École Polytechnique Fédérale de Lausanne

FACULTY OF MANAGEMENT, TECHNOLOGY AND ENTREPRENEURSHIP

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Semester Project:
Technical Report

Professor:

Michaël Aklin

Students (Group Y):

Rose Schlageter: 329114

Amelia Bertolaso: 387434

Victoria Rochat: 325805

Simone Palazzotto: 394896

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Project Summary and Approach

Research question. *What is the optimal number of students that can simultaneously use the EPFL gym, given its space, equipment, and budget constraints, so as to maximize fair and comfortable access for all users?*

Model overview. We optimize three operational decisions: the number of concurrent users N, equipment units n, and daily opening hours H_{oper}. These variables enter a composite welfare function

$$U = w_A f_A^1 + w_C f_C^1 + w_D f_D^3,$$

where all components are normalized to $[0, 1]$. The weights

$$(w_C, w_A, w_D) = (0.50, 0.35, 0.15)$$

reflect an explicit priority for equity over average welfare and cost efficiency.

Scope. The analysis focuses on the gym training area only and on short-term operational decisions. Structural expansion, pricing, and reservation systems are excluded. Calibration relies exclusively on the provided datasets. Safety and comfort are enforced through explicit constraints on maximum occupancy and crowding.

Components. Student welfare f_A^1 captures access, waiting times, and crowding; social equity f_C^1 penalizes under-representation of women and students with disabilities; and institutional constraints f_D^3 model maintenance costs as a convex function of utilization beyond an overuse threshold.

Ethical Framework

We adopt an egalitarian framework with prioritarian aggregation because the EPFL gym is a subsidized public service aimed at inclusive student welfare. The objective is not to maximize average satisfaction, but to ensure fair and usable access, especially for structurally disadvantaged groups.

This ethical framework determines the weighting of the utility components: equity receives the largest weight, followed by average student welfare, while costs are handled both through a smaller weight and explicit constraints. Normalization and penalties prevent high averages from masking inequitable outcomes, and comfort-density caps ensure no group bears excessive crowding or delay.

Component Selection, Mathematical Framework and Parameter Estimation

Category A: Student Welfare – Individual Satisfaction (f_A^1)

Scope and rationale. Among the different possible welfare dimensions, *Individual Satisfaction* most directly captures students' immediate experience of the gym environment. The project emphasizes that overcrowding, insufficient access to equipment, and excessive waiting times are the main sources of dissatisfaction. Focusing on satisfaction allows the model to represent the short-term welfare impact of operational decisions (such as opening hours, capacity limits, and equipment allocation) without resorting to speculative long-term proxies such as physical health or stress reduction. Empirical data from the *EPFL Student Gym Survey* and the *Wait-Times Study* provide explicit measures of perceived satisfaction and acceptable waiting times, allowing a data-driven calibration. In the leisure-service literature, satisfaction is the conventional measure of welfare because it integrates both utilitarian (access, comfort) and affective (stress, crowding) components [1–3].

Functional form. The individual satisfaction component is expressed as:

$$f_A^1(N, n, H_{\mathrm{oper}}) = \alpha_{\mathrm{A}}\, A(N, n, H_{\mathrm{oper}}) - \beta\, B(N, n) - \delta\, C(N), \quad \alpha_{\mathrm{A}} + \beta + \delta = 1. \tag{1}$$

It combines three intuitive elements: a positive access benefit A, a waiting-time disutility B, and a crowding disutility C, each weighted on $\alpha_{\mathrm{A}}, \beta, \delta$, after being normalized (see *Optimization Formulation Section*).

Access benefit. The per-capita access time increases with both daily operating hours H_{oper} and the number of available equipment units n:

$$A(N, n, H_{\mathrm{oper}}) = \frac{H_{\mathrm{oper}}\, n}{N\, T_{\mathrm{session}}} \tag{2}$$

Waiting-time penalty. We model the expected average waiting time as the product of (i) a convex crowding curve in the number of concurrent users N and (ii) a dimensionless capacity factor that scales inversely with the total number of installed units n. Under our interchangeability and uniform-utilization assumptions (explained in details in Sec.D), aggregate service capacity is proportional to n, so waits scale with its inverse. Hence,

$$\underbrace{W_{\mathrm{wait}}(N, n)}_{\text{penalty (minutes)}} = \Big[\underbrace{(b_0 + b_1 N + b_2 N^2)}_{\text{crowding, } b_2 > 0} \left(\frac{n_0}{n}\right) \Big]_+,$$

where n_0 is the baseline total unit count. This specification is unit-consistent, ensures that adding units lowers waits, and reduces to the linear first-order approximation around n_0 (see Appendix B for parameter estimation details).

Thus, the waiting penalty is

$$B(N,n) = \left(\frac{W_{\text{wait}}(N,n)}{W_{\text{tol}}}\right)^2. \tag{3}$$

The quadratic exponent reflects the convex perception of delay: experimental evidence shows that perceived waiting disutility typically grows between 1.5 and 2 times faster than actual delay [4].

Crowding penalty. Crowding discomfort depends on the occupancy ratio $\rho(N) = N/N_{\text{capacity}}$, with N_{capacity} computed such that $\rho(N) = C_0$ for the level of W_{tol} defined (baseline $\rightarrow$ 8 minutes). We define

$$C(N) = \left(\frac{\rho(N) - C_0}{1 - C_0}\right)_+^2, \qquad (x)_+ = \max(0,x). \tag{4}$$

The squared term captures the non-linear satisfaction drop observed in crowded environments.

Parameter summary.

Parameter	Meaning	Initial estimation / data source
$\alpha_{\text{A}}, \beta, \delta$	Weighting parameters	$(\alpha, \beta, \delta) = (0.35, 0.40, 0.25)$
H_{oper}	Daily opening hours	Decision variable
T_{session}	Average workout duration	Student survey (mean 74 min)
n	Number of equipment units	Decision variable
N	Simultaneous users	Decision variable
n_0, b_0, b_1, b_2	waiting-time penalty parameters	computations in Appendix 2
W_{tol}	Tolerated waiting time	Student survey (mean 8 min)
N_{capacity}	Physical maximum capacity	274 (EPFL gym)
C_0	Comfort-density threshold	0.8 (literature [1, 5])

TABLE 1
Parameter definitions and empirical estimates for $f_A^1(N, n, H_{\text{oper}})$.

Weight calibration. We chose the baseline weights $(\alpha_{\text{A}}, \beta, \delta) = (0.35, 0.40, 0.25)$ to reflect behavioral evidence that waiting time has the strongest negative influence on satisfaction, followed by access limitations and then perceived crowding [1–3]. The higher value of β emphasizes the pronounced aversion to waiting observed in leisure-service studies and in delay perception research, where perceived waiting costs often exceed actual time disutility [4]. This allocation keeps α and δ at comparable levels to balance accessibility and comfort effects while remaining consistent with the satisfaction levels and utilization patterns reported in the EPFL survey data.

Constraints. Beyond mandatory safety and scheduling limits ($N \leq 316$, $8 \leq H_{\text{oper}} \leq 16$), the following constraints ensure operational realism:

$$N \leq C_{\text{physical}} = 274 \qquad \text{(physical capacity constraint)}, \tag{5}$$

$$\rho(N) \leq 0.95 \qquad \text{(comfort-density limit preventing extreme crowding)}. \tag{6}$$

These constraints prevent the optimizer from selecting unrealistic or unsafe operating points.

Sensitivity analysis. We will test the robustness of $f_A^1(N, n, H_{\text{oper}})$ to alternative behavioral and operational assumptions. First, we will vary the comfort-density threshold $C_0 \in [0.75, 0.85]$ to reflect uncertainty in when perceived overcrowding begins to significantly reduce satisfaction, as reported in leisure-service studies. Second, we will explore alternative values for the waiting-time tolerance $W_{\text{tol}} \in [7, 9]$ minutes and for the convexity exponent in the waiting penalty, testing both linear and quadratic specifications, to capture heterogeneity in delay perception across users. Third, we will assess how changing the weight structure $(\alpha_{\text{A}}, \beta, \delta)$ within ± 0.1 of their baseline values affects the resulting welfare surface and optimal N.

