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HR analytics: a centralizing or decentralizing force?

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ABSTRACT

This study empirically analyzes the relationship between the application of HR analytics and the assignment of decision-making authority in Swiss organizations. From a theoretical standpoint the direction of this relationship is ex-ante unclear as opposing forces are at work simultaneously. While HR analytics can reduce the local information advantage or even take over decision-making processes, acting as a centralizing force, it can also generate additional local information and dampen the hidden action problem, resulting in the decentralization of decision-making processes. The empirical results, relying on doubly robust ATE estimations, are in line with a decentralizing force of HR analytics. More precisely, a comprehensive measure of decision rights as well as operational and strategic decisions are more decentralized in organizations that apply HR analytics. Overall the findings suggest that Swiss organization currently combine the use of HR analytics with employee empowerment and do not use it to create a dystopian work environment as feared by proponents of *digital taylorism*.

KEYWORDS

HR analytics; people analytics; decision-rights assignment; authority in organizations; doubly robust ATE estimation

1. Introduction

The digital transformation deeply changes the environment businesses operate in. Subsumed under the term human-resource analytics (HR analytics), the increasing use of digital technologies and data analytics also affects the field of human resources.[1] Comprehensive in nature, HR analytics ranges from more basic tools, for example, included in enterprise resource planning software, to cutting-edge technologies such as artificial intelligence, machine learning and Internet of Things sensors (e.g. Aral et al., 2012; Giermindl et al., 2022; Shet et al., 2021). Practical applications range from Starbucks using a scheduling software that analyzes data including weather and pedestrian patterns (Tursunbayeva et al., 2022),

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Tesco reusing its customer analytics tool to better understand its employees, McDonalds leveraging information about management behavior and staff attitude to optimize restaurant performance (Angrave et al., 2016; Sparrow et al., 2015), to an offshore drilling company using statistical analyses to compare the success of their graduate program with competitors (Rasmussen and Ulrich, 2015). These practical examples show that HR analytics can provide new insights into employee behavior and the inner workings of companies. Through this, it has the power to impact the organization of firms and various business outcomes (e.g. Giermindl et al., 2022; Van Den Heuvel & Bondarouk, 2017). Theoretical studies and literature reviews suggest that HR analytics and related concepts can influence employee autonomy, managerial control structures and decision rights assignment in organizations (e.g. Ioakeimidou et al., 2025; Kellogg et al., 2020; Meijerink & Bondarouk, 2023; Parent-Rocheleau & Parker, 2022). Furthermore, several empirical investigations point to an interdependence between these two dimensions (e.g. Bechter et al., 2022; Kinowska & Sienkiewicz, 2023; Labro et al., 2023). The distribution of decision-making authority within organizations is highly relevant, as it shapes the everyday working conditions of employees and has broader implications for workplace design and firm performance.

Against the background of this emerging theoretical and empirical literature, the present paper investigates the relationship between the application of HR analytics and the hierarchical level to which decision rights are allocated within firms. To achieve this, it combines a theoretical framework with an empirical analysis. The focus is on firms in the traditional economy and those operating in the gig economy are explicitly excluded.[2]

In the definition of HR analytics, I follow Marler and Boudreau (2017, p. 15), who define it as *a HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision making*. This definition is widely applied in the HR analytics literature (e.g. Álvarez-Gutiérrez et al., 2022; Bonilla-Chaves & Palos-Sánchez, 2023; Margherita, 2022; McIver et al., 2018; Tursunbayeva et al., 2018; Wang et al., 2024). HR analytics is, therefore, a process lying at the intersection between information technology and personnel management.

For the present study, the inclusiveness of this definition is appealing, namely that the outcome dimension of HR analytics is characterized very broadly.[3] While the term HR analytics focuses on the analytics part, the collection of data is inherently part of this process (e.g. Falletta & Combs, 2021). I measure HR analytics as the presence of

artificial intelligence or data analytics tools as a supporting means to collect information that can be used during the implementation of employee development or performance evaluation. This measure of HR analytics only includes people already working for the organization, therefore, excluding the recruitment process.

A concept closely related to HR analytics is algorithmic management (e.g. Baiocco et al., 2022; Deng et al., 2025; Kinowska & Sienkiewicz, 2023; Noponen et al., 2024; Parent-Rocheleau & Parker, 2022). In general, algorithmic management can be considered a subcategory of HR analytics, as its definition is narrower and focuses on the application of algorithms in the management of employees. For example, Deng et al. (2025) state that algorithmic management may *enhance*, but does not constitute, HR analytics.

The outcome of interest captures the distribution of decision-making authority within organizations. This concept reflects the degree of centralization, as centralization indicates on which level in the hierarchical order the locus of decision-making authority lies (Camps and Luna-Arocas, 2009; Galbraith, 1973; Pugh et al., 1968; Wang and Feeney, 2016). In essence, centralization describes a continuum, where in highly centralized organizations, decision-making power is held by very few, and in decentralized organizations by most employees (Tata and Prasad, 2004). A closely related concept is job autonomy, which refers to the degree of decision-making authority of employees (Hackman and Oldham, 1975; Zhao and Wu, 2023). Here, decision-making authority denotes an index which classifies organizations from decentralized to centralized. This index is based on information about a comprehensive list of decision types, covering nine different areas. Additionally, the empirical investigation separately considers operational and strategic decisions.

The baseline research question leaves the direction of the relationship open, leading to the formulation of both a *centralization hypothesis* and a *decentralization hypothesis*. The theoretical analysis supports the notion that the relationship between HR analytics and the assignment of decision-making authority in organizations is ex-ante ambiguous. HR analytics acts as a decentralizing force as it dampens the hidden action problem through its function as a monitoring tool. Additionally, the data-generating processes associated with HR analytics may produce localized information at lower hierarchical levels. This can increase information asymmetries within the organization and, in turn, encourage greater delegation of decision-making authority. Conversely, HR analytics functions as a centralizing force when it reduces the local information advantage by providing information about work processes to higher hierarchical levels or when refined tools take over decision-making processes that were previously delegated to lower level employees.

To empirically test these hypotheses, I use a data source that we collected by ourselves and call the *Swiss Employer Survey* (SES). The SES is a cross-sectional survey that contains information about a wide range of business topics in Swiss organizations. The data set compiles information from 479 organizations. The estimation approach combines inverse probability weighting (IPW) with regression models for the potential outcome equations. This leads to a doubly robust average treatment effect (ATE) estimator.

The empirical results uncover a statistically significant relationship between the application of HR analytics and more decentralized organizations. In other words, the use of HR analytics is more likely to occur in organizations where decision-making authority is delegated to lower levels of the hierarchy. This result holds for an overarching measure of decision-making authority (*DRA*) and for explicitly operational (*opDRA*) and strategic decisions (*strDRA*). On a more granular level, the relationship is visible for decision rights in the areas of work planning, task definition, and regarding investments in machinery or equipment. For *DRA* as well as for *opDRA*, the results are in line with a shift of responsibility away from the top management and towards non-managerial employees. For *strDRA* the results are consistent with a shift of decision rights from the top to the lower and middle management.

