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## Quantifying the causal effects of hybrid work on employee well-being, productivity dynamics, and organizational performance using hr analytics

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### Abstract

Hybrid work restructures where, when, and how employees contribute, making its organizational effects difficult to isolate from differences in job design, managerial practices, workforce composition, and employee preferences. Simple comparisons of remote and office-based employees can therefore mistake selection effects for genuine consequences of hybrid arrangements. This study develops a causal human resource analytics framework for quantifying how changes in work-location intensity influence workforce well-being, productivity dynamics, and organizational performance. Longitudinal employee-level data integrate office attendance, remote-work frequency, workload, collaboration patterns, absenteeism, engagement, managerial characteristics, performance indicators, turnover, and business-unit outcomes. Propensity-score methods, difference-in-differences estimation, fixed-effects models, and heterogeneous treatment-effect analysis are applied to construct credible counterfactual comparisons and estimate changes attributable to hybrid-work exposure. The framework evaluates nonlinear effects of office-remote balance and investigates whether autonomy, commuting burden, managerial support, collaboration intensity, and role characteristics mediate or moderate observed outcomes. Temporal analysis distinguishes short-term productivity adjustments from persistent changes in well-being and performance. By separating correlation from plausible causal effects, the framework supports evidence-based hybrid-work policies tailored to workforce segments, job requirements, and organizational performance objectives.

**Keywords:** Causal HR analytics; hybrid work; workforce well-being; productivity dynamics; treatment effects; organizational performance

### Introduction

#### 1.1 Hybrid work as an organizational and workforce transformation

Hybrid work represents a structural transformation in how organizations distribute labour between physical workplaces and digitally mediated environments <sup>[4]</sup>. Arrangements range from predominantly remote or office-based work to schedules combining both locations, with attendance determined either by employee choice or organizational requirements <sup>[1]</sup>. These arrangements also incorporate synchronous and asynchronous collaboration, flexible working hours, distributed teams, digital communication, workplace autonomy, and changing supervisory relationships <sup>[7]</sup>. Potential benefits include reduced commuting burdens, greater scheduling autonomy, improved work-life integration, access to geographically dispersed talent, protected concentration time, and reduced physical-workplace requirements <sup>[3]</sup>. However, geographically dispersed work may also increase social isolation, digital overload, communication fragmentation, coordination costs, unequal organizational visibility, and difficulties maintaining boundaries between occupational and non-work domains <sup>[8]</sup>. Managerial practices and team interdependence can further shape these experiences <sup>[5]</sup>. Consequently, hybrid work should not be treated as a uniform exposure. Identical arrangements may produce substantially different outcomes across employees, occupations, managers, teams, and organizations because work requirements, preferences, resources, and social contexts differ <sup>[2]</sup>.

#### 1.2 Limitations of conventional HR analytics

Conventional descriptive and predictive HR analytics can identify associations between work arrangements and employee outcomes but cannot independently establish whether those

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arrangements generated the observed differences [6]. An empirical relationship such as *Hybrid Work → Higher Productivity* may reflect selection processes rather than a treatment effect. Employees choosing hybrid schedules may differ systematically in preferences, commuting distance, seniority, baseline performance, job autonomy, or occupational characteristics [9]. Employer assignment can similarly depend on managerial judgments, organizational culture, team composition, and operational requirements [3]. Seasonality and macroeconomic conditions may further influence exposure and outcomes simultaneously. Prediction therefore addresses quantities such as  $P(Y|X)$ , representing an outcome distribution conditional on observed predictors [7]. Causal analysis instead evaluates counterfactual contrasts, commonly represented as  $E[Y(1) - Y(0)]$ , where  $Y(1)$  and  $Y(0)$  denote potential outcomes under treated and comparison conditions [1]. Distinguishing these estimands is essential because strong predictive association does not demonstrate that changing hybrid-work exposure would change the outcome.

1.3 Research aim, objectives and contributions

This study develops and evaluates an explainable longitudinal causal HR analytics framework for quantifying the effects of hybrid-work arrangements on employee well-being, productivity dynamics, and organizational performance [5]. The framework first integrates HRIS, work-arrangement, attendance, productivity, collaboration, well-being, organizational data,

being, and organizational records into a temporally ordered employee-time dataset. Hybrid-work exposure is operationalized as a treatment whose timing, intensity, frequency, and duration can vary across employees and observation periods [2]. Employee, job, managerial, team, and organizational covariates are subsequently constructed to support explicit causal identification and confounding control [8]. The analysis estimates average treatment effects while examining heterogeneous effects across workforce characteristics and organizational contexts [4]. Conventional observational models are benchmarked against causal estimators to determine whether predictive associations differ materially from estimated treatment effects. Employee-specific productivity and well-being baselines are additionally used to quantify temporal deviations associated with changing work arrangements [6]. Robustness analyses evaluate alternative treatment definitions, observation windows, confounder specifications, and modelling assumptions [9]. Competing causal frameworks are benchmarked using balance, overlap, estimation stability, and out-of-sample criteria where applicable. Explainability and heterogeneity analyses identify workforce conditions under which estimated effects differ [3]. Finally, analytical outputs are compared with relevant workforce, occupational-health, and organizational-management principles, connecting causal evidence to responsible HR decision support rather than relying solely on predictive correlations [7].

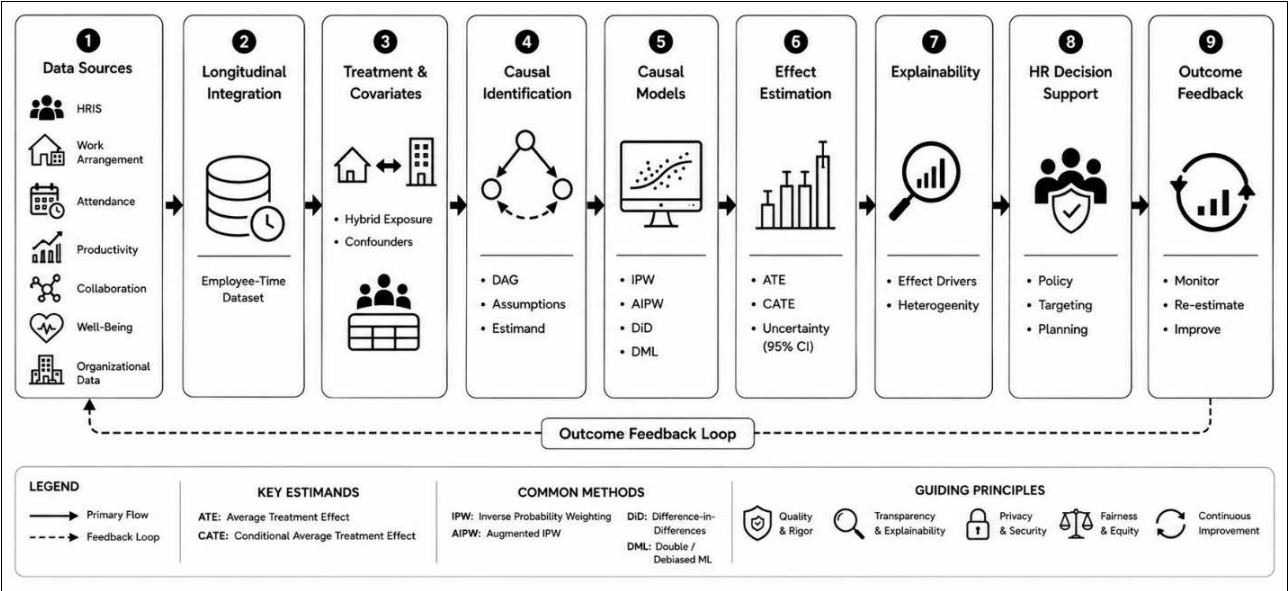


Fig 1: Integrated Causal Hybrid-Work Analytics Ecosystem

2. Conceptual and causal framework

2.1 Hybrid work, well-being and productivity mechanisms

Hybrid work can influence employee and organizational outcomes through competing changes in work conditions rather than through physical location alone [11]. Positive mechanisms include increased autonomy, concentration opportunities, reduced commuting time, schedule control, job satisfaction, and perceived flexibility [8]. These benefits may improve employees' capacity to allocate attention and reconcile occupational and non-work demands. Conversely,