Category C: Social Equity Components - Access Equality (f_C^1)

The goal is to maximize the number of students who can access the gym while ensuring inclusivity across demographic groups, particularly students with disabilities and women.

Functional form. The access–equality component is (with $H_{\text{tot}}^{\text{op}} = H'$ observed operating hours):

$$f_C^1(N, H_{\text{oper}}) = \underbrace{\alpha_{\text{C}} \frac{\#\,\text{visits/week} \cdot H_{\text{oper}} \cdot N}{H'/\text{week}}}_{\text{weekly inclusion benefit}} - \underbrace{\beta_{\text{gender}} \left(x^*_{\text{female}} N - x_{\text{female}} N\right)_+^2 - \beta_{\text{dis}} \left(x^*_{\text{dis}} N - x_{\text{dis}} N\right)_+^2}_{\text{one-sided (hinge) penalties for under-representation}}. \tag{7}$$

Calibrating the term $\frac{\#\text{visits/week}}{H'/week}$ with data provided in Dataset 1, 2 we get $\frac{2.1}{90} = 0.0233$. This yield the following formulation:

$$f_C^1(N, H_{\text{oper}}) = \underbrace{\alpha_{\text{C}} \cdot 0.0233 \cdot H_{\text{oper}} \cdot N}_{\text{weekly inclusion benefit}} - \underbrace{\beta_{\text{gender}} \left(x^*_{\text{female}} N - x_{\text{female}} N\right)_+^2 - \beta_{\text{dis}} \left(x^*_{\text{dis}} N - x_{\text{dis}} N\right)_+^2}_{\text{one-sided (hinge) penalties for under-representation}}. \tag{8}$$

Parameter	Definition and estimate
N	Number of students admitted in the time slot (decision variable to be optimised).
visits/week	Mean visits per member per week. *Estimate:* 2.1 (Dataset: Student Survey).
H_{oper}	Hours open per day, to be optimised under the constraint $H_{\text{operating}} \in [8, 16]$.
H'/week	Total observed operating hours (H') per week, set to 90 and computed as [mean(facility areas open hours during week)×5+mean(facility areas open hours during week)×2 = 14×5 + 10×2.
x_{female}	Observed female *share* among students with a gym membership. *Estimate:* 0.45 (Dataset: Student Survey).
x_{dis}	Observed disability *share* among admitted students. With only campus totals available, we proxy by campus prevalence: $x_{\text{dis}} = 312/12485 \approx 0.025$ (Dataset: Demographics).
x^*_{female}	Target share for gender equity. *Set to* 0.50 (gender parity target).
x^*_{dis}	We adopt a parity-plus uplift approach to promote equity for a historically under-represented group: $x^*_{\text{dis}} = p_{\text{dis}}\,(1+\eta)$, where $p_{\text{dis}} = 0.025$ (current prevalence from the dataset) and η is an uplift factor capturing the desired proportional improvement. Using the observed five-year growth of $+33.3\%$ in this subgroup and an additional equity margin of $\eta = 0.5$, we obtain $x^*_{\text{dis}} = 0.025 \times (1 + 0.5) = 0.0375$. A sensitivity study will be carried out as explained in the 'Sensitivity analysis' section.
α_{C}	Per-visit social inclusion benefit. *Set* $\alpha = 1.3$ (CHF/visit), consistent with WTP for community fitness access ([6]).
$\beta_{\text{gender}}, \beta_{\text{dis}}$	Penalty weights (utility per squared count deviation). To align with our ethical framework, we use $\beta_{\text{dis}} > \beta_{\text{gender}}$ (higher priority for disability). Numeric calibration is left to sensitivity analysis.
$(\cdot)_+$	One-sided (hinge) operator; penalties activate only when the observed count $x_i N$ falls below the target count $x^*_i N$.

TABLE 2
Parameters and estimates for the access equality function $f^1_C(N)$.

Rationale (literature). Eq. (8) uses a fairness-adjusted welfare structure (linear benefit; quadratic deviations from targets) as an equity-weighted access evaluation, while using a hinge loss so that only population *under-representation* is penalised (prioritarian focus on the least advantaged). The per-visit benefit α_{C} is grounded in recreation/health valuation evidence; we set $\alpha_{\text{C}} = 1.3$ (CHF per visit) consistent with willingness-to-pay estimates for community fitness access [6] .

Parameter estimation. Table 2 reports all the parameters and estimates for the access equality function.

Why asymmetric penalties. Under an egalitarian objective with prioritarian aggregation, policy should *lift under-served groups* rather than penalise over-representation. The hinge losses in Eq. (8) implement this directly: the penalty is zero whenever $x_{\text{female}} \geq x^*_{\text{female}}$ or $x_{\text{dis}} \geq x^*_{\text{dis}}$, and positive only when a group falls short of its target.

Sensitivity analysis. We will report robustness to (i) the per-visit benefit $\alpha_{\text{C}} \in [1.0, 1.5]$; (ii) the gender parity target $x^*_{\text{female}} \in [0.45, 0.50]$; (iii) the term $\eta \in [0.4, 0.6]$, corresponding to disability target $x^*_{\text{dis}} \in [0.035, 0.04]$, to ensure that policy recommendations remain stable under alternative uplift assumptions;and (iv) equity weights with $\beta_{\text{dis}}/\beta_{\text{gender}} \in [1.0, 1.6]$. For each scenario we recompute the optimal N under the operating-hour and safety constraints to verify that qualitative policy conclusions (priority to reduce under-representation while controlling crowding) remain unchanged.

Category D: Institutional Constraints - Maintenance Burden ($f_D(N, \xi)$)

Scope and rationale. Among purely *variable* operating costs, maintenance is second only to cleaning. Both variable staff effort (e.g., cleaning) and utilities scale with equipment use; therefore, by optimizing utilization - a function of the number of users N and other operational parameters ξ - we indirectly discipline these costs as well. Given the chosen numbers of concurrent users N (and, if relevant, units n), the gym can compute category-level staffing requirements via coefficients as $\widehat{S}_i = \rho_i^{\text{opt}}\, N$ (or two-driver $\widehat{S}_i = \rho_{iN}^{\text{opt}}\, N + \rho_{in}^{\text{opt}}\, n$), for $i \in \mathcal{I}$. Total staff is then $\widehat{S} = \sum_{i \in \mathcal{I}} \widehat{S}_i$, with the ρ coefficients defined by the gym to reflect desired service levels.

Assumptions.

- The current equipment mix is sized to demand; in the short run, utilization is proportionally shared across units and no single type is persistently overloaded. In fact, in the absence of further data, one can think about the gym as having two types of equipments: cardio and strength. Within each category, one can assume they are quite interchangeable. Indeed, since it is a low-price student gym (and not a premium public gym, where people have high expectations regarding the money they invested), one can assume that, within the two types of equipments, **people can switch between different equipments**. Therefore, one can assume that the **utilization rate is uniformly distributed** and that adding an equipment will reduce the waiting time for all the others.
- In the absence of detailed failure data, we treat maintenance cost as a *monotone, convex* function of equipment utilization (since it is presented in Dataset Description as a variable cost) and the additional parameters we define below (ξ), consistent with practice in the maintenance literature [7, 8]. Please notice that we model the daily maintenance cost (H_{oper} are daily opening hours).