These findings suggest that the effects of mitigating the hidden action problem and strengthening employees local information advantage outweigh the centralizing forces (i.e. reductions in the local information advantage and HRA tools that take over decisions). This indicates that Swiss organizations are currently applying HR analytics in a way that supports employee empowerment, rather than using it to create a dystopian work environment as feared by proponents of *digital taylorism*. For practitioners aiming to use HR analytics as a tool for empowerment, it is crucial to ensure that these systems do not assume excessive decision-making authority and that the generated insights are shared with employees, enabling them to actively apply this information in their daily work.

The baseline results are largely robust to a variety of robustness checks. To be precise, I apply an alternative methodological approach consisting of causal forests, reestimate the baseline model with different trimming and weighting specifications, and exclude the part of the sample whose contact information was collected via web scraping. All robustness checks support the baseline result. The results for *strDRA* show the largest degree of sensitivity as they become partially statistically insignificant.

The interest of researchers in the topic of HR analytics has been growing steadily. Sakib et al. (2024) show an annual increase of close to 10% in the number of published articles between 2008 and 2023. While many researchers paint a very positive picture about the future of HR analytics

(e.g. Schiemann et al., 2018; Sharma & Sharma, 2017; Van Den Heuvel & Bondarouk, 2017), others are more pessimistic. This pessimism is expressed in terms of possible negative effects on employees (Giermindl et al., 2022; Tursunbayeva et al., 2022), but also regarding a possible lack of effectiveness (Angrave et al., 2016).

A large part of the existing literature on HR analytics consists of conceptual papers, literature reviews, and case studies (Giermindl et al., 2022). Consequently, a major limitation of the current literature is the scarcity of rigorous empirical studies (Bonilla-Chaves and Palos-Sánchez, 2023; Giermindl et al., 2022; Greasley and Thomas, 2020; Ioakeimidou et al., 2025; Marler and Boudreau, 2017; Rasmussen and Ulrich, 2015; Shet et al., 2021; Van Den Heuvel and Bondarouk, 2017). This is particularly the case for the traditional work sector, as most existing empirical analyses focus on the gig economy (Baiocco et al., 2022; Deng et al., 2025; Kinowska and Sienkiewicz, 2023). As a result relatively little is known about the processes through which HR analytics influences organizational design and other business outcomes (Huselid, 2018; Shet et al., 2021).[4] Álvarez-Gutiérrez et al. (2022, p. 129) note that the existing literature *would appear to be more promotional than descriptive*. In general, Aral et al. (2012) are pointed to as the seminal study on HR analytics. They build a theoretical model based on agency-theory and provide causal evidence for a productivity effect of a system consisting of HR analytics, performance pay, and information technology.[5] In contrast, most early research in the field of HR analytics does not refer to an explicit theoretical framework (Marler and Boudreau, 2017).

As stated above, HR analytics lays at the intersection of HR-processes and digital technologies. Various studies look into the relationship between HR practices and changes in the hierarchical structure of organizations.[6] Additionally, a wide range of papers investigates the link between the application of digital technologies and the degree of centralization.[7] Closely related to the present paper is the study by Labro et al. (2023), who investigate the effects of predictive analytics on the assignment of decision rights. Their research differs in that it examines the usage of predictive analytics in general, rather than in the context of HR processes. Furthermore, it looks at power shifts between headquarters and local managers. They also consider possible changes in the local information advantage and stipulate that the direction of the effect is theoretically ambiguous. The theoretical framework differs in that it does not account for a direct channel of monitoring on the hidden action problem. It also does not cover the effect of decision automation. Their empirical findings suggest that predictive analytics is associated with a centralization of decision-making authority.

The theoretical argument of Meijerink and Bondarouk (2023) parallels the present study in concluding that HR analytics can both constrain and

enable employee autonomy. However, where in their framework this duality is shaped by worker resistance (*algoactivism*), the present framework argues that cooperative employees can experience empowerment.

Two additional empirical projects are closely related to the current paper, both of which draw on data from the European Company Survey (ECS).[8] Bechter et al. (2022) show that the application of HR analytics depends on both firm-level characteristics and contextual factors. They find an interaction between hierarchical complexity and HR analytics, further motivating the present analysis. More specifically, they find that the application of HR analytics increases with the number of hierarchical levels present in an organization. A key distinction is that their study treats HR analytics as an outcome variable, whereas the present paper considers it a determinant. Furthermore, while their study includes a measure for hierarchical complexity they do not consider decision-rights assignment. Kinowska and Sienkiewicz (2023) find a negative effect of algorithmic management on job autonomy. Their paper differs in various ways from the present study. As discussed above, algorithmic management is more narrowly defined than HR analytics.[9] Moreover, while job autonomy is conceptually related to the assignment of decision rights, the two are not synonymous. Finally, where both of these studies examine EU countries, the present paper focuses on organizations in Switzerland.

This paper makes both a theoretical and an empirical contribution to the existing literature. First, the theoretical analysis integrates and extends existing frameworks, offering a novel and comprehensive perspective on the mechanisms through which HR analytics may affect the allocation of decision rights within organizations. This enables me to identify the theoretical conditions that lead to centralization or decentralization. Second, the empirical analysis provides new statistical evidence on the relationship between the adoption of HR analytics and the distribution of decision-making authority. This issue is of high practical relevance, as it directly shapes employees' everyday working conditions. The empirical contribution is particularly relevant given that the HR analytics literature is still in its early stages and in urgent need of further empirical findings. The analysis is further enriched by drawing on data from Switzerland, a national context that has not yet been explored in this literature, despite the country's status as the most innovative economy in the world (Dutta et al., 2024). The combination of the theoretical framework and empirical results allows the formulation of recommendations for managers who aim to link HR analytics application with employee empowerment.

The remainder of the paper is structured as follows. Section 2 formulates the hypotheses and investigates them from a theoretical perspective. Section 3 introduces the data set (3.1), the variables of interest (3.2), and

presents descriptive statistics (3.3). Section 4 provides information about the empirical approach (4.1), the control variables (4.2), the applied weighting strategy (4.3), and reasons to trim the computed weights (4.4). Section 5 discusses the balance statistics (5.1), common support assumption (5.2), as well as the baseline estimation results (5.3) and from where in the hierarchy these relationships emerge (5.4). Section 6 tests the sensitivity of the empirical results. Finally, Section 7 concludes by discussing the theoretical contribution (7.1), practical implications (7.2), as well as the limitations of the current study (7.3).

2. Theoretical framework

As already discussed, the baseline research question of this project is how the application of HR analytics is related to the allocation of decision rights in organization. To leave the direction of the effect as open as possible, I formulate the two following rival hypotheses concerning this relationship:

> **Centralization Hypothesis:** The application of HR analytics is positively associated with the centralization of decision-making authority.

