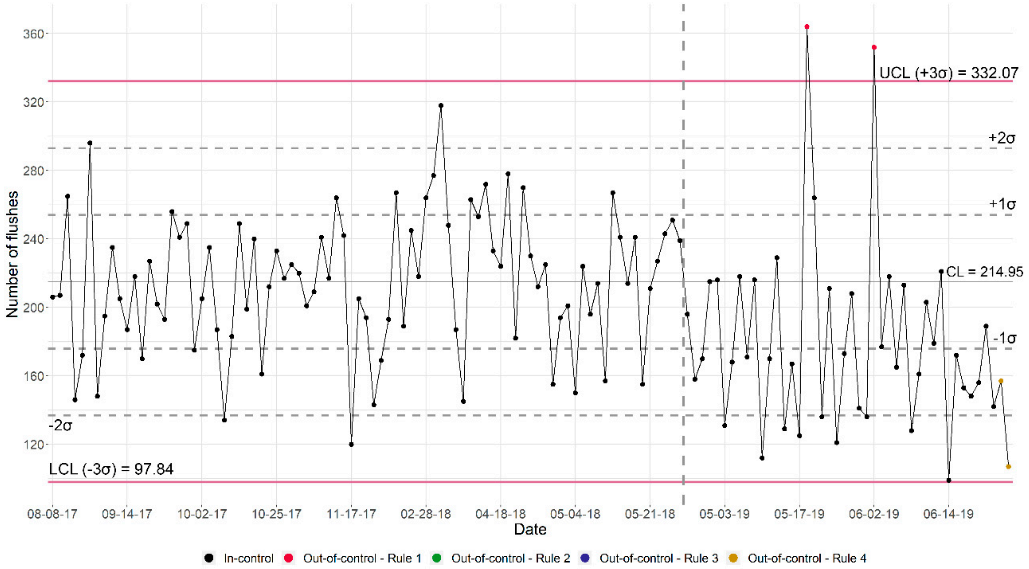

Figure 3. Shewhart Control Chart—Total number of flushes per day.

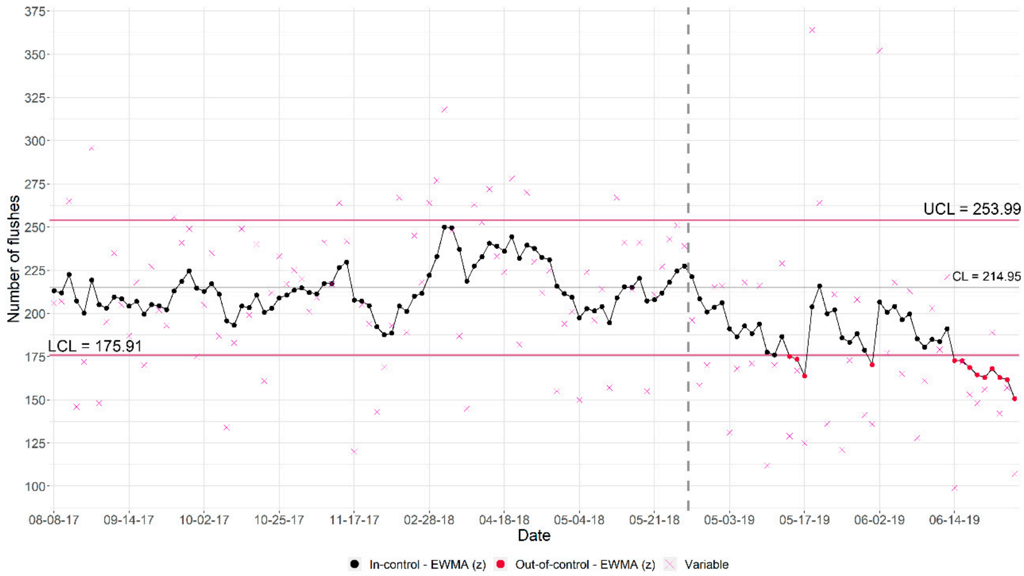

Figure 4. EWMA Control Chart—Total number of flushes per day.