Mathematical formulation. Let $U \in [0, 1]$ denote time-weighted utilization. The maintenance component enters the objective as

$$f^3_D(N, \xi) \;=\; -\,G\big(U(N, n), H_{\text{oper}}, n\big), \qquad \xi = (H_{\text{oper}}, n), \quad g \in \mathcal{G} := \big\{g:\; g(0) = 0,\; g'(U) \geq 0,\; g''(U) \geq 0\big\}.$$

We use a convex quadratic form separating proportional wear and overuse penalties for each equipment j [9]:

$g_j(U, H_{\text{oper}}) \;=\; H_{\text{oper}}\big(\lambda_j U + \theta_j (U - U^*)_+^2\big),\quad U^* \approx 0.6$ utilization knee after which **overutilization** is penalized (see Appendix A.1)

Aggregating across equipment types j with q_j yields fleet-level coefficients:

$$G(U, H_{\text{oper}}) \;=\; \sum_j q_j\, g_j(U, H_{\text{oper}}) = H_{\text{oper}}\left(\underbrace{\Big[\sum_j q_j \lambda_j\Big]}_{\lambda_{fleet}} U + \underbrace{\Big[\sum_j q_j \theta_j\Big]}_{\theta_{fleet}} (U - U^*)_+^2\right).$$

Equivalently, assuming (i) interchangeability across types so that arrivals pool and each type operates at the same utilization U (common load sharing), and (ii) an unchanged equipment mix relative to the calibration baseline n_0, the fleet coefficients scale linearly with unit count; hence $\lambda_{\text{unit}} = \lambda_{\text{fleet}}/n_0$ and $\theta_{\text{unit}} = \theta_{\text{fleet}}/n_0$. $\lambda_{\text{unit}} = \lambda_{fleet}/n_0,\ \theta_{\text{unit}} = \theta_{fleet}/n_0$ and total units $n = \sum_j q_j$. (see Appendix A.2)

$$G(U, H_{\text{oper}}) = H_{\text{oper}}\, n\left(\lambda_{\text{unit}}\, U + \theta_{\text{unit}}\, (U - U^*)_+^2\right).$$

Calibration. Industry data place annual maintenance between $3\% - 5\%$ of equipment value [10, 11]. Using the conservative upper bound $B = 0.05V$ and historical utilization data (U_t), we calibrate the fleet-level coefficients from Dataset 3 at $n_0 = 57$ units, obtaining ($\lambda = 6.42$, $\theta = 219.72$ [CHF/hour]), the per-unit coefficients are therefore $\lambda_{\text{unit}} = \lambda/n_0 \approx 0.113$ and $\theta_{\text{unit}} = \theta/n_0 \approx 3.85$.
Hence the hourly cost and the H'-hour total (with $H_{\text{oper}} = H'$) are

$$c(U; n) = n\big(0.113\, U + 3.85\, (U - 0.6)_+^2\big), \qquad \widehat{C}(N, n; H_{oper}) = H_{oper}\, n\Big[0.113\, U(W(N,n)) + 3.85\, \big(U(W(N,n)) - 0.6\big)_+^2\Big].$$

Where *Utilization* depends on the number of students N and total equipment n through an empirically fitted quadratic wait–utilization map on Dataset 3 (see Appendix A.3, B for validation of the regression fit, mathematical full formulation of $U(N,n)$ and consistency checks):

$$U(W) = \Pi_{[0,1]}\big(5.913 \times 10^{-4} W(N,n)^2 + 2.511 \times 10^{-2} W(N,n) + 0.370\big).$$

Sensitivity Analysis. We will further discuss some adjustments to the overutilization knee $U^*(W_{tol})$ as a function of the tolerated waiting time. For the baseline scenario we set it to 0.6 according to the empirical curve $U(W)$ evaluated at $W = 8$min we fit on the data. This yields a more conservative estimate than what is usually used in literature with queueing results showing sharp performance degradation above 85–90% utilization in analogous service systems [12].

Constraints. Let A denote the usable gym floor area obtained by summing cardio and weight area which are the ones where equipment is located (320 m^2) and n the total number of equipment units. Using a planning factor $\alpha \approx 5$ (m^2/unit) that includes immediate circulation by established facility guidance [13, 14], we impose the structural cap

$$n \;\le\; \left\lfloor \frac{A}{\alpha} \right\rfloor \;=\; 64.$$

In addition, we impose a minimum equipment level of 50 units, which is slightly below the current inventory (57 units) and thus preserves the existing order of magnitude of service capacity for users while still allowing for a modest reduction or increase (±7units).
We allocate the annual budget based on knowing that the staff cost equals 48% of the total which is thus $\bar{B} = 1/0.49 \times 280{,}000 \approx 572{,}000$ CHF by excluding fixed items that by definition do not depend on the decision variables (Administration 25,000; Insurance 18,000), yielding the available envelope

$$B \;=\; \bar{B} - (25{,}000 + 18{,}000) \;=\; 529{,}000 \text{ CHF/yr}.$$

Assuming constant per-student variable costs based on Dataset 4 and a calendar-based replacement plan which depends on the number of equipments, the variable cost coefficients are: [1]

$$c_N \;=\; \frac{452{,}000}{76 \text{ students}/H_{oper} \times 7 \text{ days/week} \times 48 \text{ weeks/year} \times 12.85\ H_{oper}/\text{day}} \;=\; 1.38\,\text{CHF/stud}, \quad c_n \;=\; \frac{35{,}000}{57} \;\approx\; 614\,\text{CHF/(unit)}.$$

The annual spend must thus satisfy the following constraint where we also include the annual maintenance cost $\widehat{C}_{annual} = \widehat{C} \times 7$ days/week $\times$ 48 weeks/year (Opening weeks per year [15]).

$$c_N\, N + c_n\, n + \widehat{C}_{annual} + R_n \;\le\; B \quad\Longleftrightarrow\quad 1.38{\times}48{\times}7\, N\, H_{oper} + 614\, n + \widehat{C}_{annual} + \max\left(376 \times (n - n_0), 0\right) \;\le\; 484{,}000\,.$$

Notice that we subtract from B the old cost of maintenance since we replace it for the new maintenance cost term we are optimizing for $\to 529{,}000 - 45000 = 484{,}000$. Moreover, the annual variable cost per student (first term) is computed over the total annual number of students accessing to the gym[2]. We also add the purchasing cost R_n that consider the yearly amortized cost of new equipment based on the cost per unit and the average equipment lifespan from Dataset 6 where $376 = \frac{7520 \text{ CHF/unit}}{20 \text{ avg lifetime/unit}}$. We additionally impose integrality: $N, n \in \mathbb{Z}_+$.

[1] 76 are the average students per hour computed on Dataset 3, 48 the opening weeks per year, 12.85 the average operating hours computed on Dataset 1.
[2] We recomputed the variable cost per student given by Dataset 4 to match our formulation.

Complete Optimization Problem and Sensitivity Analysis

$$\max_{H_{\text{oper}},\, N,\, n \in \mathbb{Z}_+} U(N, n, H_{\text{oper}}) = \max_{H_{\text{oper}},\, N,\, n \in \mathbb{Z}_+} \; 0.35[0.35\, A(N, n, H_{\text{oper}}) - 0.40\, B(N, n) - 0.25\, C(N)]$$

$$+ 0.5\Big[\alpha_{\text{C}}\, 0.0233\, H_{\text{oper}}\, N - \beta_{\text{gender}}\big((x^*_{\text{female}} - x_{\text{female}})N\big)_+^2 - \beta_{\text{dis}}\big((x^*_{\text{dis}} - x_{\text{dis}})N\big)_+^2\Big]$$

$$- 0.15\, H_{\text{oper}}\, n\Big(0.113\, U\big(W(N, n)\big) + 3.85\, \big(U\big(W(N, n)\big) - 0.6\big)_+^2\Big)$$

$$\text{s.t.} \quad 463.68\, N\, H_{oper} \; + 614\, n + \widehat{C} \leq 484{,}000,$$

$$\left.\begin{aligned} 0 \leq N \leq C_{\text{physical}} = 274, \\ \rho(N) \leq 0.95 \end{aligned}\right\} \quad \Longrightarrow \quad 0 \leq N \leq 260,$$

$$50 \leq n \leq 64,$$

$$8 \leq H_{\text{oper}} \leq 16.$$

Optimization resolution

To solve the above optimization problem we first normalize each component of the objective function so that they are comparable on a common scale and the optimal solution is not mechanically driven by the component with the largest numerical magnitude.

Formally, over the feasible set we apply a min–max normalization

$$\tilde{f}_i(N, n, H_{\text{oper}}) \;=\; \frac{f_i(N, n, H_{\text{oper}}) - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \;\in [0, 1], \qquad \forall i \in \{A, C, D\},$$

where $f_i^{\min}$ and $f_i^{\max}$ denote the minimum and maximum values attained by component f_i over all feasible (N, n, H_{oper}).[3] The global objective is then computed by combining the normalized components with the chosen preference weights.

Moreover, we optimize over a single value of N representing the *average* occupancy of the gym. In practice, this average is subject to substantial intra-day variability, with a marked peak in the late afternoon (see Dataset 3). If we were to treat N as a fixed scalar and ignore this variability, the resulting average number of students would lie below the activation thresholds of the hinge-loss penalties in Categories A and D, so that these equity and crowding penalties would be identically zero.