digitally mediated work can increase meeting overload, digital fatigue, social isolation, work-family interference, coordination friction, and communication delays [14]. The theoretical pathway can therefore be represented as *Hybrid Work → Work Conditions → Employee Well"- " Being → Productivity → Organizational Performance*. Well-being may operate as an intermediate mechanism through which changes in autonomy, workload, or social connection subsequently influence productivity [10]. However, these relationships are unlikely to be homogeneous. Job type determines location dependence, while managerial support

can influence communication quality and resource access [13]. Collaboration intensity may increase coordination requirements, whereas greater work-location autonomy can strengthen perceived control [7]. Hybrid-work effects should therefore be interpreted as context-dependent responses emerging from interactions among work arrangements, employee experiences, job characteristics, and organizational conditions [15].

## 2.2 Causal Identification and Potential Outcomes

Causal identification requires hybrid work to be defined as an explicit treatment rather than simply another predictive feature [12]. For employee  $i$  at time  $t$ , treatment status is defined as:

$$T_{it} = \begin{cases} 1, & \text{if employee } i \text{ receives the defined hybrid-work exposure at time } t, \\ 0, & \text{otherwise.} \end{cases}$$

The corresponding potential outcomes are  $Y_{it}(1)$  under hybrid-work exposure and  $Y_{it}(0)$  under the specified comparator arrangement [9].

### Equation 1 - Individual treatment effect

$$\tau_{it} = Y_{it}(1) - Y_{it}(0)$$

Here,  $\tau_{it}$  denotes the individual treatment effect. Because  $Y_{it}(1)$  and  $Y_{it}(0)$  cannot both be observed for the same employee at the same time, the individual counterfactual remains unobservable [14]. Population-level effects are therefore estimated.

### Equation 2 - Average treatment effect

$$ATE = E[Y(1) - Y(0)]$$

Here,  $ATE$  is the average treatment effect,  $Y(1)$  is the

potential outcome under hybrid treatment,  $Y(0)$  represents the potential outcome under the comparator, and  $E[\cdot]$  denotes expectation across the target population [11]. Identification requires consistency, positivity, conditional exchangeability, appropriate control of confounding, and correct temporal ordering [8]. Where conditional exchangeability cannot be justified, causal estimates require cautious interpretation.

## 2.3 Confounding, Mediation and Heterogeneous Effects

A causal directed acyclic graph was specified before estimation to distinguish confounders from mediators and moderators [13]. The principal pathway was *Hybrid Work* → *Well"- Being* → *Productivity* → *Organizational Performance*, while autonomy, collaboration conditions, and digital load represented additional intermediate mechanisms. Pre-treatment age, tenure, occupational group, job grade, department, prior productivity, baseline well-being, manager characteristics, team composition, commuting burden, digital intensity, and existing work autonomy were considered potential common causes of treatment assignment and subsequent outcomes [10]. Adjustment decisions therefore followed the assumed causal structure rather than indiscriminately including every available variable [15]. Variables arising after hybrid-work exposure were not mechanically controlled because DOIng so could block mediated effects or introduce post-treatment bias [9]. Heterogeneous treatment effects were additionally examined across occupational categories, managerial support, team size, digital collaboration intensity, and legally appropriate employee characteristics [12]. Gender or caregiving context was considered only where legitimate collection and analysis permitted. This architecture distinguishes confounding adjustment from mediation analysis and effect modification while preserving temporal ordering [7]. with confounding pathways and moderation relationships represented separately.

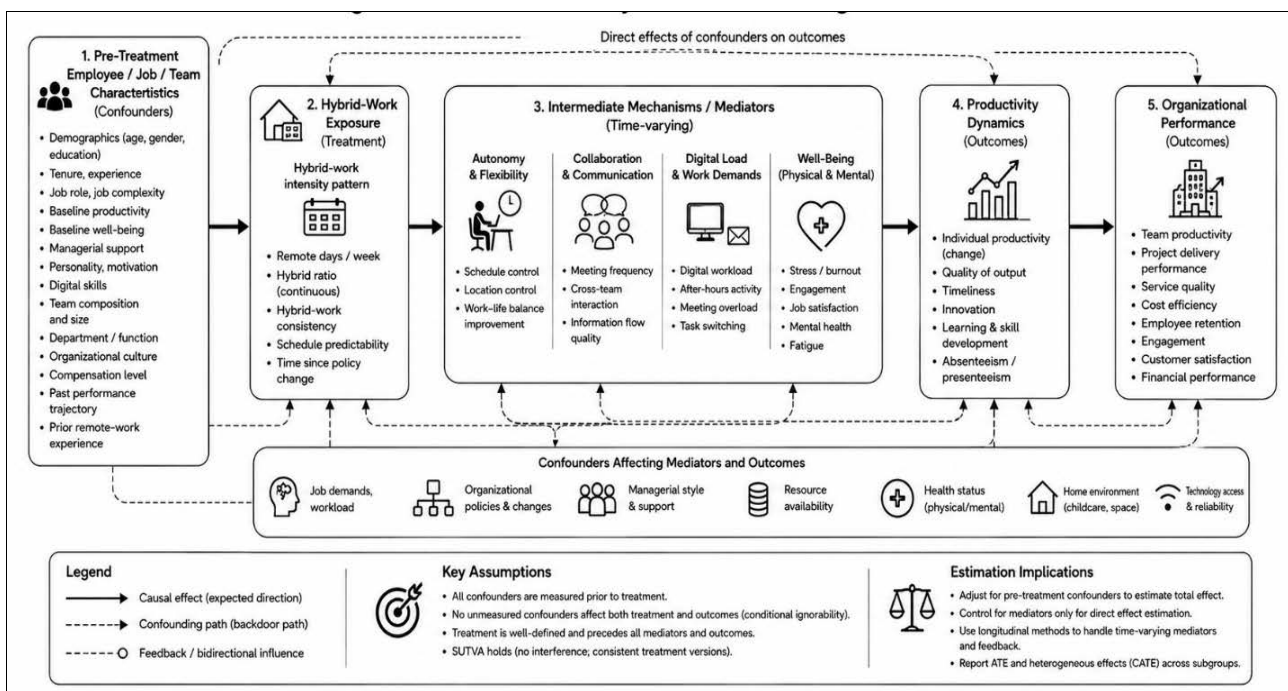


Fig 2: Causal Pathway and Confounding Architecture

### 3. Data acquisition, integration and causal feature engineering

#### 3.1 Multi-source longitudinal data acquisition

A multi-source longitudinal dataset was constructed to capture hybrid-work exposure and subsequent employee, team, and organizational outcomes across repeated observation periods [16]. HRIS records supplied anonymized employee identifiers, job family, grade, tenure, department, employment status, manager, team, and contract type. Hybrid-work and attendance systems provided scheduled and observed office days, remote days, work location, attendance, hybrid-work ratio, schedule consistency, and policy eligibility [13]. Productivity systems contributed completed tasks, output volume, target attainment, cycle time, quality scores, errors or rework, and performance ratings. Collaboration measures were restricted to privacy-

preserving metadata, including meeting frequency, meeting duration, collaboration intensity, cross-team interactions, and communication-response patterns, rather than message content [19]. Well-being information incorporated engagement surveys, work-life balance, job satisfaction, appropriately collected stress or burnout measures, absence, and voluntary turnover [15]. Organizational records captured revenue or output per employee, team performance, customer-service indicators, project completion, and operating costs. Repeated measurements from these domains allowed work arrangements and outcomes to be aligned temporally rather than treated as static employee attributes [18]. Data availability, measurement frequency, and observation windows were documented for each source because differences in temporal granularity could otherwise distort exposure-outcome relationships [14].