Figures 5 and 6 present, respectively, a Shewhart control chart and an EWMA control chart of the average volume per flush per day. The LCL and UCL in Figures 5 and 6 were calculated using Equations (1), (3), (6) and (8). By observing rule 1, the first out-of-control point in Figure 3, it is possible to notice that it happened simultaneously (on the same day) as the lowest point in Figure 5. On that specific day, a significant number of small volume flushes were registered, which could represent a leakage, bringing the average volume per flush down and, consequently, causing the unusual spikes observed in both control charts.

The average water consumption was 7.51 L per flush per day in Phase 1 and 5.24 L per flush per day in Phase 2. During both phases, toilets were equipped with dual flush systems. The reduction in water consumption was caused by the replacement of the toilets by new models in compliance with Brazilian technical standard NBR 16727-1 [42]. Regarding the volume per flush, Gao et al. [47] mentioned that ordinary toilet flushing systems are commonly mentioned in the literature using 9 LPF (liters per flush), while dual flush toilets use either 3 or 6 LPF. Anand and Apul [9] conducted a study considering different technologies for toilet flushing and considered standard and high-efficiency toilets consuming 6.0 and 4.8 L per flush, respectively.

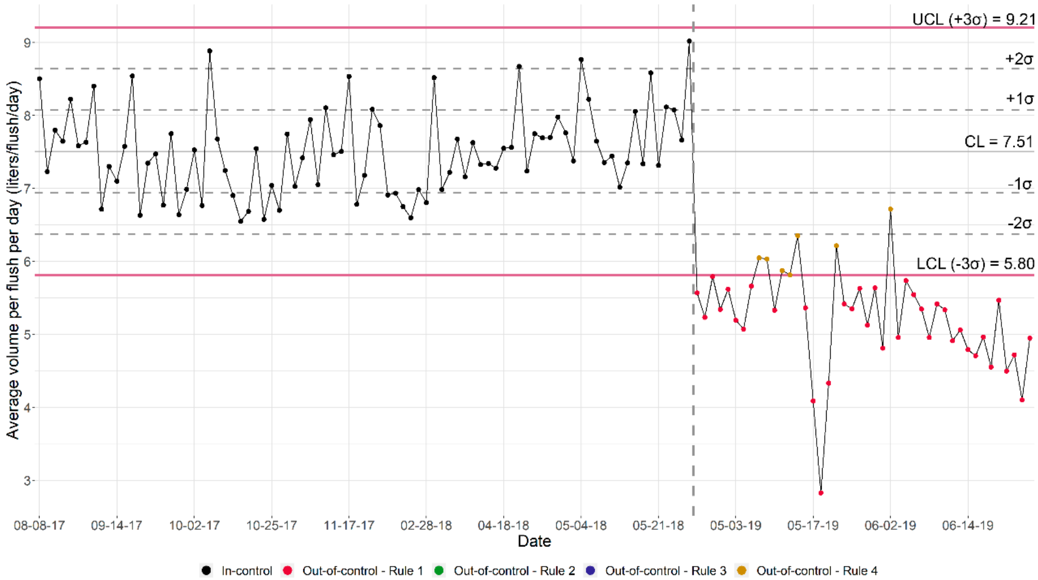

Figure 5. Shewhart Control Chart—Average volume per flush per day.