> **Decentralization Hypothesis:** The application of HR analytics is positively associated with the decentralization of decision-making authority.

The remainder of this section theoretically examines the postulated relationships and investigates which forces shape the direction of the effect. The arguments mainly rely on agency theory. Therefore, the starting point is a simple principal-agent model. Two defining features of the relationship between the principal and the agent are that the agent has more information than the principal and that there is a conflict of interest between the two actors.

The information asymmetry arises because the agent has more knowledge, for example, about the production process, the workflow, the applied technology, and their specific actions. Consequently, the agent has more localized information, based on which they can make more informed and more productive decisions than the principal. Thus, it can make sense for a principal to delegate decision rights to the agent and avoid noisy communication between the two actors (e.g. Dessein, 2002). An additional consequence of the present information asymmetry is that the principal cannot directly observe the agent's effort. This lack of total control over the agent, combined with the fact that the interests of the two are not necessarily aligned, results in agents making decisions that maximize their own utility and not the utility of the organization, for example, by reducing their effort (e.g. Holmström, 1979; Laffont & Martimort, 2002). A phenomenon termed the *hidden action problem*.

The principal now faces the challenge of maximizing the utility of the organization in deciding on the ideal level of delegation. In doing so, they need to consider that an increase in the delegation of decision-making authority increases the level of utilized local knowledge but, at the same time, increases the possibility of counter-productive behavior by the agent (e.g. Acemoglu et al., 2007; Hitt & Brynjolfsson, 1997). All else equal, the level of delegation increases with the information advantage of the agent and decreases when the principal suspects a higher degree of diverging interests (Labro et al., 2023). When a principal decides to introduce HR analytics into this model-organization the optimization problem changes which potentially affects the ideal level of decision-rights assignment. Whether this leads to increased centralization or decentralization is not clear ex-ante, as there are four different and opposing forces working simultaneously. The following paragraphs discuss the nature of these forces.

In its essence HR analytics consists of data analytics enabling data-driven decision-making regarding HR processes. From this follows that the application of HR analytics inherently generates new information. The data can include both information about workflows and the way employees act.

When HR analytics generates information about the actions of employees it functions as a monitoring tool. Examples of such HR applications are plentiful and range from analyses of data contained in human capital management (HCM) software (Aral et al., 2012), human resource management systems (HRMS) (Shet et al., 2021), to real-time HR dashboards (Álvarez-Gutiérrez et al., 2022). Increasingly, HR analytics also relies on data from more dubious and invasive sources such as sociometric sensors or voice analysis software (Falletta and Combs, 2021). Employers use monitoring tools to incentivize employees to act in ways that benefit the organizations and not the employees themselves. In this sense, control instruments help align the employees' actions with the goals of the organization and decrease the agency problems arising from the information asymmetry, i.e. they dampen the hidden action problem (e.g. Camps & Luna-Arocas, 2009; Levy, 2015; McIver et al., 2018; Mocetti et al., 2017; Sharma & Sharma, 2017). As Gerten et al. (2022) summarize, policies such as employee monitoring can be used to balance the benefits of using the available local knowledge with the associated losses of control. Thus, HR analytics can act as a decentralizing force, as it reduces hidden action problems through employee monitoring.

As stated before, HR analytics not only generates additional information about the actions of employees but also about, for example, workflows, production processes, or customer interactions. This is the case when the aforementioned HR softwares are in use (e.g. HCM, HRMS, or HR dashbords), but also when data from external sources, such as the weather or

pedestrian patterns (Tursunbayeva et al., 2022) is compiled and analyzed.[10] The effect HR analytics has on the organizational architecture through the provision of this information depends on the actor who can profit most from this newly available information. If the application of HR analytics increases the provision of information to employees in higher hierarchical position and/or decreases the difficulty of transmitting existing local information up the hierarchy, a decrease in the local information advantage will follow (e.g. Bloom et al., 2014; Labro et al., 2023). This follows the argument that the access to high-quality data diminishes the uneven distribution of information, consequently decreasing the information asymmetry between principal and agent. Such developments have been linked to changes in decision-making processes in firms, for example, in connection with the introduction of new information technology (e.g. Acemoglu et al., 2007; Jensen & Meckling, 1992; Mocetti et al., 2017; Szukits & Móricz, 2024). An example is Bloom et al. (2014), who show that when the introduction of new information technology leads to a reduction in the communication cost, the centralization of decision-making power follows. Thereby, the application of HR analytics can act as a centralizing force. The reverse is true, if lower level employees can profit more from the additional information than the employees who work higher up in the hierarchy. As this would suggest an increase in the local information advantage, increased delegation should follow. Due to the information advantage of the agents, it is plausible that the data-generating processes associated with HR analytics can produce information that is valuable to lower level employees. For example, the literature suggests that employee monitoring tools can enhance the information level of employees by clarifying key performance indicators and strategic goals, offering accurate insights into production processes, providing real-time feedback on individual performance, supporting on-the-job learning, and even serving a mentoring function (Aral et al., 2012; Belloc et al., 2023; Deng et al., 2025; Gensler et al., 2024; Labro et al., 2023; Noponen et al., 2024). Adhvaryu et al. (2022) provide a real-life example of these two forces operating simultaneously. In their study, a newly implemented software system in a quick-service restaurant tracks the progress of drive-through orders. The information is reported not only to managers but also to employees working in food preparation and at the cashier station. Whether this information is more valuable to employees or to managers determines if the software increases or decreases the local information advantage.

Giermindl et al. (2022) propose a fourth possible channel through which HR analytics influences decision-rights assignment in organizations. They argue that refined applications of HR analytic tools, including machine learning or AI, could take over decision-making processes themselves. Meijerink and Bondarouk (2023) refer to this as *decision automation*. In an extreme

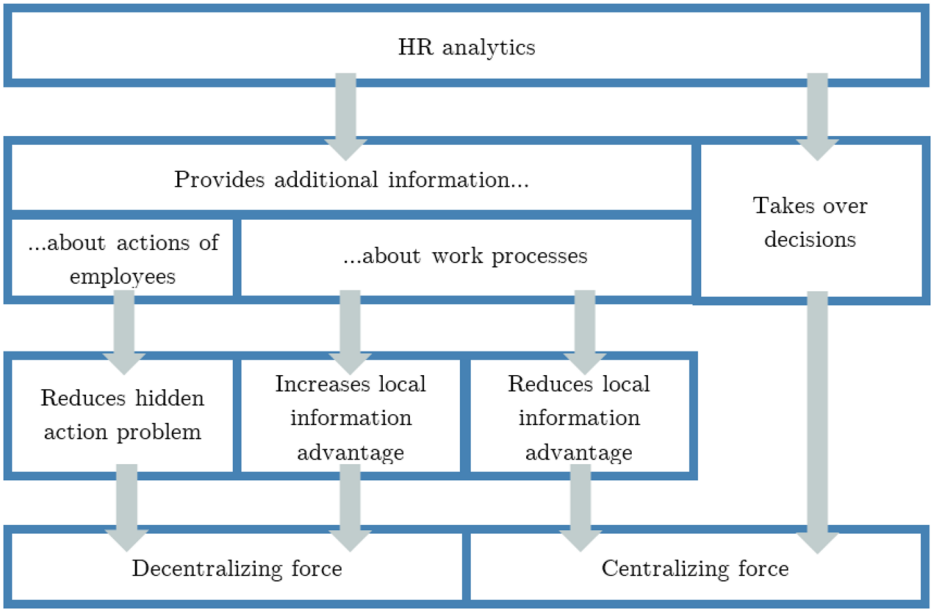


Figure 1. Theoretical framework.