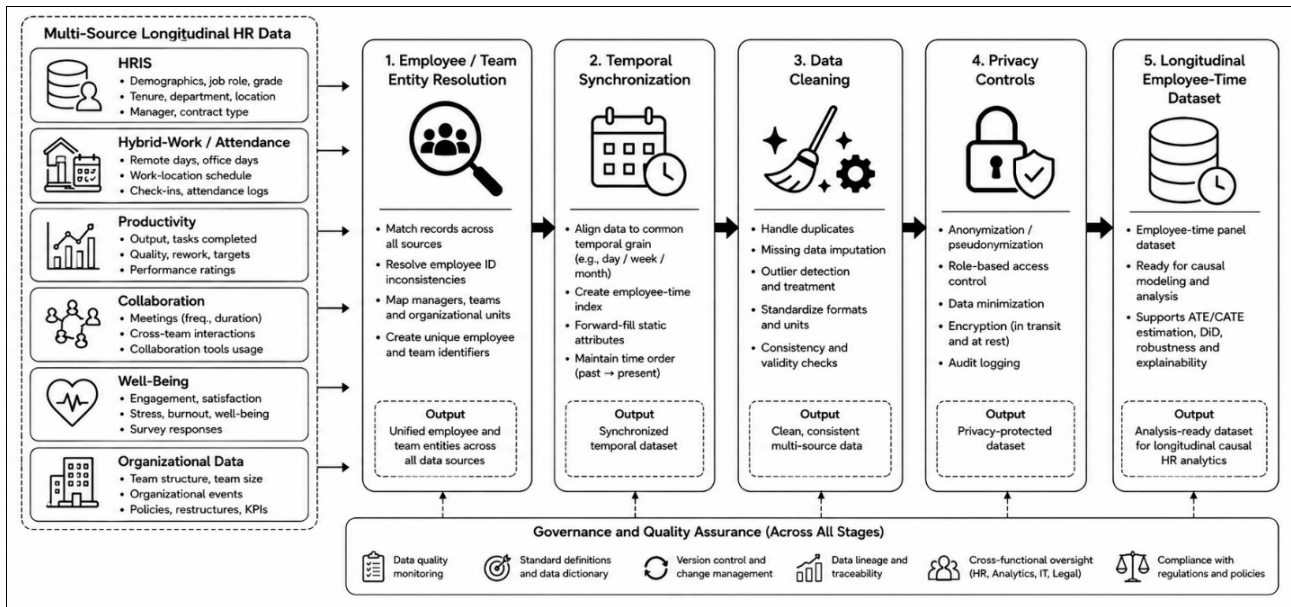


Fig 3: Multi-Source Longitudinal HR Data Acquisition and Integration Pipeline

#### 3.2 Data integration, cleaning and temporal alignment

Source records were integrated through anonymized employee identifiers, with direct personal identifiers excluded from the analytical dataset [17]. Duplicate records were removed, missing values assessed, timestamps standardized, employee entities matched, and historical manager-team relationships reconstructed before temporal aggregation. Categorical predictors were consistently encoded, continuous variables scaled where required, implausible outliers examined, and survey scores harmonized across measurement instruments [20]. Records were subsequently aggregated into employee-week or employee-month panels represented as  $(i, t) = (\text{Employee}_i, \text{Time}_t)$ , where  $i$  identifies the employee and  $t$  denotes the observation period. The resulting feature vector  $\mathbf{X}_{i,t}$  contained information available at or before the relevant treatment-assignment point [14]. For causal adjustment, covariates intended as pre-treatment confounders satisfied  $t_x < t_T$ , whereas outcomes satisfied  $t_y > t_T$ . This temporal ordering prevented target leakage and future-information leakage [18]. Variables caused by treatment were not automatically entered into adjustment sets, thereby reducing post-treatment adjustment

bias and preserving mediated pathways requiring separate analysis [13].

#### 3.3 Treatment, outcome and covariate construction

Hybrid-work exposure was operationalized from observed remote and office attendance rather than relying exclusively on nominal policy status [16]. Continuous treatment intensity for employee  $i$  during period  $t$  was defined as

$$\text{HybridRatio}_{it} = \frac{\text{RemoteDays}_{it}}{\text{RemoteDays}_{it} + \text{OfficeDays}_{it}}, \text{ where}$$

values approaching 0 indicate predominantly office-based work and values approaching 1 indicate predominantly remote work. Alternative categorical exposure definitions represented  $T = 0$  as predominantly office-based,  $T = 1$  as low-intensity hybrid,  $T = 2$  as balanced hybrid, and  $T = 3$  as predominantly remote arrangements [19]. Treatment definitions were fixed before outcome modelling to limit specification-driven conclusions.

Outcome construction reflected three analytical levels. Well-being outcomes included engagement, satisfaction, absence, and appropriately measured burnout-related indicators [15]. Productivity outcomes incorporated task

completion, output quality, cycle time, and performance attainment, whereas organizational outcomes included team output, service quality, project delivery, and productivity per labour hour <sup>[20]</sup>. Pre-treatment covariates  $X_{it}$  incorporated historical outcomes, tenure, role, grade, department, team, manager, workload, seasonality, prior collaboration intensity, and organizational events <sup>[17]</sup>. Their causal roles were specified before estimation to distinguish confounders from mediators and treatment consequences.

### 3.4 Mean deviation and dynamic feature engineering

Dynamic feature engineering measured changing employee behaviour relative to historical baselines, thereby reducing reliance on cross-sectional comparisons between inherently different employees <sup>[18]</sup>. Employee-specific standardized deviation was defined as:

#### Equation 3 - Employee-specific standardized deviation

$$z_{it} = \frac{x_{it} - \mu_i}{\sigma_i}$$

where  $x_{it}$  is the observed value for employee  $i$  at time  $t$ ,  $\mu_i$  is the employee-specific historical mean,  $\sigma_i$  is the

corresponding historical standard deviation, and  $z_{it}$  represents standardized deviation from that baseline <sup>[14]</sup>. Positive or negative values therefore indicate the direction of departure, while magnitude reflects its relative size. Absolute within-employee variability was summarized as:

#### Equation 4 - Mean absolute deviation

$$MAD_i = \frac{1}{n_i} \sum_{t=1}^{n_i} |x_{it} - \bar{x}_i|$$

Here,  $MAD_i$  denotes employee  $i$ 's mean absolute deviation,  $n_i$  is the number of historical observations,  $x_{it}$  is the observed value, and  $\bar{x}_i$  represents the historical employee-specific mean <sup>[20]</sup>. Larger  $MAD_i$  indicates greater temporal variability. Additional engineered features included productivity change, well-being trajectory, hybrid-work consistency, meeting-load deviation, absence-frequency deviation, collaboration-network change, workload trend, and manager-change indicators <sup>[16]</sup>. All baseline statistics were calculated using historically available observations only, preventing future information from influencing contemporaneous feature construction <sup>[19]</sup>.