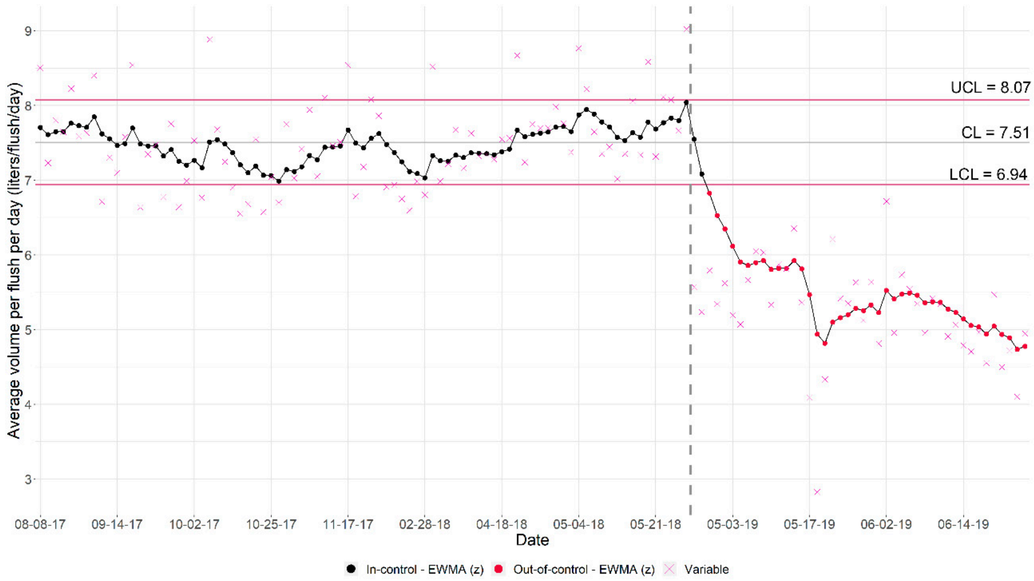

Figure 6. EWMA Control Chart—Average volume per flush per day.

In a study conducted in India, Welling et al. [48] measured the sewage volume in squat toilets and found an average of 7.5 L/use, which was similar to the average water consumption per flush found in Phase 1 of this research, despite the differences in plumbing fixtures. Horsburgh et al. [49] determined the average volume per activation in the toilets of a University in the United States, which was 7.46 and 8.02 L per flush per day in the women's and men's restrooms, respectively. Tables 2 and 3 show the descriptive statistics for Phases 1 and 2 in female and male restrooms, respectively. Shewhart control charts for average volume per flush per day in female and male restrooms are presented in Figures 7 and 8. The LCL and UCL in Figures 7 and 8 were calculated using Equations (1) and (3), respectively.

Table 2. Female Restrooms—Phases 1 and 2 summaries.

		Total Volume Per Day (L/Day)	Average Volume Per Flush Per Day (L/Flush/Day)	Number of Flushes
Phase 1	Minimum	584.40	6.17	72.00
	Maximum	1289.10	8.37	197.00
	Average	961.70	7.18	134.40
	Standard Deviation	179.22	0.47	25.27
Phase 2	Minimum	260.20	3.68	56.00
	Maximum	1570.70	6.57	239.00
	Average	614.70	5.22	116.52
	Standard Deviation	215.78	0.69	31.08

Table 3. Male Restrooms—Phases 1 and 2 summaries.

		Total Volume Per Day (L/Day)	Average Volume Per Flush Per Day (L/Flush/Day)	Number of Flushes
Phase 1	Minimum	276.40	5.60	42.00
	Maximum	920.40	9.17	119.00
	Average	570.30	7.54	75.00
	Standard Deviation	130.16	0.83	16.51
Phase 2	Minimum	155.90	1.67	27.00
	Maximum	793.80	7.03	234.00
	Average	322.10	5.42	62.68
	Standard Deviation	113.40	1.00	32.46