case, this could result in a situation described by the literature as *digital taylorism*, in which employees are limited to performing tasks assigned, designed, and controlled by these new HR analytics tools (e.g. Baiocco et al., 2022; Faraj et al., 2018; Holford, 2019; Noponen et al., 2024). Through this, the application of HR analytics might shift decision-making power away from low-level employees, leading to a more centralized workplace.

Figure 1 summarizes these four different lines of argument. HR analytics acts as a centralizing force when it reduces the local information advantage or when self-learning algorithms take over decision-making processes. In contrast, it functions as a decentralizing force when it mitigates hidden action problems or generates additional local information. Regarding the formulated rival hypotheses, this theoretical analysis indicates that the *centralization hypothesis* holds if the reduction of the local information advantage and the effect of self-learning algorithms taking over decision-making outweigh the decentralizing forces. Conversely, the *decentralization hypothesis* is supported if the reduction of the hidden action problem and the provision of additional local information outweigh the centralizing forces.

3. Data, variables, and descriptive statistics

3.1. Data and sampling process

This study relies on organization-level data to investigate the present research question of interest.[11] The applied data set has been collected as

a primary data set by the chair of Human Resources and Organization at the University of Basel and covers organizations with at least 10 employees. We refer to this data set as the *Swiss Employer Survey* (SES). It is based on a cross-sectional survey covering information of the year 2020 or 2022.

The SES was conducted in two steps. In a first step, we contacted a representative sample of 10'000 organizations.[12] The contact with the organizations was established by letter. Organizations that did not react at first contact received a second letter which was intended as a reminder. Unfortunately, the response rate did not meet our goals and reached about six percent, including organizations which did not provide all information of interest (the target was a 'typical' response rate of about 20%). The main reason for this was that the timing of the survey coincided with the heights of the COVID-19 pandemic, a time where organizations certainly had other concerns than participating in our survey. After excluding observations which did not provide the necessary information for the present empirical analysis, this first part of the sample comprises 313 observations.[13]

In a second step, we increased the sample size by contacting a sample of organizations whose information we acquired via web scraping. To accomplish this, we first manually compiled a list of employer and industry associations. Subsequently, the contact details of the member companies listed on the association's websites were extracted either manually (for smaller associations) or automatically using a Python script (for larger associations). The compiled sample included the e-mail addresses of the organizations, which we used to establish contact. This approach allowed us to increase the sample size of the present study by 166 observations that meet the exclusion restrictions of the SFSO sample.[14] This brings the total number of observations to 479.

The SES covers a wide range of topics with a focus on the technological development of Swiss companies. Most importantly, it includes information on the use of HR analytics and a nine-item question on the distribution of decision-making authority within organizations. Furthermore, it provides information on workforce structure, corporate culture and strategies, the application of digital technologies, personnel planning, performance measurement, remuneration policies, and additional general information. The availability of a comprehensive set of supplementary information about the organizations is of special importance in the present case, since the estimation approach relies on a selection-on-observables design. The broad nature of the SES allows to control for a variety of covariates to move the estimated relationship closer to the true underlying effect.

There are two main problems following from the present sampling and surveying process. First, that the survey took place during the COVID-19

pandemic, and second, that a subsample relies on information from organizations that are not part of the sample provided by the SFSO, but which we identified through web scraping. Lehmann and Beckmann (2025) examine whether the descriptive results of the SES are close to comparable data sets from Switzerland conducted before the COVID-19 pandemic. Finding similar results, they conclude that there is no fundamental bias in the data set. Section 6.3 of the sensitivity analysis addresses possible heterogeneity between the two subsamples. It does this by comparing the mean values of the included variables between the two subsamples and by reestimating the baseline models without the web scraped subsample.

3.2. Variables of interest

The outcome variables of interest focus on the hierarchical level to which decision rights are assigned in companies. Table 1 shows the exact structure of the survey question that the SES poses regarding decision-rights assignment and introduces the abbreviations for the items. The organizations provide information about the specific hierarchical level (non-managerial employees; lower and middle management; or top management) that mainly makes the decisions in nine distinct areas. The broadness of the covered areas reflect that decision-rights assignment within companies is a multifaceted object. The survey items include decisions about typical supervisory activities, such as work planning and definition of tasks, as well as decisions regarding very specific duties such as the replenishment of materials and supplies or customer contact. In addition, there is information on strategic decisions, such as investments in machinery and equipment, and the granting of compensation, bonuses and promotions.

Table 1. Who mainly makes the following decisions in your company?

	Non-managerial employees	Lower and middle management	Top management	Abbreviation
	(1)	(2)	(3)	(4)
Work planning	◯	◯	◯	*WP*
Definition of tasks	◯	◯	◯	*Def*
Pace of work	◯	◯	◯	*Pace*
Sequence of work	◯	◯	◯	*Seq*
Customer contact	◯	◯	◯	*Cust*
Quality control of work	◯	◯	◯	*Qual*
Replenishment of materials and supplies	◯	◯	◯	*Repl*
Investments in machinery or equipment	◯	◯	◯	*Inv*
Award of compensation, bonus & promotions	◯	◯	◯	*Award*

Source: Swiss Employer Survey (SES).

To combine the available information of these nine distinct items into more comprehensive measures of decision rights assignment within a specific organization, this analysis makes use of the double standardization approach or double-z-score. *Standardization* (*STD*) implies the subtraction of the mean of a variable and the division by its standard deviation, resulting in a variable that has a mean of zero and a standard deviation of one by construction. The double-standardization procedure now adds up different standardized variables and standardizes this sum a second time. The goal of this transformation is the construction of an overarching index reflecting the dimension of interest through information present in different indicators.[15]

The index for decision rights assignment (*DRA*) includes all nine items present in Table 1 and takes the following form:

$$DRA_j = STD\{STD(WP_j) + STD(Def_j) + STD(Pace_j) + STD(Seq_j) + STD(Cust_j) + STD(Qual_j) + STD(Repl_j) + STD(Inv_j) + STD(Award_j)\},$$

where *j* refers to the organization. Decisions made at a lower hierarchical level are coded as smaller values, therefore, a low value of *DRA* indicates a high degree of decentralization.[16]

To gain a more granular insight into the assignment of the decision-making authority within organizations the empirical analysis does not only concentrate on *DRA* but further separates this indicator. To achieve this, I follow a similar approach as Camps and Luna-Arocas (2009) and differentiate between strategic and operational decision making.[17] Where strategic decision making has a more global impact, while operational decisions focus on the day-to-day activities. Regarding the nine items present in *DRA* and depicted in Table 1, I classify the first seven items as part of operational decision making and the last two as belonging to the strategic dimension.