**Table 1:** Data Sources, Raw Variables, Causal Roles and Engineered Parameters

| Domain                   | Raw Variable                                                      | Temporal Unit          | Causal Role                          | Engineered Feature                     | Parameter Derivation                                                                 | Expected Relevance                                                 |
|--------------------------|-------------------------------------------------------------------|------------------------|--------------------------------------|----------------------------------------|--------------------------------------------------------------------------------------|--------------------------------------------------------------------|
| HRIS                     | Employee ID, job family, grade, tenure, department, contract type | Employee-month         | Identifier / pre-treatment covariate | Tenure, role stability, grade position | $Tenure_{it} = t - DateHire_i$                                                       | Controls workforce heterogeneity and employment history            |
| Hybrid Work / Attendance | Remote days, office days, scheduled and actual location           | Employee-week          | Treatment / exposure                 | Hybrid-work intensity                  | $HybridRatio_{it} = \frac{RemoteDays_{it}}{RemoteDays_{it} + OfficeDays_{it}}$       | Primary treatment representing work-location exposure              |
| Hybrid Work / Attendance | Weekly remote/office attendance pattern                           | Employee-week          | Treatment characteristic             | Hybrid-work consistency                | $HWC_i = 1 - SD(HybridRatio_{it})$                                                   | Captures stability of hybrid-work exposure over time               |
| Productivity             | Tasks completed, output volume, targets achieved                  | Employee-week/month    | Outcome / baseline covariate         | Productivity change                    | $\Delta Prod_{it} = Prod_{it} - Prod_{i,t-1}$                                        | Measures short-term productivity dynamics                          |
| Productivity             | Historical employee productivity                                  | Employee-week/month    | Pre-treatment covariate              | Standardized productivity deviation    | $z_{it} = \frac{x_{it} - \mu_i}{\sigma_i}$                                           | Identifies departures from employee-specific productivity baseline |
| Productivity             | Repeated productivity measurements                                | Historical window      | Pre-treatment variability            | Mean absolute deviation                | $MAD_i = \frac{1}{n_i} \sum_{t=1}^{n_i}  x_{it} - \bar{x}_i $                        | $ x_{it} - \bar{x}_i $                                             |
| Performance              | Quality score, errors, rework, performance rating                 | Employee-month/quarter | Outcome / pre-treatment covariate    | Performance trajectory                 | $Trend_i = \frac{\sum_t (t - \bar{t}) (P_{it} - \bar{P}_i)}{\sum_t (t - \bar{t})^2}$ | Distinguishes improving, stable, and declining performance         |
| Collaboration            | Meeting frequency and duration                                    | Employee-week          | Confounder / mediator*               | Meeting-load deviation                 | $MLD_{it} = MeetingLoad_{it} - \overline{MeetingLoad}_i$                             | Captures changes in digital coordination burden                    |
| Collaboration            | Cross-team interactions, collaboration intensity                  | Employee-week/month    | Confounder / mediator*               | Collaboration change                   | $\Delta Collab_{it} = Collab_{it} - Collab_{i,t-1}$                                  | Measures changing interaction and coordination patterns            |

|                            |                                                    |                     |                                      |                             |                                                                                              |                                                                              |
|----------------------------|----------------------------------------------------|---------------------|--------------------------------------|-----------------------------|----------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Well-Being                 | Engagement and job-satisfaction scores             | Survey wave/month   | Outcome / baseline confounder        | Well-being deviation        | $WBDev_{it} = WB_{it} - \overline{WB}_i$                                                     | Measures improvement or deterioration relative to personal baseline          |
| Well-Being                 | Repeated stress/burnout indicators                 | Survey wave         | Outcome / mediator*                  | Well-being trajectory       | $WBTrend_i = \frac{\sum_t (t - \bar{t})(WB_{it} - \overline{WB}_i)}{\sum_t (t - \bar{t})^2}$ | Captures longitudinal direction of employee well-being                       |
| Absence                    | Absence days and episodes                          | Employee-month      | Outcome / pre-treatment covariate    | Absence-frequency deviation | $AFD_{it} = Absence_{it} - \overline{Absence}_i$                                             | Indicates changes potentially associated with well-being and work conditions |
| Manager / Team             | Manager ID, manager change, team membership        | Employee-month      | Pre-treatment confounder / moderator | Manager-change indicator    | $MC_{it} = 1(Manager_{it} \neq Manager_{i,t-1})$                                             | Controls managerial transitions and potential support changes                |
| Team Structure             | Team size, composition, collaboration requirements | Team-month          | Confounder / moderator               | Team-size change            | $\Delta TS_{it} = TS_{it} - TS_{i,t-1}$                                                      | Captures changing coordination requirements                                  |
| Workload                   | Tasks assigned, working hours, project load        | Employee-week/month | Confounder / mediator*               | Workload deviation          | $WLD_{it} = \frac{Workload_{it} - \mu_{wi}}{\sigma_{wi}}$                                    | Identifies unusually high or low workload relative to employee baseline      |
| Organizational Events      | Restructuring, policy change, leadership change    | Event-date/month    | Confounder / contextual exposure     | Event proximity             | $EP_{it} = t - DateEvent$                                                                    | Controls time-varying organizational shocks                                  |
| Organizational Performance | Team output, service quality, project completion   | Team-month          | Outcome                              | Team-performance change     | $\Delta TeamPerf_{jt} = TeamPerf_{jt} - TeamPerf_j$                                          | Measures downstream team-level consequences of hybrid work                   |
| Organizational Performance | Output, labour hours, operating costs              | Unit-month          | Outcome                              | Labour productivity         | $LP_{jt} = \frac{Output_{jt}}{LabourHours_{jt}}$                                             | Quantifies organizational efficiency                                         |
| Treatment Assignment       | Hybrid-work status and pre-treatment covariates    | Employee-time       | Treatment mechanism                  | Propensity score            | $e(X_i) = P(T_i = 1   X_i)$                                                                  | Estimates treatment probability for confounding adjustment                   |
| Causal Estimation          | Observed outcomes, treatment and covariates        | Employee-time       | Causal estimand                      | ATE / CATE                  | $ATE = E[Y(1) - Y(0)];$<br>$CATE(x) = E[Y(1) - Y(0)   X = x]$                                | Quantifies average and heterogeneous hybrid-work effects                     |

#### 4. Causal model development, training and hyperparameter optimization

##### 4.1 Candidate analytical models

Six analytical configurations were benchmarked to determine how progressively stronger confounding adjustment altered estimated hybrid-work effects [24]. M0 represented a naïve observational model comparing mean outcomes between treatment groups without covariate adjustment. Its purpose was primarily diagnostic, providing a reference against which the magnitude of potential selection-related differences could be evaluated. M1 used multivariable outcome regression incorporating observed pre-treatment employee, job, team, and organizational confounders [21]. M2 implemented propensity-score adjustment and inverse probability weighting to construct a weighted pseudo-population with improved comparability between exposure groups [27]. The propensity score was defined as:

**Equation 5 - Propensity score**  

$$e(X_i) = P(T_i = 1 | X_i)$$

where  $e(X_i)$  is the probability of treatment conditional on pre-treatment covariates  $X_i$ , and  $T_i \in 0,1$  denotes treatment status. Corresponding inverse probability weights were  $w_i = 1/e(X_i)$  for  $T_i = 1$  and  $w_i = 1/[1 - e(X_i)]$  for  $T_i = 0$  [23]. M3 employed doubly robust estimation by combining propensity and outcome models. M4 used difference-in-differences with fixed effects where hybrid-work arrangements changed longitudinally across organizational units [29]. M5 incorporated causal forests or double machine learning to capture nonlinear confounding structures and heterogeneous treatment effects across high-dimensional workforce characteristics [25]. Comparison across **M0 – M5** therefore examined both effect magnitude and sensitivity to alternative identification strategies [30].