To incorporate variability explicitly, we exploit the empirical (right-skewed) distribution of the number of students observed during the week. Assuming this distribution is representative of the yearly pattern, we treat N as a random variable following the empirical distribution rescaled so that its mean coincides with the decision variable (average occupancy) used in the optimization. We then optimize the *expected* penalties, that is

$$\mathbb{E}\big[C(N)\big], \qquad \mathbb{E}\big[U(W(N, n))\big],$$

where the expectation is taken with respect to this scaled empirical distribution. Intuitively, we slide and stretch the observed histogram (see Fig. 3 in Appendix C.1) so that its center matches the chosen average N, and evaluate crowding and maintenance on the whole implied distribution of realized occupancies rather than on a single point.

Baseline optimal configuration and implied maximum number of students. Solving the normalized optimization problem under the baseline parametrisation yields the following optimal configuration (see Fig. 4 in Appendix C.2 for a visual plot of the evolution of the objective function in the feasible space):

$$(N^*, n^*, H^*_{\text{oper}}) = (58, 58, 16).$$

Overall, the baseline optimization suggests that:

- the gym should operate at full opening hours $H^*_{\text{oper}} = 16$ and with slightly more machines than currently observed; this represents an increase relative to the current schedule (14 hours on weekdays and 10 on weekends on average) and enlarges the time window over which demand can be spread, making it easier to keep instantaneous occupancy below the crowding threshold while still serving more distinct users over the course of the day;
- the optimal daily average occupancy should be around $N^* = 58$ students, significantly lower compared to the current one ($\approx$ 76 students/hour).
- the optimal number of equipments is $n^* = 58$, which results in the addition of one unit to the current number of machines.
- operating and maintenance costs are endogenous and increase with the number of students: the linear wage/operation term in the budget constraint and the maintenance cost term both scale with N, so admitting more students is attractive from an equity/access point of view but becomes increasingly expensive in terms of staff time and wear of the machines;

[3] The value of the composite objective should therefore be interpreted as a *relative* index of optimality within [0, 1], rather than as an absolute welfare level.

Moreover, using the scaled empirical distribution, we can translate the optimal average number of students into an implied *maximum* instantaneous occupancy: when we rescale the weekly distribution of students so that its mean equals $N^* = 58$, the right tail of the distribution reaches approximately

$$N^*_{\max} \approx \mathbf{123} \text{ students.}$$

Therefore, *under the chosen equity, crowding and maintenance trade-offs, the gym can safely accommodate at most about 123 students at the same time*.

From a cost perspective, the optimal solution also leads to a sizeable reduction in maintenance expenditure. At the optimum, annual maintenance costs are approximately $\widehat{C}^*_{\text{annual}} \approx 17{,}053$ CHF, compared to an initial level of about $45{,}000$ CHF. This represents a reduction of roughly 60%, achieved while simultaneously improving access and reducing expected waiting time and crowding according to the composite index.

Following these considerations and results, the following question will guide our policy recommendations:

> *How can EPFL limit access so that instantaneous occupancy stays below roughly 123 students? And how can access be managed so that students are more evenly distributed throughout the day, reducing the right-skewed peak in the afternoon?*

Answering these questions is crucial because a more even time distribution of visits would allow an increase in the *total* number of students benefiting from the gym, without triggering the crowding penalty and while maintaining the access-equality standards encoded in Category C.

Sensitivity to extreme parameter configurations. We assess the robustness of the baseline recommendation $(\bar{N}, \bar{n}, \bar{H}_{\text{oper}}) = (58, 58, 16)$ by considering two opposite configurations of the model parameters that lie at the extremes of the plausible range of parameters that we defined in the previous sections.[4]

Strict extreme. We first impose a stricter equity and crowding regime, with a lower utilization threshold UTIL_THRESHOLD $= 0.75$, a tighter waiting-time target of 7 minutes, and inner weights $(u_1, u_2, u_3) = (0.30, 0.40, 0.30)$ that down-weight access and increase the relative penalty on crowding and waiting. Equity targets are set to $x^*_{\text{female}} = 0.50$ and $x^*_{\text{dis}} = 0.04$, implying positive gaps relative to the status quo, and higher penalty weights $\beta_{\text{gend}} = 1.85$, $\beta_{\text{dis}} = 2.00$. Solving the optimization problem under this configuration yields the new optimum

$$(N^*, n^*, H^*_{\text{oper}}) = (34, 50, 16),$$

with a normalized objective value $U(N^*, n^*, H^*_{\text{oper}}) \approx 0.756$. Evaluating the objective at the baseline operating point $(58, 58, 16)$ under the same strict parameters gives $U(58, 58, 16) \approx 0.709$, i.e. the baseline configuration retains about 94% of the maximum attainable normalized welfare in this scenario. The strict scenario corresponds to a lower optimal average occupancy and thus a smaller implied maximum number of simultaneous users, signaling that if EPFL chose much stricter equity and crowding standards it would need to reduce both average and peak attendance.

Lenient extreme. We then consider a lenient configuration with UTIL_THRESHOLD $= 0.85$, a more relaxed waiting-time constraint of 9 minutes, and inner weights $(u_1, u_2, u_3) = (0.50, 0.30, 0.20)$ that give more importance to access and less to waiting and crowding. Gender parity is set close to the status quo ($x^*_{\text{female}} = 0.45$, yielding zero gender gap), while the disability target is only slightly lower ($x^*_{\text{dis}} = 0.035$), with milder penalties $\beta_{\text{gend}} = 1.25$, $\beta_{\text{dis}} = 1.30$. Under this lenient extreme the optimizer again selects

$$(N^*, n^*, H^*_{\text{oper}}) = (58, 58, 16),$$

and the corresponding objective value is $U(N^*, n^*, H^*_{\text{oper}}) \approx 0.654$. Evaluating the objective at the baseline solution $(58, 58, 16)$ obviously yields the same value, so the recommended operating point and the implied maximum of about 123 students remain unchanged in this scenario.

Scenario	$\tilde{f}_{tot}(N^*, n^*, H^*_{\text{oper}})$	$\tilde{f}_{tot}(58, 58, 16)$	Performance Ratio[5],
Strict extreme	0.756	0.709	0.94
Lenient extreme	0.654	0.654	1.00

TABLE 3
Performance of the baseline configuration $(58, 58, 16)$ relative to the scenario-specific optimum.

It is noteworthy that in all scenarios the optimizer sets H_{oper} at the upper bound of the feasible interval. This does not indicate a flaw in the formulation, but rather reflects the fact that, given the current budget and cost parameters, extending opening hours is the cheapest way to improve access and reduce crowding per student, even after accounting for the additional wage and maintenance costs that scale with N and H_{oper}.

Taken together, these results indicate that the baseline optimal configuration $(58, 58, 16)$, and the associated maximum of about 123 simultaneous students, is *robust* to substantial changes in the modelling assumptions. Even when we simultaneously tighten or relax the utilization thresholds, waiting-time targets, inner weights and equity penalties, the recommended number of machines and operating hours remain unchanged, and the optimal average occupancy moves within a relatively narrow band. This supports the use of the baseline solution as a stable policy recommendation and provides a clear quantitative target for the subsequent discussion on *how* EPFL could

[4] Analyzing all combinations of parameter values would be prohibitively expensive computationally, so we focus on two opposite scenarios designed to bracket the baseline case.

design access rules and time-allocation mechanisms to enforce this maximum while serving as many students as possible over the course of the day.

Policy Recommendations

Using the optimal configuration $(N^*, n^*, H^*_{\text{oper}}) = (58, 58, 16)$, the implied maximum safe instantaneous occupancy (≈ 123 students), and the equity-first ethical framework of our utility function, we recommend a coordinated bundle of four operational policies. Each policy addresses a specific mechanism identified in the model, and feasibility is analysed accordingly.

1. Hard Occupancy Cap with Real-Time Monitoring

Recommendation. EPFL should implement a strict instantaneous occupancy limit of 123 students, enforced via badge-access counts at the entrance of the gym. A real-time occupancy dashboard should be displayed both at the gym entrance and online (EPFL Sports app or website), providing current load, short-term forecasts based on historical data, and a colour-coded congestion indicator (for example green < 70, orange 70-100, red > 110).