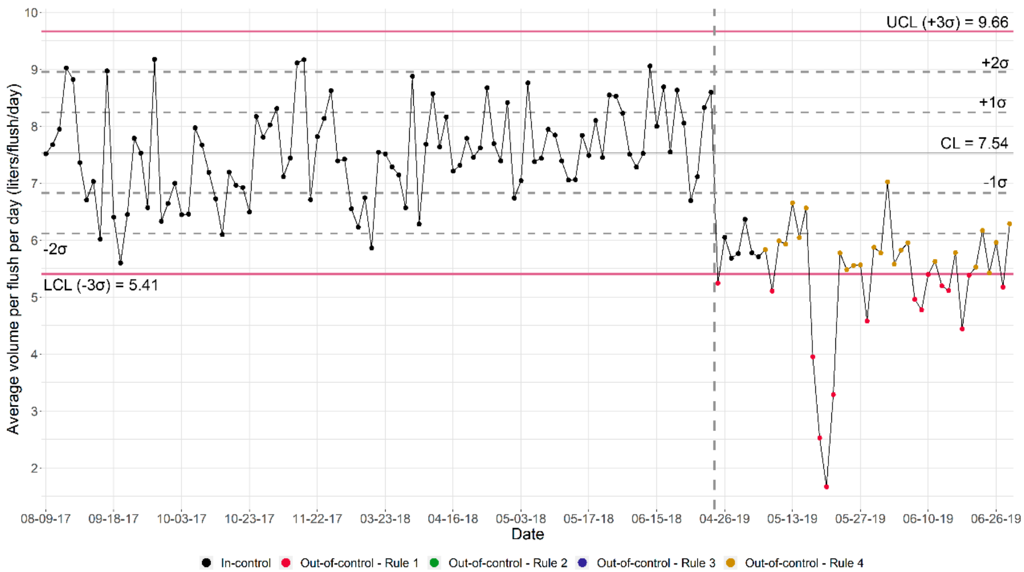

Figure 7. Shewhart Control Chart—Average volume per flush per day (male restrooms).

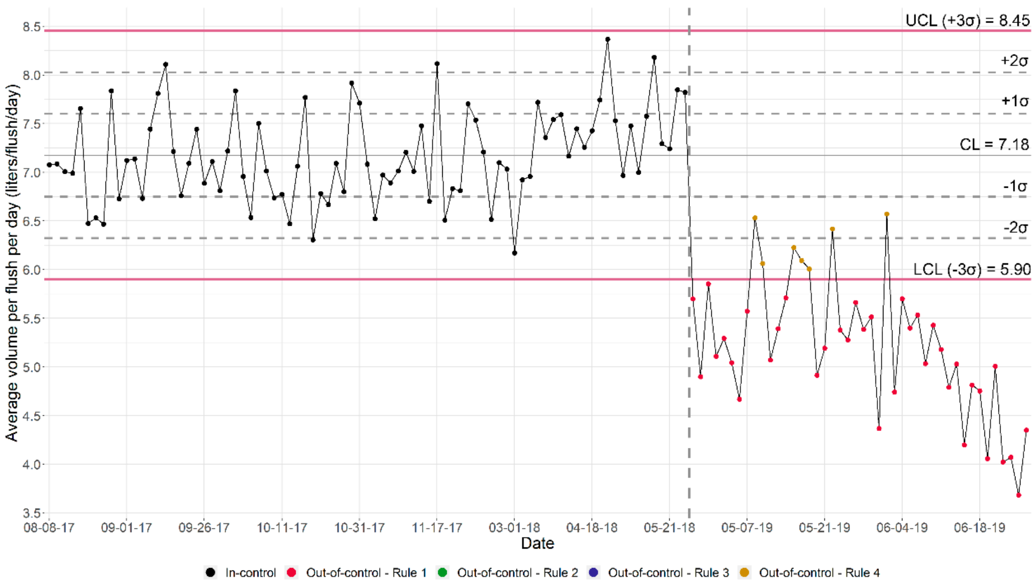

Figure 8. Shewhart Control Chart—Average volume per flush per day (female restrooms).