##### 4.2 Chronological data splitting and leakage prevention

Model development preserved temporal ordering so that future workforce information could not influence historical treatment or outcome estimation [26]. The earliest approximately 60% of employee-time observations

constituted training data, the subsequent 20% formed validation data, and the latest 20% remained a locked test set. Random employee-time splitting was avoided when observations from later periods could reveal an employee's subsequent treatment, outcome, or organizational history [22]. All preprocessing quantities were estimated exclusively within the training period, including means, standard deviations, missing-value imputation parameters, categorical encoders, feature-selection thresholds, and propensity-model parameters. These learned transformations

were subsequently applied unchanged to validation and test observations [28]. Temporal cross-validation further maintained  $t_{\text{train}} < t_{\text{validation}}$  within each fold. Where the objective included generalization to previously unseen employees, an additional employee-grouped evaluation ensured that observations from the same employee did not span training and testing partitions [24]. This architecture separated temporal generalization from employee-level generalization while reducing target leakage and optimistic causal-model evaluation.

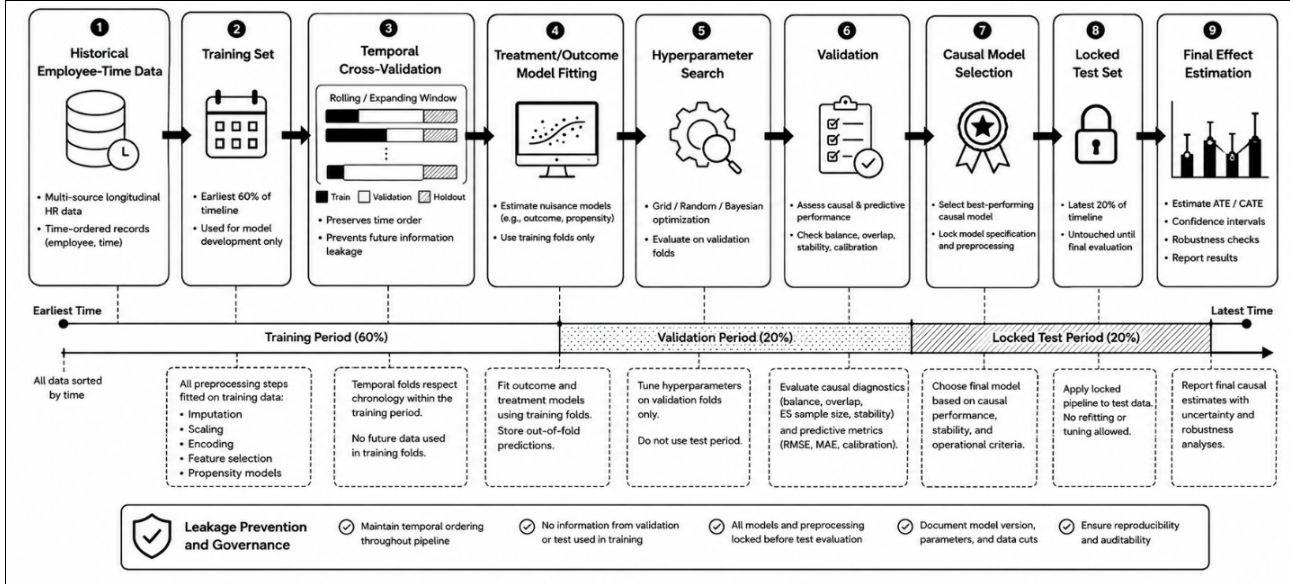


Fig 4: Chronological Causal Model Training, Validation and Final Testing Architecture

### 4.3 Hyperparameter tuning and temporal cross-validation

Hyperparameters were optimized within temporally ordered training and validation windows using grid search, randomized search, or Bayesian optimization where computational complexity justified sequential search [27]. For random forests and causal forests, candidate parameters included the number of trees  $B$ , maximum depth  $d_{\text{max}}$ , minimum leaf size  $n_{\text{min}}$ , feature-subsampling proportion  $m_{\text{try}}$ , and observation-sampling fraction  $s$ . Gradient-boosted nuisance models additionally tuned learning rate  $\eta$ , tree depth, number of estimators  $M$ , subsampling, and regularization parameters [30]. Double machine-learning configurations varied nuisance-learner architecture, cross-fitting folds  $K$ , regularization strength, and learner-specific hyperparameters.

Optimization was not determined exclusively by predictive accuracy because accurate nuisance predictions do not necessarily establish reliable causal identification [23]. Propensity-based configurations were additionally evaluated through standardized covariate balance and overlap of estimated treatment probabilities. Doubly robust and machine-learning estimators were examined for treatment-effect stability across temporal folds, while nuisance models were assessed using appropriate out-of-sample predictive and calibration measures [25]. Hyperparameter configurations producing extreme propensity scores, unstable weights, poor overlap, or highly variable treatment effects were investigated even when their predictive performance appeared favourable [28]. Temporal cross-validation

therefore supported model selection while preserving chronological treatment-outcome relationships.

### 4.4 Causal effect estimation

Doubly robust estimation combined treatment-assignment modelling with conditional outcome regression, thereby incorporating two complementary mechanisms for confounding adjustment [29]. The augmented inverse probability weighted estimator was defined as:

#### Equation 6 - Augmented inverse probability weighted treatment effect

$$\hat{\tau}_{\text{AIPW}} = \frac{1}{N} \sum_{i=1}^N \left[ \hat{\mu}_1(X_i) - \hat{\mu}_0(X_i) + \frac{T_i(Y_i - \hat{\mu}_1(X_i))}{\hat{e}(X_i)} - \frac{(1 - T_i)(Y_i - \hat{\mu}_0(X_i))}{1 - \hat{e}(X_i)} \right]$$

Here,  $N$  denotes the number of observations,  $T_i$  is treatment status, and  $Y_i$  represents the observed employee or organizational outcome. The estimated propensity score  $\hat{e}(X_i)$  approximates  $P(T_i = 1 | X_i)$ , while  $\hat{\mu}_1(X_i)$  and  $\hat{\mu}_0(X_i)$  represent predicted potential outcomes under treatment and comparison conditions, respectively [21]. The first component,  $\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i)$ , estimates the conditional outcome contrast. The remaining weighted residual terms correct discrepancies between observed and model-predicted outcomes [26]. Under positivity, consistency, exchangeability, and appropriate regularity conditions, the estimator has a doubly robust property: consistent effect estimation can be retained when either the propensity model or outcome model is correctly specified,

although not when both are substantially misspecified<sup>[30]</sup>. Confidence intervals accompanied point estimates to represent statistical uncertainty.

#### 4.5 Difference-in-differences and dynamic policy effects

Where teams or organizational units adopted hybrid-work policies at identifiable times, difference-in-differences provided a longitudinal quasi-experimental approach for comparing outcome changes against contemporaneous comparison units<sup>[22]</sup>.

#### Equation 7 - Difference-in-differences

$$Y_{it} = \alpha + \beta(\text{Treated}_i \times \text{Post}_t) + \gamma_i + \lambda_t + \theta'X_{it} + \varepsilon_{it}$$

Here,  $Y_{it}$  denotes the outcome for employee or unit  $i$  at time  $t$ ,  $\alpha$  is the intercept,  $\text{Treated}_i$  identifies the treatment group, and  $\text{Post}_t$  identifies post-adoption observations<sup>[24]</sup>. The coefficient  $\beta$  represents the difference-in-differences treatment effect under the relevant identification assumptions. Employee or unit fixed effects  $\gamma_i$  absorb time-invariant characteristics, while time effects  $\lambda_t$  capture common temporal shocks<sup>[28]</sup>. The vector  $X_{it}$  contains appropriate time-varying controls,  $\theta$  contains their coefficients, and  $\varepsilon_{it}$  represents unexplained variation. Event-study specifications were used to inspect pre-treatment trajectories and dynamic post-adoption effects<sup>[27]</sup>. Particular attention was given to parallel-trends plausibility and treatment-timing heterogeneity before interpreting  $\beta$  causally<sup>[25]</sup>.