Rationale and feasibility. This measure directly enforces the safe maximum occupancy (≈ 123 students) beyond which crowding penalties $C(N)$ and overuse costs escalate sharply in our model. The required infrastructure is minimal: EPFL already relies on badge-access systems, and similar real-time monitoring technologies are deployed elsewhere on campus. In particular, the EPFL Library collaborates with the startup *Affluences* [16], which provides live occupancy levels, historical trends, and predictive congestion forecasts for specific zones of the Rolex Learning Center [17]. A screen at the library entrance (see Figure 5) displays the current occupancy percentage, while the same information is accessible online. This proves the technical feasibility and student familiarity with such tools.

Examples of application. When instantaneous occupancy reaches the threshold (e.g. 123 students), entry is temporarily restricted through the turnstiles, and students receive a clear message such as: *"Gym full - Estimated wait: 10 minutes."*

Data from sensors or badge counts are transmitted to the online dashboard, where students can observe real-time occupancy and forecasted congestion based on past usage patterns. EPFL could collaborate with *Affluences* to deploy the same measurement, prediction, and communication tools already used in many libraries, public spaces, and sports centers across France. This promotes transparency, helps students plan their visits, and aligns actual occupancy with the comfort and safety targets of the model. Installing turnstiles and occupancy sensors involves an upfront cost. However, EPFL already operates badge-access systems and collaborates with *Affluences* for real-time occupancy monitoring in the campus library, which could allow reuse of existing expertise and potentially discounted sensor solutions. As the turnstile is a one-time investment and the optimal policy reduces annual maintenance costs by about 60%, the system is likely to be cost-neutral over time.

Additional clarification. Unlike the gym, the EPFL Library does not restrict entry when it becomes full: students can still enter even when all seats are occupied. This often leads to users wandering for long periods in search of a study place, creating both frustration and noise that disturbs others. Such a situation would be unacceptable in the gym context, where overcrowding directly impacts safety (equipment density), waiting times, and user comfort. A hard cap is therefore necessary to prevent the negative congestion externalities observed in the library and to ensure compliance with the crowding and maintenance constraints encoded in our welfare function.

Effectiveness. *High.* A hard cap is the only intervention that directly enforces the model-implied maximum instantaneous occupancy (≈ 123). By preventing entry beyond the threshold, it mechanically limits the realizations of N in the right tail of the occupancy distribution, thereby avoiding the sharp increases in crowding disutility $C(N)$ and overuse costs in f_D^3.

Sustainability (in time). *High.* Once access-control logic and occupancy displays are deployed, the policy is stable over time and requires limited operational effort (routine monitoring and occasional calibration of thresholds/forecasts). Its effectiveness does not rely on continued user motivation, unlike purely behavioural interventions.

Potential negative side effects. The main cost is access denial at peak times: students may face short queues, be turned away, or perceive reduced spontaneity. If unmanaged, this can reduce perceived welfare for users with rigid schedules (e.g. lab blocks) and may create fairness concerns if access is effectively allocated to those who can queue longer.

Negative feedback loops (dynamic effects). Two risks arise. First, repeated saturation can induce strategic arrival behaviour (students arriving earlier and clustering before peak periods), creating new mini-peaks and congestion at the entrance. Second, frequent rejection may discourage some users from attending altogether, lowering overall participation and potentially worsening under-representation if affected groups have less schedule flexibility.

Mitigation and recommendation. The cap should be implemented as part of a portfolio rather than as a standalone tool. Extended opening hours (Policy 2) increase temporal capacity and reduce the frequency of binding caps, while behavioural nudges and real-time forecasting (Policy 3) shift demand away from peak periods and reduce strategic clustering. To protect equity, the gym should prioritise transparent rules (clear thresholds, wait estimates) and monitor whether rejection rates differ across groups, adjusting communication and support measures accordingly.

2. Extension and Rebalancing of Opening Hours to 16 Hours/Day

Recommendation. EPFL should adopt a stable 16-hour daily schedule (e.g. 06:30–22:30), with:

- staggered staff shifts to maintain supervision and safety throughout,
- cleaning and maintenance placed in low-usage windows (late morning),

- communication emphasising convenience for early-risers and evening users.

Rationale and feasibility. The optimizer always selects the upper bound $H_{\text{oper}} = 16$ in all parameter scenarios. Extending hours expands the time denominator of the access-benefit term $A(N, n, H_{\text{oper}})$ and lowers average occupancy, thus reducing both waiting-time penalties $B(N, n)$ and expected crowding. The extra staffing and utilities remain within the annual variable-cost envelope derived in Category D.

Examples of application. Opening earlier enables students with morning class schedules (e.g. lab-intensive sections) to train before campus congestion begins. Evening hours benefit students with long school days or part-time jobs.

Effectiveness. *High.* Extending opening hours directly increases temporal capacity and is systematically selected by the optimizer across all parameter scenarios. By spreading visits over a longer daily window, this policy lowers average and peak occupancy, reducing waiting-time penalties $B(N, n)$ and expected crowding costs in both Categories A and D. It is therefore a necessary condition for achieving the optimal average occupancy $N^* = 58$ while accommodating a large total number of distinct users.

Sustainability (in time). *Medium to high.* From an operational perspective, a stable 16-hour schedule is feasible using staggered staff shifts and planned cleaning windows. However, long-term sustainability depends on sustained off-peak usage: if early-morning or late-evening slots remain underutilised, the additional staffing and utility costs may outweigh the welfare gains.

Potential negative side effects. The main risk is inefficient resource use if extended hours do not attract sufficient demand. This could increase cost per visit and reduce overall cost efficiency. There is also a staff-related concern: longer operating hours may increase fatigue or scheduling constraints if not properly managed through shift rotation.

Negative feedback loops (dynamic effects). If users continue to coordinate on traditional peak periods despite longer hours, the extension may fail to reduce congestion, creating a situation where costs increase without alleviating crowding. In such a case, the perceived ineffectiveness of the policy could reduce institutional willingness to maintain extended hours in the future.

Mitigation and recommendation. Extended hours should not be implemented in isolation. Behavioural nudges and real-time information (Policy 3) are essential to actively redirect demand toward newly available time slots, while the occupancy cap (Policy 1) provides a strong incentive to do so. Regular monitoring of slot-level utilisation should be used to adjust communication strategies and, if necessary, fine-tune staffing intensity across the day.

3. Behavioural Nudges and Non-Monetary Incentives for Off-Peak Use

Recommendation. EPFL should use behavioural tools to shift part of peak demand to underused times. We recommend:

- Weekly congestion heatmaps (summary of busiest and quietest hours),
- Push notifications triggered when occupancy moves into the red zone, offering alternative time suggestions (e.g. "The gym is full; expected availability at 19:45."),
- Off-peak challenges (digital badges for attending in green slots), and "Bring-a-friend off-peak" weeks that reward recruiting peers into quieter slots,
- Social incentives such as recognition boards, small prizes, or participation credits for student associations.

Rationale and feasibility. Redistributing demand reduces the right tail of N's empirical distribution, thereby lowering expected crowding $\mathbb{E}[C(N)]$ and overuse $\mathbb{E}[U(N, n)]$. Nudges are low-cost, maintain EPFL's egalitarian non-price approach, and rely on existing communication channels (email, app, Instagram).

Examples of application. A badge for attending early mornings five times in a month; leaderboard for clubs whose members reduce peak-time usage the most; personalised weekly "recommended gym times".

Effectiveness. *Medium.* Behavioural nudges influence users' timing decisions but do not impose binding constraints on access. Their impact on congestion therefore depends on voluntary compliance and varies across individuals. While nudges can reduce the right tail of the occupancy distribution and lower expected crowding $\mathbb{E}[C(N)]$ and overuse $\mathbb{E}[U(N, n)]$, they cannot by themselves guarantee that instantaneous occupancy remains below the optimal threshold.

Sustainability (in time). *Medium.* Nudges are inexpensive and easy to deploy using existing communication channels, but their effectiveness may decay over time as users habituate to repeated messages or incentives. Maintaining impact requires periodic redesign of communication and incentives.