From this follows, through the double-standardization process, that the indicator measuring the centralization regarding operational decisions (*opDRA*) is defined as:

$$opDRA_j = STD\{STD(WP_j) + STD(Def_j) + STD(Pace_j) + STD(Seq_j) + STD(Cust_j) + STD(Qual_j) + STD(Repl_j)\},$$

and for strategic decisions (*strDRA*) it takes the following form:

$$strDRA_j = STD\{STD(Inv_j) + STD(Award_j)\}.$$

In addition to the three aggregated variables (i.e. *DRA*, *opDRA*, and *strDRA*), the baseline empirical analysis also considers the standardized versions of the nine underlying items in order to identify potential drivers of the effects observed for the aggregated variables.

The explanatory variable of interest captures the presence of artificial intelligence or data analytics tools as a supporting means to collect information that can be used during the implementation of employee development or performance evaluation. In other words, this variable is a binary indicator that captures the presence of data-based measures which are used in personnel management, where personnel management covers the areas of performance evaluations and employee development. In the following this variable is denoted as *HRA*, which is short for HR analytics.

Table A2 in the appendix and the next section provide descriptive statistics for all variables of interest.

3.3. Descriptive statistics

This section presents descriptive insight into the dependent and explanatory variables of interest. To ensure that the descriptive statistics calculated from the SES are representative of the Swiss business sector, they include sampling weights. The weighting procedure calibrates the underlying sample to mirror the effective distribution of Swiss organizations. It takes geographical characteristics, the specific industry and the number of employees into account.[18]

Figure 2 shows the distribution of the outcome variable of interest in the firm population. More specifically, it depicts the hierarchical level to which the organizations assign the decision-making power for all nine items that

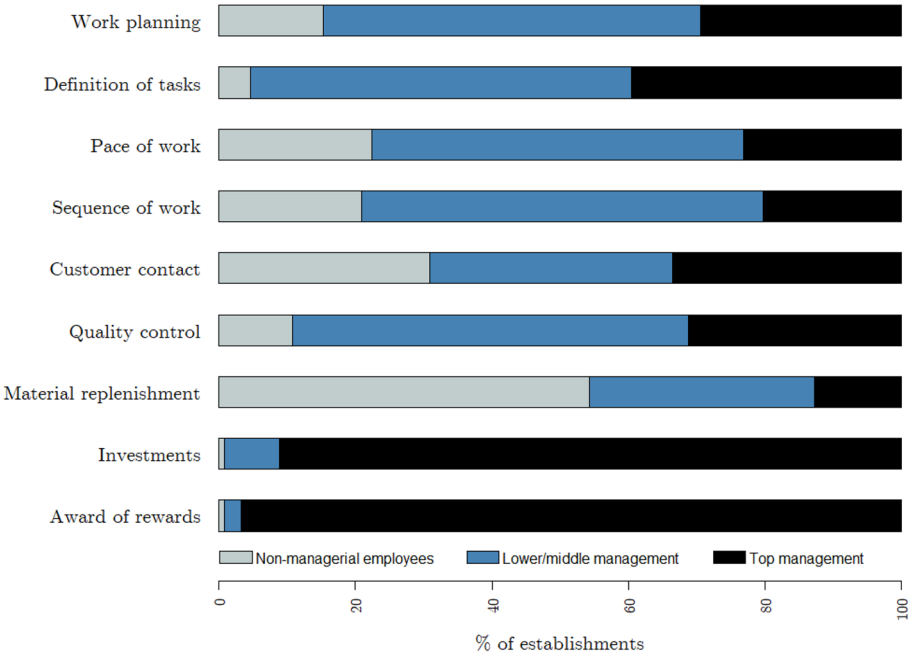


Figure 2. Distribution of decision rights. *Source*: Swiss Employer Survey (SES); own calculations. *Notes*: Number of observations: 479. Shares include sample weights.

define *DRA*. Not surprisingly, it reveals significant differences in the hierarchical levels responsible for decision making across the various areas. At first glance, a notable contrast emerges between operational and strategic decisions, with strategic decisions being predominantly the responsibility of the top management. For instance, in 97% of organizations, the top management oversees decisions related to the award of compensation, bonuses, and promotions. Similarly, in 91% of organizations, they are in charge of investment decisions concerning machinery or equipment. These observations indicate that strategic decision-making in organizations is already highly centralized, leaving little room for further centralization. In contrast, the seven items capturing operational decision making show greater variability between the hierarchical levels. Non-managerial employees are most often responsible for decisions related to the replenishment of materials and supplies, taking charge in 54% of organizations. Meanwhile, decisions on quality control and the sequence of work fall primarily under the control of the lower and middle management (both in close to 60% of organizations), as do decisions regarding work planning, pace of work, and definition of tasks (all around 55%). Finally, decisions regarding customer contact are distributed most evenly across the hierarchical levels. In summary, while the top management almost consistently oversees strategic decisions, the assignment of decision rights regarding operational matters varies significantly across Swiss organizations.

Regarding the explanatory variables of interest, about 15% of organizations utilize HR analytics, as they collect data that can be used during the implementation of employee development or performance evaluations. While the adoption of HR analytics is not yet widespread in Swiss firms, a significant number of employees are nonetheless affected by its application. This underscores the relevance of the current investigation for a broader public in Switzerland. When comparing this share with other European countries, as depicted by Bechter et al. (2022) for 2019, considerable cross-national variation emerges. Switzerland belongs to the group of countries with relatively low implementation rates, similar to that in Germany (13%) and Sweden (17%), but markedly lower than in countries such as Romania (50%) and Croatia (45%).