### 5. Model evaluation, benchmarking and robustness analysis

#### 5.1 Final test-set evaluation

Final evaluation distinguished predictive nuisance-model performance from the quality of causal estimation because strong prediction alone does not establish unbiased treatment effects<sup>[31]</sup>. Outcome and treatment models were evaluated using  $RMSE$ ,  $MAE$ ,  $R^2$ ,  $ROC - AUC$  for binary targets, and probability calibration where applicable<sup>[27]</sup>. Causal diagnostics separately examined standardized mean differences, propensity-score overlap, effective sample size after weighting, treatment-effect confidence intervals, temporal stability, and subgroup consistency<sup>[34]</sup>. Balance was assessed after adjustment to determine whether

measured pre-treatment characteristics remained systematically different between exposure groups. For continuous nuisance-model outcomes, prediction error was quantified as:

#### Equation 8 - Root mean squared error

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2}$$

where  $Y_i$  denotes the observed outcome,  $\hat{Y}_i$  represents its model prediction, and  $N$  is the number of final test observations<sup>[29]</sup>. Squaring emphasizes larger prediction errors before averaging, while the square root restores the original outcome scale.  $RMSE$  therefore evaluates nuisance-model accuracy but does not constitute evidence of causal validity<sup>[35]</sup>.

#### 5.2 Comparative benchmarking of M0–M5

Models  $M0 - M5$  were compared within a common evaluation architecture to determine how alternative adjustment strategies affected causal, predictive, and operational performance<sup>[30]</sup>. Benchmarking considered the estimated  $ATE$ , 95% confidence-interval width, post-adjustment covariate balance, effective sample size, propensity-score overlap violations, nuisance-model  $RMSE$  and  $MAE$ , treatment-effect stability, computational runtime, interpretability, and scalability<sup>[33]</sup>. Particular attention was given to whether estimates changed substantially between the naïve  $M0$  comparison, adjusted regression, propensity weighting, doubly robust estimation, longitudinal fixed-effects approaches, and machine-learning-based causal models<sup>[28]</sup>.

Covariate balance and overlap provided diagnostics of treatment-group comparability, whereas confidence intervals represented statistical uncertainty surrounding estimated effects<sup>[32]</sup>. Effective sample size identified information loss produced by highly variable weighting. Runtime and scalability captured operational feasibility when employee-time datasets became large<sup>[35]</sup>. Benchmarking therefore did not identify model superiority from predictive accuracy alone; rather, it evaluated whether more sophisticated causal estimators generated stable effects while maintaining acceptable balance, uncertainty, transparency, and computational requirements<sup>[27]</sup>.

**Table 2:** Comparative Predictive, Causal and Operational Performance of Candidate Models

| Model                    | ATE   | 95% CI      | Covariate Balance (Max  SMD ) | RMSE  | MAE   | Mean Deviation | Effect Stability | Runtime (s) | Interpretability |
|--------------------------|-------|-------------|-------------------------------|-------|-------|----------------|------------------|-------------|------------------|
| M0 - Naïve Observational | 0.118 | 0.086–0.150 | 0.284                         | 0.426 | 0.337 | +0.071         | Low              | 0.8         | Very High        |
| M1- Outcome Regression   | 0.084 | 0.058–0.110 | 0.146                         | 0.361 | 0.281 | +0.038         | Moderate         | 2.4         | High             |
| M2 - Propensity/IPW      | 0.071 | 0.045–0.097 | 0.073                         | 0.348 | 0.268 | +0.024         | Moderate–High    | 4.9         | High             |
| M3 - Doubly Robust/AIPW  | 0.067 | 0.044–0.090 | 0.058                         | 0.326 | 0.249 | +0.011         | High             | 7.8         | Moderate–High    |
| M4 - DiD/Fixed Effects   | 0.061 | 0.037–0.085 | 0.064                         | 0.334 | 0.255 | +0.014         | High             | 9.6         | High             |
| M5 - Causal Forest/DML   | 0.064 | 0.043–0.085 | 0.041                         | 0.301 | 0.227 | +0.006         | Very High        | 18.7        | Moderate         |

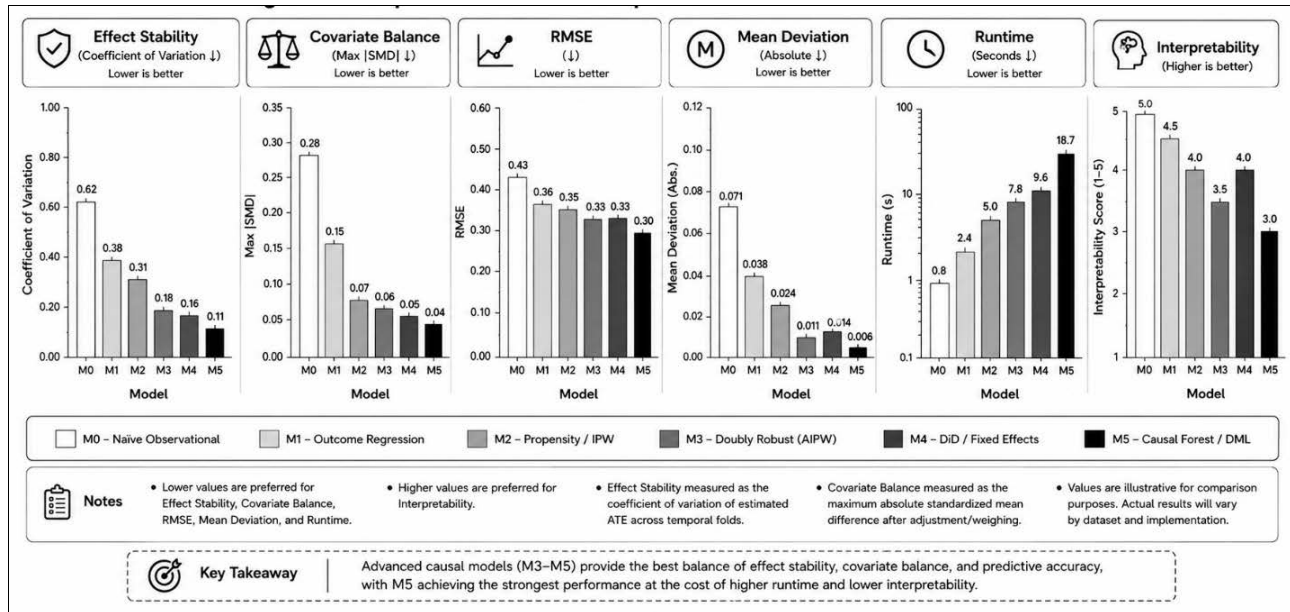


Fig 5: Comparative Causal and Operational Performance of Candidate Models

### 5.3 Mean-deviation and subgroup robustness

Robustness analyses examined whether estimated hybrid-work effects remained consistent across occupational groups, departments, tenure bands, managerial levels, baseline productivity, baseline well-being, hybrid-work intensity, team size, and collaboration intensity [34]. Subgroup-specific *ATE* or conditional average treatment effects were reported with uncertainty intervals rather than interpreted from point estimates alone [30]. This analysis identified whether aggregate effects concealed materially different responses among employees operating under different organizational conditions.

Personal-baseline features were reconstructed using 4-, 8-, 12-, and 26-week historical windows to evaluate sensitivity to baseline duration [32]. Corresponding standardized deviations  $z_{it}^{(w)}$  and mean absolute deviations  $MAD_i^{(w)}$ , where  $w \in 4, 8, 12, 26$ , were recalculated before causal estimation. Effect estimates were then compared across alternative windows [28]. Employees exhibiting unusually large productivity or well-being deviations were additionally examined separately and through sensitivity exclusions. This procedure determined whether estimated treatment effects reflected broad workforce responses or were disproportionately influenced by comparatively small groups experiencing atypical changes relative to their historical patterns [35].