Regarding the assumptions, Phase 1 average volume per flush per day data showed adherence to the normal distribution: men's restrooms (p-value = 0.3353) and women's restrooms (p-value = 0.1225). Furthermore, the data did not show autocorrelation: men's restrooms average volume per flush per day (p-value = 0.08055); women's restrooms average volume per flush per day (p-value = 0.1304). The average total volume per day in Phase 2 for the men's restrooms was 322.10 L/day, with an average of 62.68 flushes per day, while in the women's restrooms, the average total volume per day, also for Phase 2, was 614.70 L/day with an average of 116.52 flushes per day. This difference strongly indicates the impact that urinals have on reducing the overall usage of toilets.

Regarding water consumption patterns in women's and men's restrooms, Talpur et al. [50] mentioned that there were significant differences, since in men's rooms there were toilets and urinals, while in women's there were only toilets. In the study developed by Horsburgh et al. [49], the results showed that women used approximately twice as much water as men per restroom visit. The authors attributed this mainly to the fact that men's rooms offered urinals. The authors found urinal utilization rates 593% higher than toilet utilization rates (plumbing fixture flush per restroom user).

In this research, the control charts showed a significant reduction in water consumption brought about by the toilets being replaced. The proposed charts can be implemented to monitor other fixtures and the building's total water consumption. According to the CBCS [51], the adoption of technological measures for water management, such as the modernization of water supply systems in buildings and the installation of metering systems, can produce a strong impact in reducing water consumption. Similarly, the importance of planning and introducing programs to replace or adapt fixtures such as toilets, as well as installing tap aerators and other solutions, were mentioned by the authors.

The use of the control chart in this case study shows its application to identify the effects of a system improvement. Furthermore, the same graphics can be applied to monitor water consumption and signal problems such as leaks and increased consumption, as well as to indicate actions aimed at reducing water consumption over time.

Water conservation in building systems requires targeted and specific programs and actions. The proposed method can be used to monitor water consumption in buildings, which includes the evaluation of water losses. According to Carretero-Ayuso et al. [52], further studies on water losses and leakages in building systems are needed in order to determine the resulting technical, economic, and environmental impacts. In conclusion, the results found in this study agree with Coswosk et al. [53], who argued that it was necessary to go beyond the infrastructure in order to guarantee the rights to water and sanitation. For the authors, education institutions represent a privileged space for the shaping of critical and reflecting citizens. From that perspective, the education environment can be a place to experience simple actions that lead to the perception of what water conservation is. It is possible to create educational programs to show students the importance of replacing damaged plumbing devices, the need for maintenance, the reasons why laws are changing, and the role each citizen has in this context.

6. Conclusions

The control charts used in this work proved very useful to detect the water consumption drop after the toilets were replaced. The average water consumption in Phase 1 was 7.51 L per flush per day. After replacing the toilets, it dropped to 5.24 L per flush per day, a 30.22% reduction. Water consumption in toilets is significant, and these research results are important to confirm the effectiveness of the implementation of public policies for reducing water consumption. Measures to mitigate the effects of unequal water distribution and water waste have been on the agenda of nations around the world, and the creation of laws and regulations that lead to water conservation practices can be an effective tool.

The control charts were also able to pinpoint irregular days in the water consumption process. This is a good indication that the control charts can be used for continuous monitoring, providing fast and reliable feedback. The importance of a water consumption monitoring system (e.g., control charts) is evident, as it provides a method to analyze water consumption at regular intervals to detect data variance and its implications.

As a suggestion for future works, the control charts can be used to monitor other fixtures such as taps and showers or even monitor larger-scale projects, such as whole water distribution systems. Complementarily, in order to improve the overall monitoring process, the use of different types of control charts are suggested, e.g., the application of non-parametric charts, modified control charts, and multivariate control charts such as Hotelling's T^2 and Multivariate Exponentially Weighted Moving Average control charts. Besides investigating the application of different types of graphics and techniques, comparing the performance of these different approaches is essential to identify the best solutions, considering the specifics of the process. Control charts, in general, possess a high degree of flexibility, thus they can be modified to display more accurate and reliable information for a given process while considering its specificities.

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