Figure 3 presents the mean values of three composite variables (i.e. *DRA*, *opDRA*, and *strDRA*) separated by treatment status. Specifically, the figure contrasts the mean values between organizations that utilize HR analytics and those that do not. A lower observed mean value indicates that the decision-making authority lays further down the hierarchy. While the absolute levels of the standardized means are not inherently insightful, the figure demonstrates that, across all three variables, decision-making authority tends to be situated at a lower hierarchical level in organizations where HR analytics is present. This observation provides preliminary support for the hypothesis that the implementation of HR analytics is linked

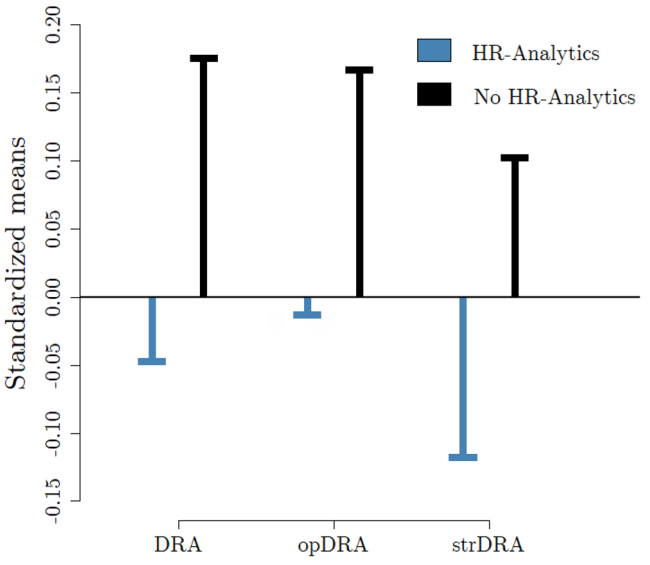


Figure 3. Degree of centralization by treatment status (*HRA*). *Source*: Swiss Employer Survey (SES); own calculations. *Notes*: Number of observations: 479. Calculations include sample weights.

to a greater delegation of decision rights. However, while informative, this descriptive finding does not substitute for more rigorous econometric analysis, as it does not account for potential confounding factors.

4. Empirical methodology

4.1. Estimation approach

The starting point of our empirical analysis are two regression models used to predict outcomes for all observations (Cameron & Trivedi, 2022, p. 1292):

$$DRA_{1,i} = X_i\beta_1 + U_{1,i} \quad \text{if } HRA_i = 1 \tag{1}$$

$$DRA_{0,i} = X_i\beta_0 + U_{0,i} \quad \text{if } HRA_i = 0, \tag{2}$$

where DRA_1 and DRA_0 represent the dependent variables on decision-rights assignment, i.e. *DRA*, *opDRA*, and *strDRA*. The index i denotes the respective firm. *HRA* is a binary treatment variable indicating a firm's utilization of HR analytics. All of these variables of interest were introduced in Section 3.2. X is the matrix of control variables which will be discussed in Section 4.2, while the vectors β_1 and β_0 represent the parameters to be estimated. Finally, U_1 and U_0 denote stochastic error terms with zero mean and finite variance.

I am interested in estimating the average treatment effect (ATE) of HR analytics utilization on the level of decision-rights assignment in Swiss companies. For this purpose, I apply a doubly robust estimation strategy for the ATE developed in Robins et al. (1994). The doubly robust ATE estimator combines inverse probability weighting (IPW) with the specified regression models for the potential outcomes (1) and (2).

This estimation strategy is a three-step approach. The first step is a probit maximum likelihood estimation of the parameters of the treatment probability model

$$p(X_i) = Pr(HRA = 1 \mid X = X_i) = HRA_i = \Phi(X_i\beta), \tag{3}$$

where Φ is the cumulative distribution function of the standard normal distribution. These estimates, define the propensity score $\widehat{p}(X_i)$ and the IPWs (Austin, 2011; Austin and Stuart, 2015). After estimating the propensity scores, the analysis enforces common support within the sample.[19]

The second step estimates the regression models (1) and (2) and predicts the treatment-specific outcomes $\widehat{DRA}_{1,i} = x_i'\widehat{\beta}_1$ and $\widehat{DRA}_{0,i} = x_i'\widehat{\beta}_0$ for the entire sample to impute the unobserved counterfactual (Cameron & Trivedi, 2022, p. 1292). The third step incorporates the first two steps and estimates the potential outcomes by including a weighted residual term (Cameron & Trivedi, 2022, p. 1296). The doubly robust ATE is then computed by the difference of these weighted averages (e.g. Abdia et al., 2017; Cameron & Trivedi, 2022, p. 1296; Funk et al., 2011).[20]

This three-step procedure provides consistent estimates that can be interpreted in terms of causal inference if the stable unit treatment value assumption (SUTVA), the conditional independence assumption (CIA), and the common support assumption (CSA) are satisfied (e.g. Abdia et al., 2017; Austin, 2011; Imbens, 2004; Li, 2013; Narita et al., 2023).

For the present empirical analysis, CIA is the most critical assumption. This is because the analysis can only draw on cross-sectional data. However, in order to convincingly estimate causal ATEs within the scope of a selection-on-observables approach such as doubly robust ATE estimation, the availability of a comprehensive panel data set including pre-treatment control variables and post-treatment outcome variables would be required.

Although it appears unlikely that the ATEs resulting from the doubly robust estimator can be interpreted in terms of causal inference, the doubly robust property makes this estimator superior to parametric OLS or other semiparametric estimators such as IPW. The doubly robust property means that the estimator provides consistent ATEs even if either the regression models for the potential outcomes (1) and (2) or the IPW model (3) is

incorrectly specified (Abdia et al., 2017; Funk et al., 2011). In contrast, OLS and IPW require correct specification of the assumed functional form for the outcome model (OLS) or the treatment probability model (IPW).

4.2. Control variables

As discussed in the previous section, the econometric modeling approach applied in this analysis relies on selection-on-observables. Consequently, the validity of the econometric results depends critically on the inclusion of the appropriate control variables. To reduce ambiguity within the selection process of the covariates, this analysis grounds it on a solid theoretical framework. Specifically, it employs the three-legged stool framework as developed by Brickley et al. (2021, chapter 11). Central to this model is the concept of organizational architecture, which is viewed as a coherent system consisting of three interrelated components (or stool legs): the assignment of decision rights, the reward system, and the performance evaluation system. This organizational architecture is, in turn, shaped by the strategic choices, which are in themselves influenced by the broader business environment. The business environment comprises the technological factors, markets, and regulatory conditions an organization faces.

The core of this theoretical framework encompasses both the dependent and explanatory variables of interest. On the one hand, decision rights assignment is a distinct component, on the other hand, *HRA* relates to both the performance-evaluation and the reward system, as it both incorporates aspects of performance assessment as well as personnel development. Through this, the three-legged stool model presents itself as a natural candidate to aid in the selection process of the covariates. Following Brickley et al. (2021, chapter 11), the choice of the covariates will supplement information within the present stool-legs of the organizational architecture, cover the applied strategy, as well as the three elements that characterize the business environment.

To account for the technological dimension, the covariates include a standardized measure based on an organization's self-assessment of its technological state. Furthermore, a composite variable is incorporated, constructed using the double standardization approach. This composite variable integrates information on the proportion of employees and managerial staff equipped with mobile devices, the share of total training expenses allocated to technology-induced training, the percentage of recruitments requiring digital skills, and the proportion of investments directed towards digital equipment.[21] The market environment is captured by a standardized measure of the competitive pressure an organization faces, along with its geographic location, which accounts for local demand conditions. The geographic location is classified according to

Switzerland's seven greater regions (e.g. Espace Mittelland, Région lémanique, and Ticino). The regulatory environment is represented by the legal form of the company (private vs. capital company), the presence of an in-house employee representation (works council), and a dummy variable indicating whether the organization operates independently or as part of a larger organization.