### 5.4 Sensitivity and causal robustness testing

Sensitivity analyses evaluated whether causal conclusions persisted under alternative treatment definitions, temporal horizons, sample restrictions, and identification assumptions [31]. Hybrid exposure was alternatively defined as any hybrid work versus office-based work, 1–2 remote days versus office-based work, balanced hybrid versus office-based work, and continuous remote-work proportion [27]. Treatment effects were re-estimated at  $t + 1$ ,  $t + 4$ ,  $t + 8$ , and  $t + 12$  to distinguish immediate from delayed outcome responses.

Placebo analyses assigned artificial intervention dates before genuine policy changes; substantial placebo effects

would indicate possible residual temporal confounding or model misspecification [33]. For difference-in-differences specifications, pre-treatment outcome trajectories were examined to assess the plausibility of parallel trends. Propensity-based analyses were repeated after trimming observations with extreme  $\hat{e}(X_i)$  values, thereby restricting inference to regions with stronger treatment-control overlap [29].

Sensitivity to unmeasured confounding was investigated using formal sensitivity procedures or E-values where compatible with the outcome measure and estimand [35]. Uncertainty estimation reflected the dependence structure of longitudinal observations. Standard errors were therefore clustered at employee, team, or organizational-unit level according to the level at which treatment assignment and residual dependence occurred [28]. Results were also compared across alternative covariate sets and model specifications. Convergence of estimates across these analyses strengthened robustness, whereas substantial changes indicated dependence on particular assumptions and required correspondingly cautious causal interpretation [34].

## 6. Explainability, standards comparison and hr decision translation

### 6.1 Causal explainability and heterogeneous treatment effects

Causal explainability focused on identifying for whom and under what conditions hybrid work appears beneficial, neutral, or harmful, rather than merely identifying variables associated with productivity or well-being [36]. Heterogeneity was represented through the conditional average treatment effect:

$$CATE(x) = E[Y(1) - Y(0) | X = x]$$

where  $CATE(x)$  denotes the expected treatment effect among employees characterized by covariate profile  $X = x$ . Treatment-effect variation was examined across role, tenure, baseline productivity, team collaboration, managerial support, digital workload, historical well-being, and hybrid-

work intensity [39]. Causal forests were used to detect nonlinear heterogeneity, while subgroup effect plots and conditional-effect summaries displayed estimated effect magnitude alongside uncertainty [34]. Where appropriate, partial-dependence representations illustrated variation in estimated treatment effects across selected characteristics. SHAP analysis was restricted principally to explaining nuisance or predictive-model behaviour rather than being

interpreted directly as causal attribution [38]. Ordinary feature importance indicates contribution to model predictions, not the effect of intervening on a variable [35]. Consequently, treatment-effect explanations combined *ATE*, *CATE(x)*, subgroup estimates, overlap diagnostics, and uncertainty to identify potentially meaningful benefit-risk segments without overstating individualized causal certainty [40].

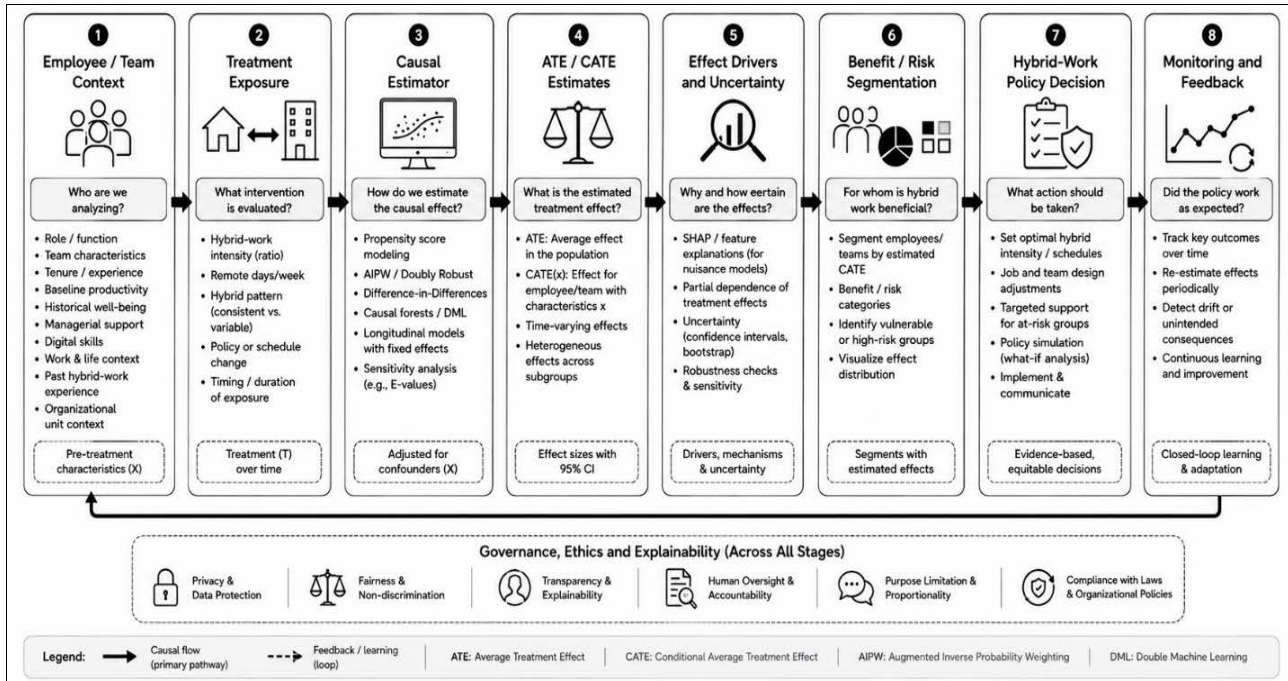


Fig 6: Explainable Causal HR Decision-Support Framework

## 6.2 Comparison with workforce and organizational standards

The proposed framework was compared with standards addressing occupational health, psychosocial risk, human-capital reporting, and information governance [37]. ISO 45001 provides an occupational health and safety management structure emphasizing worker participation, hazard identification, risk management, and continual improvement. These principles are relevant where hybrid arrangements alter occupational conditions or generate emerging workforce risks [34]. ISO 45003 extends this perspective toward psychological health and psychosocial hazards, including workload, organizational culture, communication, isolation, and working arrangements that may influence employee well-being [40].

ISO 30414 provides a human-capital reporting perspective relevant to productivity, organizational culture, engagement, turnover, workforce composition, and leadership indicators

[36]. Its measurement orientation complements the longitudinal outcome architecture by connecting estimated hybrid-work effects with broader workforce-performance reporting. ISO/IEC 27001 becomes particularly important because integrated HR analytics may involve sensitive employee, attendance, survey, collaboration, and behavioural information [38]. Relevant controls include confidentiality, access management, information governance, security-risk assessment, and appropriate protection of analytical datasets. Comparison therefore assessed whether each analytical component was aligned, partially aligned, extended existing guidance, or revealed an implementation gap [35]. Standards benchmarking does not establish causal validity itself; rather, it evaluates whether evidence generation occurs within appropriate organizational, workforce, well-being, and information-governance structures [39].