Potential negative side effects. If incentives are poorly calibrated, nudges may overshift users from peak to off-peak periods, creating new mini-peaks in previously quiet time slots. In addition, nudges may primarily benefit users with flexible schedules, leaving others less able to respond.

Negative feedback loops (dynamic effects). Repeated notifications can generate message fatigue, reducing responsiveness and weakening the marginal effect of nudges. Strategic behaviour may also emerge, with users concentrating visits only in incentivised windows, increasing volatility once incentives are adjusted or removed.

Mitigation and recommendation. Behavioural nudges should be adaptive and data-driven, with congestion heatmaps and incentive windows updated regularly based on observed usage. They should be implemented strictly as a complement to structural measures such as extended opening hours (Policy 2) and the hard occupancy cap (Policy 1), which provide the necessary capacity and enforcement to ensure overall effectiveness.

Note on the existing "off-peak" pass at the UNIL–EPFL sports centre. The UNIL–EPFL sports centre already offers an "off-peak" ("heures creuses") subscription granting access during low-demand hours [18]. This pass is not available to EPFL or UNIL students (category A), but to other user groups such as exchange students, visiting researchers, alumni, university staff, and partner institutions (categories B to E). It provides access to the entire sports centre, including weight rooms and group classes, during restricted time windows (typically 07:00–12:00 and 14:00–16:00 on weekdays, with extended hours on weekends). Despite being marketed as discounted, it is more expensive (CHF 120 per semester or CHF 200 per academic year) than the student gym-only subscription (CHF 70 per semester or CHF 90 per academic year [19]), reflecting broader access and lower subsidisation. Introducing a similar differentiated tariff for students would conflict with the egalitarian and prioritarian framework adopted in this project. Price-based differentiation would disadvantage students with rigid schedules (e.g. laboratory sessions, teaching duties, part-time jobs) who cannot shift to off-peak hours, creating income- and schedule-based inequalities. This directly contradicts the role of the equity component f_C^1, whose hinge penalties aim to reduce structural disparities, and violates our modelling assumption of uniform access costs across students. While such pricing could be defensible under a utilitarian framework prioritising aggregate usage and average welfare, it is incompatible with the equity-first objectives of our analysis.

4. Priority and Support Windows for Under-Represented Groups

Recommendation. EPFL should offer a few weekly "priority access and support" windows designed for women and students with disabilities. Features include:

- a slightly lower occupancy cap during these windows (e.g. 80-100),
- increased staff presence for support and safety,
- a welcoming environment for beginners (intro sessions, technique help).

Rationale and feasibility. This directly reduces the hinge-loss penalties in f_C^1 by improving access for groups currently below target prevalence levels (x^*_{female}, x^*_{dis}). Since category C carries the highest weight in the welfare function ($w_C = 0.5$), even small gains in inclusion generate large welfare improvements. Implementation requires only scheduling and communication, not additional infrastructure.

Examples of application. A bi-weekly 90-minute "Inclusive Lift Session" with on-floor assistance; a quieter early-evening block non-exclusively marketed towards female students and students with disabilities seeking a less intimidating environment. The UNIL–EPFL sports centre already offers a free one-hour "initiation course" with a coach for first-time users [19]. Scheduling some of these beginner sessions within the priority windows would reinforce their supportive role: calmer periods facilitate learning and confidence-building while preserving the option to attend initiation sessions during peak hours. This improves effective accessibility without restricting opportunities for other users.

Effectiveness. *Medium.* Priority and support windows do not mechanically reserve access for specific groups, since excluding other students would conflict with the egalitarian framework adopted in this project. Members of non-targeted groups (e.g. men without disabilities) are therefore still allowed to enter during these windows as long as capacity is not reached. The policy relies partly on good-faith behaviour and social norms: students who do not belong to the target groups are expected to self-select out of these periods when alternatives are available. As a result, the policy is effective at improving perceived and practical accessibility for under-represented groups, but its impact depends on voluntary compliance rather than strict enforcement.

Sustainability (in time). *Medium.* The policy is easy to sustain operationally, as it mainly requires scheduling and targeted communication. Its long-term effectiveness, however, depends on continued awareness and acceptance of equity goals within the student population. If norms erode or communication weakens, the self-selection mechanism may become less effective.

Potential negative side effects. Concerns about exclusivity can be mitigated by keeping sessions non-exclusive but strongly marketed to the target groups, and by emphasising equity-driven motives. If non-targeted users systematically ignore the intended purpose of the priority windows, the supportive environment may be diluted, reducing their effectiveness for the intended groups. Conversely, overly strong messaging could create perceptions of informal exclusion or discomfort among other users, even if access remains formally open.

Negative feedback loops (dynamic effects). If priority windows become crowded due to insufficient self-selection, members of under-represented groups may stop attending these sessions, reinforcing under-representation rather than correcting it. On the other hand, if social norms function well and most non-targeted users avoid these periods, participation by the target groups may increase, strengthening the norm and improving effectiveness over time.

Mitigation and recommendation. While access cannot and should not be restricted by identity, the reduced occupancy target during priority windows can still be enforced mechanically via the turnstile system, ensuring a calmer environment overall. Clear communication emphasising respect, inclusion, and collective responsibility is essential to encourage self-selection. The timing and frequency of these windows should be adjusted based on observed participation patterns, and they should be combined with the general occupancy cap (Policy 1) and demand-shifting nudges (Policy 3) to limit conflicts between equity objectives and overall capacity use.

Complementarity of the Full Policy Package

These four policies are strongly complementary. The occupancy cap (Policy 1) ensures instantaneous usage never exceeds the maximum safe level (≈ 123 students) derived from the optimisation. Extended hours (Policy 2) supply the additional temporal capacity required for the cap to function without excessive rejection. Behavioural nudges (Policy 3) actively redistribute students across the 16-hour window, aligning the realised occupancy distribution with the optimal average $N^* = 58$ and reducing peak penalties in both f_A^1 and f_D^3.

Finally, targeted priority windows (Policy 4) safeguard equity so that the combination of cap and nudges does not reinforce existing under-representation, directly improving the fairness component f_C^1. Because of all these considerations, we deemed partial policy packages, combining only some of the recommended policies, as ineffective and leading to foreseeable side effects. Hence, we recommend to implement the full bundle, which overcomes the shortcomings of partial packages, as explained through the negative side effects and mitigation sections of the single policies, and translates the model's optimal solution into a realistic operational regime that maximizes comfort, sustainability, and inclusive access.

Implementation Timeline and Policy Sequencing

To ensure both operational feasibility and robustness to behavioural feedback effects, the four recommended policies should be implemented sequentially rather than simultaneously. The proposed sequencing is designed so that, at each stage, the main negative feedback loops generated by a policy are mitigated by the next one introduced.

In the short term, the gym should first implement the hard occupancy cap combined with real-time monitoring (Policy 1). This intervention is the only measure that directly enforces our model's maximum instantaneous occupancy and immediately prevents excessive crowding, safety risks, and equipment overuse. Deploying the occupancy dashboard at the same time is important to preserve transparency and perceived fairness, reducing frustration associated with denied entry. However, alone, a binding cap risks creating repeated rejections, strategic early arrivals, and access inequities for students with strict schedules.

For this reason, the extension and rebalancing of opening hours to 16 hours per day (Policy 2) should be implemented in the same initial phase. Extended hours increase temporal capacity at low marginal cost and directly reduce the frequency with which the occupancy cap binds. Together, Policies 1 and 2 form a coherent structural backbone: the cap defines a safe upper limit, while longer opening hours make that limit socially and operationally sustainable. Without extended hours, the cap would generate persistent congestion at peak times; without the cap, longer hours alone would not prevent unsafe crowding.

In the medium term, behavioural nudges and non-monetary incentives (Policy 3) should be introduced once students have adapted to the new operating system. Nudges are most effective when clear capacity constraints and extended hours already exist, as they then redirect demand toward underused time slots rather than just shifting congestion across peaks. Implementing nudges earlier would risk limited effectiveness and message fatigue, while implementing them later allows empirical occupancy data to guide targeted and adaptive communication.