The strategic decisions dimension includes the industry in which the organization operates (sixteen NOGA classes aggregated into nine categories, see Table A2) and two dummy variables that capture the organization's make-or-buy strategies over the past five years (internal and external expansion strategies, business unit sales, and outsourcing decisions). Two dummy variables indicating the use of performance targets and performance evaluations complement the coverage of the performance-evaluation system. The reward system is supplemented by the existence of a pay for performance scheme.[22]

Last, the analysis includes additional general covariates, namely, the existence of company supported further training measures, the number of employees at the organization (six size classes), and a dummy indicator reflecting that the survey was conducted at two different points in time.

The identification of possible confounders and the subsequent selection of control variables aligns and also relies on the existing literature. Specifically, Bechter et al. (2022) put forward the idea that dimensions such as the incentive and reward system as well as further market factors are key determinants of HR analytics. Furthermore, Schiemann et al. (2018) emphasize the relevance of firm-specific characteristics, while Bondarouk and Brewster (2016) conceptualize the importance of regulatory context, firm size, and industry affiliation for the development of electronic human resource management systems. While using a differing theoretical model as starting point, the present selection of control variables builds on prior research in the field.

Table A2 in the appendix provides descriptive statistics for all control variables.

4.3. Sampling weights

The use of sampling weights is discussed controversially in the literature. On the one hand, survey weights may be essential to avoid bias when estimating population means and they can mitigate potential non-response bias that may result from low response rates. On the other hand, their unnecessary use can lead to an inefficient estimator without reducing bias (Bollen et al., 2016; Busemeyer et al., 2022; Solon et al., 2015). In response, the literature urges researchers to check whether the estimated

results are overly sensitive to the chosen approach, namely by reporting both weighted and unweighted estimates, as this serves as a useful test against model misspecification (Solon et al., 2015).

Overall, the inclusion of sampling weights seems appropriate in the present situation, since the main goal of the investigation is to produce estimates representative for the Swiss Economy.[23] In addition, reliable information is available on the population distribution of the characteristics considered in the weighting procedure. However, to address the points raised by the literature the empirical analysis covers both possibilities. The baseline estimation process (Section 5) incorporates sampling weights. Additionally, Section 6.2 checks whether the ATE estimates are driven by the applied sample weighting procedure by reporting unweighted estimates.

The weighting process calibrates the underlying sample to fit the actual distribution of Swiss organizations with more than ten employees regarding the geographical location (seven Swiss greater regions), sector (sixteen sections according to the NOGA classification 2008), and number of employed people (three company size classes: small, medium, and large organizations).

4.4. Trimming

Treated companies with a propensity score close to zero and non-treated companies with a propensity score close to one can receive very large IPWs. Extreme weights can also be generated by the sample weighting procedure when a firm belongs to an under-sampled part of the firm population. If, as in the present case, both IPW and sample weighting are combined, the presence of extreme weights can be exacerbated because both weights are multiplied with each other. The existence of extreme weights can negatively impact the precision of the ATE estimate (Austin and Stuart, 2015). In such cases, trimming extreme weights (i.e. setting weights below and above a certain threshold value equal to the weight at the selected threshold) can effectively reduce the sampling variance of ATE estimates. However, this comes at the cost of an increased mean square error and generally leads to a deterioration in the achieved covariate balance (e.g. Cole & Hernán, 2008; Potter & Zheng, 2015).

Since trimming weights always entails the mentioned trade-off, there are various viable options to set the cut-off percentiles for trimming. The trimming thresholds most commonly discussed in the literature are the 1^{st} and 99^{th} percentile, the 2.5^{th} and 97.5^{th} percentile as well as the 95^{th} and 5^{th} percentile (e.g. Austin & Stuart, 2015; Hashimoto & Yasunaga, 2022; Lee et al., 2011; Stürmer et al., 2010; Thoemmes & Ong, 2016). Section 5.1 will discuss the impact of these various trimming thresholds on the covariate balance and argue for the optimal trimming cut-off in

the present case. Additionally, Section 6.2 checks if the applied approach has a large impact on the estimation results by reestimating the baseline results with differing trimming thresholds.

5. Empirical analysis

5.1. Balance diagnostics

Intuitively speaking, the goal of IPW is to create a synthetic sample which balances the observed covariates across the treatment variable. The level of achieved balance is, therefore, a crucial indicator about the goodness of the IPW. It follows that for an analysis applying IPW it is important to investigate the obtained balance and find the optimal modeling approach before the coefficients of interest are estimated. The most widely used approach to quantify the remaining level of covariance imbalance after IPW is to report the absolute standardized mean differences (ASMD) (e.g. Abdia et al., 2017; Austin, 2011; Austin & Stuart, 2015; Li, 2013; Narita et al., 2023). As indicated by the name, the ASMD detects differences in the means of covariates between the subgroups of treated and non-treated observations. A high level of ASMD after weighting could imply that the propensity score model is not correctly specified (Austin, 2011). In the literature, different thresholds for ASMD are considered acceptable. For example, Abdia et al. (2017) tolerate differences up to 20%. More commonly, however, a threshold of 10% is regarded as viable (e.g. Austin & Stuart, 2015). In any case, the modeling approach should aim to minimize the remaining imbalance between covariates, all else being equal.

The upper part of Table 2 presents summary statistics for the ASMD for different model specifications. Column (1) presents the ASMDs before

Table 2. Covariate balance diagnostics (ASMD).

	Pre-weighting (1)	Post-weighting (2)	Post-weighting (3)	Post-weighting (4)	Post-weighting (5)
Trimming percentiles			$1^{st}/99^{th}$	$2.5^{th}/97.5^{th}$	$5^{th}/95^{th}$
Average ASMD	0.069	0.060	0.045	0.039	0.042
Highest ASMD	0.264	0.186	0.154	0.102	0.109
N^0 >0.1	8	7	3	1	2
N^0 non-treated observations	413	377	378	379	376
N^0 treated observations	66	65	65	65	65
N^0 observations	479	442	443	444	441

Source: Swiss Employer Survey (SES); own calculations.