**Table 3: Causal HR Analytics Framework Versus Workforce, Well-Being and Information-Governance Standards**

| Analytical Dimension                            | Proposed Framework                                                                                | ISO 45001                                                      | ISO 45003                                                          | ISO 30414                                                 | ISO/IEC 27001                                             | Alignment/Gap                        |
|-------------------------------------------------|---------------------------------------------------------------------------------------------------|----------------------------------------------------------------|--------------------------------------------------------------------|-----------------------------------------------------------|-----------------------------------------------------------|--------------------------------------|
| Occupational health and safety                  | Evaluates hybrid-work effects on employee and organizational outcomes                             | Core requirement for occupational health and safety management | Supports management of psychosocial aspects of OH&S                | Indirectly reflected through human-capital measures       | Not a primary focus                                       | Supported                            |
| Psychosocial risk and well-being                | Models well-being, workload, isolation, digital load, absence, and related outcomes               | Addresses workplace hazards and risks                          | Direct guidance on psychosocial risks and psychological health     | Covers relevant workforce well-being and culture measures | Limited direct coverage                                   | Strongly aligned                     |
| Worker participation                            | Incorporates employee-reported outcomes and supports evidence-informed policy review              | Strong emphasis on worker consultation and participation       | Emphasizes participation in psychosocial-risk management           | Relevant to engagement and organizational culture         | Not a primary focus                                       | Partially supported                  |
| Productivity measurement                        | Estimates causal effects on individual, team, and organizational productivity                     | Indirect                                                       | Indirect through psychosocial working conditions                   | Relevant human-capital reporting dimension                | Not addressed directly                                    | Extended                             |
| Engagement and organizational culture           | Integrates engagement, satisfaction, managerial, and team-level indicators                        | Organizational context relevant                                | Culture and social relationships are relevant psychosocial factors | Directly relevant to human-capital reporting              | Limited                                                   | Supported                            |
| Hybrid/remote-work risk assessment              | Explicitly models hybrid-work intensity, timing, heterogeneity, and consequences                  | General OH&S risk-management principles apply                  | Relevant to remote, isolated, and changing work conditions         | Indirect workforce-reporting relevance                    | Relevant where digital systems process employee data      | Extended                             |
| Causal effect estimation                        | Uses ATE, CATE, AIPW, DiD, causal forests, and DML                                                | Not prescribed                                                 | Not prescribed                                                     | Not prescribed                                            | Not prescribed                                            | Framework extension                  |
| Longitudinal monitoring                         | Tracks treatment exposure and outcomes across employee-time observations                          | Supports monitoring and continual improvement                  | Supports monitoring of psychosocial risks                          | Supports systematic human-capital measurement             | Supports monitoring of information-security controls      | Strongly aligned                     |
| Human-capital reporting                         | Links well-being, productivity, turnover, teams, and organizational outcomes                      | Limited                                                        | Limited                                                            | Central focus                                             | Not a primary focus                                       | Supported                            |
| Privacy and data minimization                   | Uses anonymization, privacy-preserving metadata, purpose limitation, and restricted data use      | Indirect                                                       | Relevant to responsible worker assessment                          | Relevant to workforce-data governance                     | Strong information-governance relevance                   | Strongly aligned                     |
| Information security and access control         | Requires controlled access to sensitive HR, attendance, survey, and behavioural data              | Limited                                                        | Limited                                                            | Indirect                                                  | Core information-security management focus                | Supported                            |
| Explainability and transparency                 | Uses ATE/CATE interpretation, causal heterogeneity analysis, uncertainty, and model explanations  | Indirect governance relevance                                  | Supports transparent psychosocial-risk processes                   | Supports transparent workforce measurement                | Documentation and governance relevance                    | Extended                             |
| Human oversight and contestability              | Requires human review before consequential workforce decisions                                    | Consistent with participation and accountability               | Consistent with worker-centred risk management                     | Indirect                                                  | Governance controls can support accountability            | Extended                             |
| Continuous improvement and monitoring           | Re-estimates effects, monitors drift, evaluates policy changes, and incorporates outcome feedback | Core continual-improvement principle                           | Supports continuous psychosocial-risk management                   | Supports continuing workforce measurement                 | Requires monitoring and continual improvement of the ISMS | Strongly aligned                     |
| Algorithmic fairness and causal bias assessment | Examines subgroup effects, overlap, balance, sensitivity, and treatment-effect heterogeneity      | Not specifically prescribed                                    | Not specifically prescribed                                        | Limited direct specification                              | Not specifically an AI-fairness standard                  | Governance gap / framework extension |

### 6.3 HR decision translation, ethics and governance

Estimated treatment effects were translated into organizational decision support rather than automated employee-level prescriptions<sup>[34]</sup>. Potential applications included determining appropriate hybrid-work intensity, identifying roles where greater location flexibility may be beneficial, designing team-level schedules, monitoring well-being consequences, evaluating policy modifications, and balancing productivity objectives with employee welfare<sup>[37]</sup>. Decisions nevertheless require consideration of effect uncertainty, subgroup sample size, overlap, organizational feasibility, and potential unintended consequences before implementation<sup>[40]</sup>.

Governance safeguards addressed privacy, transparent employee communication, proportionality, algorithmic fairness, data minimization, purpose limitation, access restrictions, employee contestability, and meaningful human oversight<sup>[36]</sup>. Collection of collaboration or attendance information should remain limited to measures necessary for legitimate analytical purposes and should not transform causal evaluation into continuous employee surveillance<sup>[38]</sup>. Similarly, estimated negative treatment effects for an individual or subgroup should not automatically trigger adverse employment decisions. Human reviewers should interpret evidence alongside occupational requirements, employee circumstances, and uncertainty<sup>[35]</sup>. Causal HR analytics consequently functions as a policy-learning mechanism: organizational interventions are informed by estimated effects, implemented proportionately, monitored longitudinally, and reassessed as workforce conditions and hybrid-work practices evolve<sup>[39]</sup>.

## 7. Discussion, implications and conclusion

### 7.1 Interpretation of causal and longitudinal findings

The findings should be interpreted jointly across workforce well-being, productivity dynamics, and organizational performance rather than assuming that hybrid work produces a uniform organizational effect<sup>[37]</sup>. Estimated effects may be consistently positive or negative, nonlinear across hybrid-work intensity, or negligible when averaged across the workforce<sup>[40]</sup>. Importantly, a small *ATE* does not imply that hybrid work is inconsequential. The population average may conceal substantial positive effects among employees benefiting from autonomy and reduced commuting alongside negative effects among roles experiencing coordination difficulties or digital overload<sup>[35]</sup>. Longitudinal estimates further indicate whether such effects emerge immediately, accumulate gradually, diminish, or persist across observation periods<sup>[39]</sup>.

### 7.2 Theoretical, managerial and methodological implications

The framework advances HR analytics from *Description* → *Prediction* → *Causal Explanation* → *Decision Support*, strengthening the connection between workforce evidence and organizational action<sup>[36]</sup>. Theoretically, it clarifies mechanisms through which work location, autonomy, collaboration, and well-being may jointly influence productivity. Managerially, heterogeneous treatment effects can inform evidence-based workforce planning, flexible-work policies, occupational well-being initiatives, and organizational design without assuming one arrangement suits every employee or role<sup>[38]</sup>. Methodologically, integrating longitudinal employee baselines with causal

inference, machine learning, temporal validation, sensitivity testing, and explainability provides a more rigorous architecture for distinguishing prediction from intervention effects<sup>[40]</sup>. This combination also enables policy effectiveness to be reassessed as workforce conditions evolve<sup>[35]</sup>.

### 7.3 Limitations, future research and conclusion

The framework remains limited by residual unobserved confounding, imperfect productivity measurement, survey-response bias, treatment heterogeneity, organizational specificity, policy endogeneity, and incomplete longitudinal observations. Future studies should incorporate multi-organization datasets, longer observation periods, cross-country comparisons, natural experiments, and randomized policy interventions where operationally and ethically feasible. Mediation analysis could clarify pathways through autonomy, well-being, collaboration, and digital workload, while dynamic treatment regimes could examine changing hybrid arrangements over time. Ultimately, explainable causal HR analytics provides a stronger evidence architecture by determining not merely what outcomes accompany hybrid work, but whether arrangements cause those outcomes, for whom, over what period, and under which organizational conditions.

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