Finally, priority and support windows for under-represented groups (Policy 4) should be phased in after the general access system has stabilised. Introducing these windows too early could create confusion or perceptions of unfairness before students understand the broader capacity logic. Once Policies 1–3 have reduced overall congestion and smoothed demand, priority windows can effectively improve inclusion without increasing crowding or generating pushback. In this sequence, each policy offsets the main negative feedback loops of the previous ones, resulting in a coherent, realistic, and equity-consistent implementation strategy aligned with both the optimisation results and the institutional context of a university gym.

Conclusion

This project developed an operational optimization model to determine how the EPFL gym can maximise fair and comfortable access within its space, equipment, and budget constraints. Using an egalitarian–prioritarian framework, we jointly optimized concurrent users N, equipment units n, and opening hours H_{oper}, yielding the robust configuration $(58, 58, 16)$ and an implied maximum safe instantaneous occupancy of approximately 123 students. Operating above this threshold would sharply worsen waiting times, crowding, and equipment overuse. The solution also reduces annual maintenance costs by roughly 60%, demonstrating that improving equity and comfort is compatible with cost control.

The four recommended policies translate the optimization results into practice while reflecting the trade-offs revealed in the model. A hard occupancy cap protects comfort and safety but must be paired with extended hours and, a bit later on, behavioral nudges to avoid excessive rejection and maintain equitable access. Nudges improve temporal distribution but require careful calibration to avoid creating new mini-peaks. Priority windows support under-represented groups but must remain non-exclusive to preserve inclusiveness and avoid perceptions of preferential treatment. These interactions illustrate the core tension embedded in our framework: protecting fairness and comfort for vulnerable groups while still serving as many students as possible under fixed spatial and financial constraints.

Several modeling assumptions also entail trade-offs. Uniform equipment utilization simplifies maintenance modeling but ignores heterogeneity in machine wear. Treating N as a distribution scaled to a single mean captures peak risk but not temporal dynamics in arrivals. Access equality is evaluated through parity-based hinge losses, which capture under-representation but do not model behavioral responses of specific groups. Finally, excluding pricing mechanisms aligns with the egalitarian framework but removes potentially effective levers that a utilitarian perspective might consider acceptable. Future improvements could address these limitations. Collecting real-time utilization and waiting-time data would allow more accurate modeling of congestion and wear. Incorporating hourly arrival processes or agent-based simulations would provide finer-grained predictions of peak behavior and nudge effectiveness. Studying heterogeneous user preferences could refine the equity component, while scenario analysis of alternative equipment mixes or spatial layouts would connect operational optimization to long-term planning. Such extensions would support even more precise and evidence-based management of the gym while remaining aligned with EPFL's goals of fairness, comfort, and sustainability.

Appendix A – Maintenance Burden: Extended Derivations and Justifications

A.1 Overutilization Knee (Derivation)

To estimate $U^* = \tau$, recall that utilization rate is assumed to be uniformly distributed among the different types of equipment. We adopt an operational service standard of $W^\star = 8$ minutes as the maximum acceptable average wait (based on survey responses in Dataset 2). Let $W(U)$ denote the calibrated wait–utilization map. We define the utilization knee as

$$\tau \equiv W^{-1}(W^\star) \in (0,1),$$

so that the system is deemed *overutilized* precisely when

$$U > \tau \iff W(U) > W^\star.$$

This choice is conservative relative to common practice (which typically uses a higher knee), ensuring that any instance exceeding the 8-minute standard is classified as overutilization. This yields $\tau \approx 0.6$

A.2 Parameter Estimation Procedure

The annual maintenance cost M decomposes as $M = B + R$ with $B = 0.05V$ (baseline) and $R = M - B$ (over-knee utilization). For $H^{'} = H^{op}_{tot}$ observed hours, we denote as $\widehat{C}(U, H^{'})$ as the cumulative maintenance over a horizon H'

$$\widehat{C}(U, H^{'}) = \sum_{t=1}^{H} [\lambda U_t + \theta (U_t - \tau)_+^2] = \lambda S_1 + \theta S_2,$$

where $S_1 = \sum U_t$, $S_2 = \sum (U_t - \tau)_+^2$. Moment-matching using Dataset 3 and the costs given in the Dataset description (adjusted - i.e., divided by 48 [6] - to match the weekly data) yields

$$\lambda = \frac{B}{S_1}, \qquad \theta = \begin{cases} \frac{R}{S_2}, & S_2 > 0, \\ 0, & S_2 = 0. \end{cases}$$

Substituting $V = \frac{7{,}520 \times 57}{48}$ CHF, $M = \frac{45{,}000}{48}$ CHF gives $\lambda = 6.42,\ \theta = 219.72$.

A.3 Empirical Fits and Consistency Checks

Empirically, we can see that the scatter (W_t, U_t) is well approximated by a quadratic which basically overlaps with the hyperbolic fit (see Fig. 1). Thus, we fit

$$\boxed{U(W) \;=\; a_2 W^2 + a_1 W + a_0}$$

by ordinary least squares:

$$(a_2, a_1, a_0) \;=\; \arg\min_{a_2, a_1, a_0} \sum_{t=1}^{H} \left(U_t - (a_2 W_t^2 + a_1 W_t + a_0)\right)^2.$$

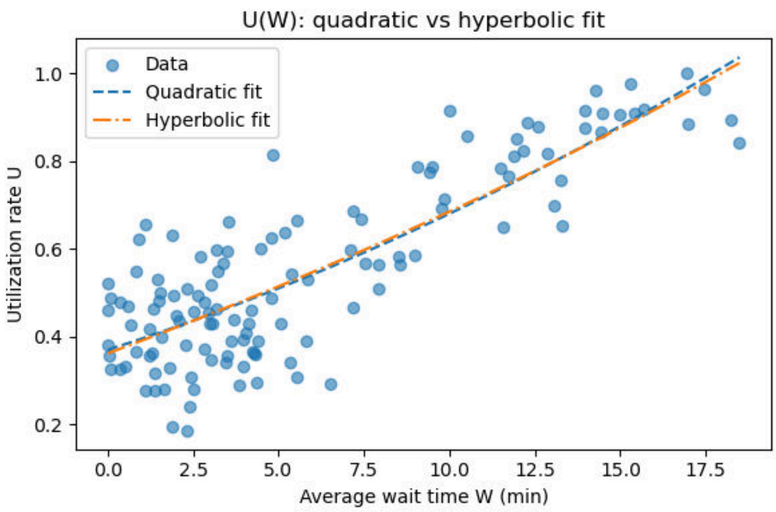

FIGURE 1
Empirical scatter and quadratic fit $U(W)$ used for calibration.

[6] Opening weeks per year [15]

We obtain

$$\boxed{\widehat{U}(W) \;\approx\; (5.913\times10^{-4})\,W^2 \;+\; (2.511\times10^{-2})\,W \;+\; 0.370}$$

with W in minutes and $\widehat{U}\in[0,1]$.

Appendix B - Waiting Time Formulation

Let $W(N,n)$ denote average wait given N students and n total units. We model it as the product of (i) an empirical crowding curve that depends only on the number of students present N and (ii) a *dimensionless* capacity factor that depends only on the total number of equipment units n.

We can first find the empirical relation between the number of users and the waiting time through Dataset 3. We chose a quadratic specification because the data show a smooth, convex rise in waits as crowding increases, without evidence of a near-capacity "blow-up" (see Fig. 2).

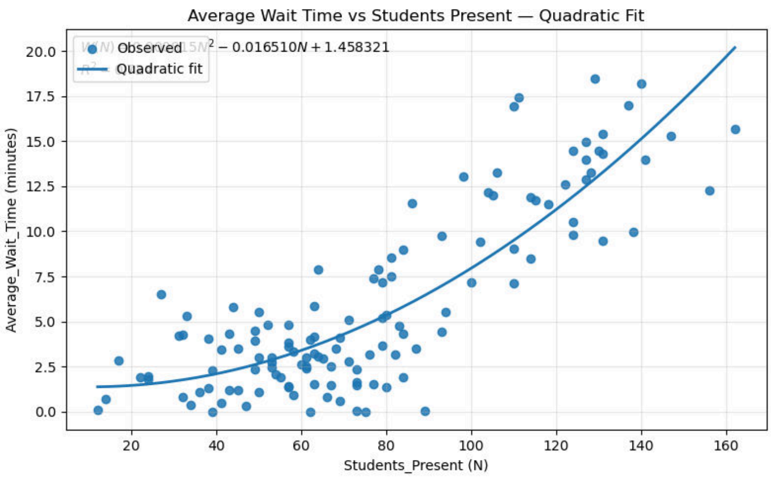

FIGURE 2
Empirical scatter for $W(N)$ calibration.

Thus we fit:

$$\boxed{W_{\text{quad}}(N) = b_0 + b_1 N + b_2 N^2}$$

and, by OLS on Dataset 3, obtain

$$\boxed{W_{\text{quad}}(N) = 1.458321 - 0.016510\,N + 0.000815465\,N^2}$$

Incorporating equipment via an average-capacity approximation. We can now consider the contribution of the number of equipments in the formulation.

From the assumptions stated in the explanation of Category D, along with the fact that service capacity scales proportionally with the total unit count n, we can consider that equipments effects can be collapsed into a single *average per-unit capacity* computed at baseline; thereafter, only the total count n matters.

Capacity scaling and unit consistency. Let q_i be the baseline quantity of type i and

$$\mu_i \;=\; \frac{\text{MaxUsers}_i}{\text{SessionMin}_i} \qquad \text{[users/min per unit]}$$

its per–unit service rate. Baseline capacity and count are

$$C_0 \;=\; \sum_i q_i\,\mu_i, \qquad n_0 \;=\; \sum_i q_i, \qquad \bar{\mu}_0 \;=\; \frac{C_0}{n_0} \quad \text{[users/min per unit]}.$$

Under interchangeability and uniform utilization, capacity for any total count n is

$$C(n) \;\approx\; n\,\bar{\mu}_0.$$

Since waits fall as total capacity rises, a natural, unit-consistent correction is to scale the crowding curve by the *inverse capacity ratio*. Introducing an elasticity parameter α (baseline $\alpha = 1$) yields

$$W(N,n) \;=\; \left[W_{\text{quad}}(N)\,\left(\tfrac{C_0}{C(n)}\right)^{\alpha} \right]_+ \;=\; \left[W_{\text{quad}}(N)\,\left(\tfrac{n_0}{n}\right)^{\alpha} \right]_+ .$$

This specification is rigorous under the assumptions above: the factor $(n_0/n)^\alpha$ is dimensionless, has the correct monotonicity in n, and preserves nonnegativity via $[\cdot]_+$.

Final formulation (baseline choice). We adopt $\alpha = 1$ as the baseline (first-order inverse-capacity scaling):

$$\boxed{W(N, n) \;=\; \left[W_{\text{quad}}(N)\,\frac{n_0}{n} \right]_+}.$$

This choice is (i) simple and interpretable, (ii) consistent with queueing intuition that aggregate service capacity is proportional to the number of parallel servers, and (iii) robust to moderate deviations in n from the baseline n_0.

Appendix C - Optimization Formulation

C.1 Empirical Distribution of Students

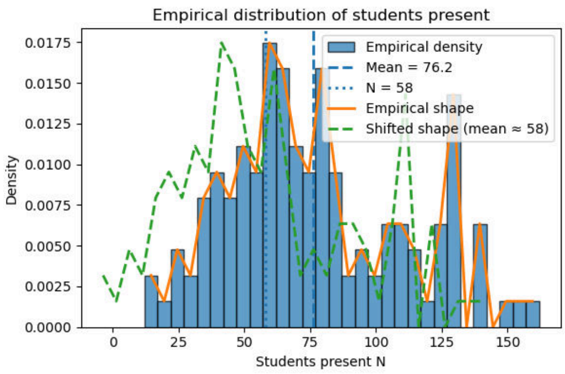

FIGURE 3
Empirical distribution of students present (blue bars, orange line) and the rescaled distribution whose mean matches the optimal average occupancy $N^* = 58$ (green dashed line).

C.2 Histogram of the objective landscape

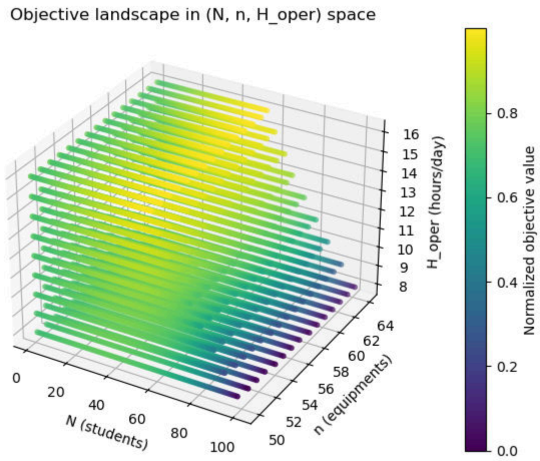

FIGURE 4
Normalized objective function over the feasible region under baseline parameters.

Appendix D - Policy recommendations

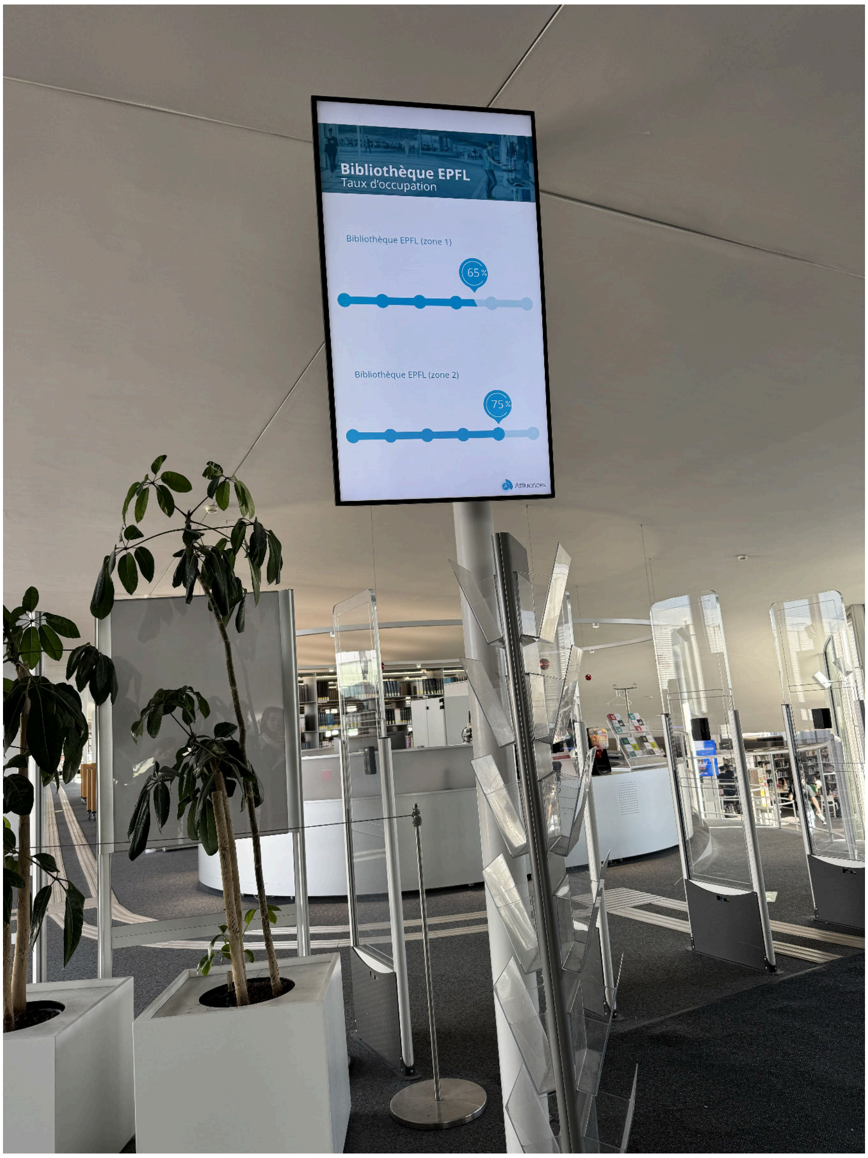

FIGURE 5
Picture of the occupancy dashboard at the entrance of the EPFL library

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