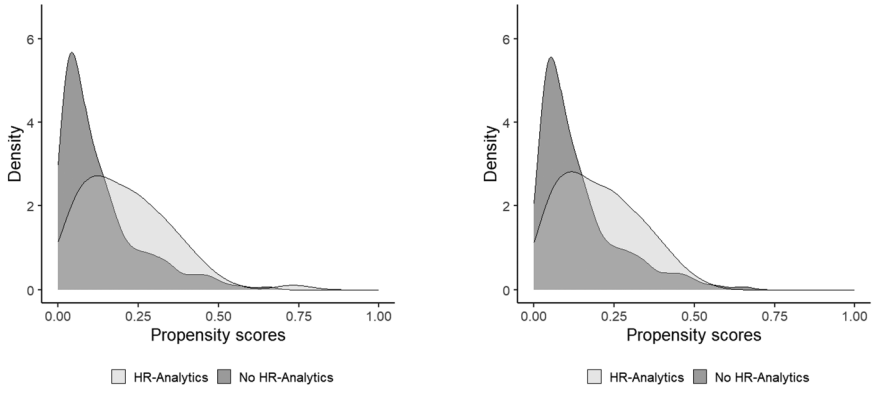
Notes: Average ASMD refers to the mean of the absolute standardized mean differences (ASMD) across all included covariates. *Highest ASMD* shows the highest value of ASMD associated with one of the covariates. $N^0 > 0.1$ denotes the number of covariates which have an ASMD higher than 10%. Common support is enforced in columns (2)–(5). Section 3.2 defines the explanatory variable of interest and Section 4.2 the control variables. Calculations include sample weights.

the weighting took place, i.e. in the unaltered original data set. Columns (2)–(5) show the values after weighting and enforcing common support with different trimming cut-offs. In column (2) no trimming of the weights takes place. In columns (3)–(5) the weights are trimmed at the $1^{st}/99^{th}$, $2.5^{th}/97.5^{th}$, or $5^{th}/95^{th}$ percentile, respectively.

Prior to applying the weights, eight covariates display an ASMD exceeding 10%, with the highest ASMD being 26%. While weighting the observations and enforcing common support decreases the highest ASMD, it remains above 10% but below 20% in all of the four specifications in columns (2) to (5). Using the 2.5^{th} and 97.5^{th} percentiles as a cut-off minimizes all three of the depicted summary statistics. Namely, the associated average ASMD (0.039), the maximum ASMD (0.102), as well as the number of covariates exceeding the threshold of 10% are lower than in any other specification. Even though, the differences are sometimes small (e.g. compare column (4) to column (5)) these cut-offs are clearly best suited to minimizes the difference in the distributions of the observed covariates across the treatment variable. The baseline estimation approach, therefore, uses the 2.5^{th} and 97.5^{th} percentiles as trimming cut-offs.

5.2. Common support

Figure 4 provides information on the distribution of the propensity scores by treatment status before and after enforcing common support. It applies the chosen baseline trimming cut-off at the 2.5^{th} and 97.5^{th} percentiles. It achieves this by showing the density functions of the propensity scores for organizations that adopt HR analytics and those that do not. For the empirical analysis to yield meaningful results, a substantial overlap



(a) Before enforcing common support (b) After enforcing common support

Figure 4. Propensity score densities. *Source*: Swiss Employer Survey (SES); own calculations. *Notes*: Number of observations: 479 before and 444 after enforcing common support.

between these two distributions is desirable (Busso et al., 2014). Subplot (a) presents the density functions prior to enforcing common support, while subplot (b) depicts them after common support has been enforced.

Overall, the plots reveal that although the mass of the PDF for organizations without HR analytics lies a little bit further to the left, there is a substantial degree of overlap between the two distributions even before enforcing common support. Comparing the two subplots shows that in subplot (b) the right tail of the distribution depicting observations with HR analytics is clipped, a look at Table 2 indicates that this observation relates to the one treated observation that is excluded. Furthermore, the left tail of the distribution without HR analytics becomes steeper. This reflects the impact of the 34 non-treated observations that are dropped.[24] Overall the PDFs provide convincing evidence that the there is no problem regarding common support in the present empirical investigation.

5.3. Baseline regression results

This section presents the doubly robust ATE estimation results regarding the empirical relationship between the application of HR analytics and decision rights assignment within organizations. As discussed in Section 2, from a theoretical perspective HR analytics can drive both centralization and decentralization. The present econometric approach measures the net effect over the centralizing and decentralizing forces which are at work simultaneously. Since higher hierarchical levels are coded as higher numbers, a positive coefficient would associate *HRA* with increased centralization, while a negative coefficient would associate *HRA* with increased decentralization.

The upper part of Table 3 presents the estimated relationship between the treatment variable *HRA* and the three composite outcomes of interest covering all types of decisions (*DRA*), and focusing on operational (*opDRA*) or strategic (*strDRA*) decisions.

The results indicate a negative and significant effect for all three composite variables at least on a 5% level. The application of *HRA*, therefore, exhibits a statistically significant relationship with decision rights being present on lower hierarchical levels in organizations. The presence of *HRA* is associated with a downward shift in the hierarchical level on which decisions are made by 0.320 standard deviations. The same interpretation applies to operational (−0.265 standard deviations) and strategic decisions (−0.296 standard deviations).

The bottom two parts of Table 3 now show the relationship between HR analytics and each of the nine underlying items, to explore on a more granular level where the observed relationships for the aggregate variables emerge from. For the individual items only one of the

Table 3. Average treatment effects: HR analytics on decision rights assignment.

Composite DRA	*HRA* (1)	*HRA* (2)	*HRA* (3)
DRA	−0.320***		
	(0.120)		
opDRA		−0.265**	
		(0.115)	
strDRA			−0.296**
			(0.120)

Operational DRA	*HRA* (1)	*HRA* (2)	*HRA* (3)	*HRA* (4)	*HRA* (5)	*HRA* (6)	*HRA* (7)
Work planning	−0.296**						
	(0.142)						
Definition of tasks		−0.451***					
		(0.156)					
Pace of work			0.023				
			(0.118)				
Sequence of work				−0.101			
				(0.114)			
Customer contact					−0.238		
					(0.145)		
Quality control						−0.025	
						(0.143)	
Replenishment							−0.155
							(0.146)

Strategic DRA	*HRA* (1)	*HRA* (2)
Investments	−0.424***	
	(0.158)	
Award		−0.065
		(0.109)

Source: Swiss Employer Survey (SES); own calculations.
Notes: $N = 444$. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The values in parentheses are robust standard errors. Table 2 denotes the balance statistics. Calculations include sample weights and IPW. Section 3.2 defines the variables of interest and Section 4.2 the control variables. Table A1 depicts the full regression results for the three models visible in the uppermost panel.

estimated coefficients is positive, this is regarding decisions about the pace of work. However, this coefficient is small and clearly not statistically significant (p-value = 0.85). All eight other depicted coefficients are negative. Three of the items seem to be the main drivers of the observed effects for the composite variables, as their coefficients are statistically significant. Among these three items are two belonging to the operational dimension (*Work planning* and *Definition of tasks*) and one who is part of the strategic dimension (*Investments in machinery or equipment*).

Overall the ATEs resulting from the doubly robust estimation approach provide strong evidence for the hypothesis that the application of HR analytics is related to delegating decision rights to lower levels in the hierarchical structure of organizations. From a theoretical perspective, this suggests that the effects of a reduction of the hidden action problem and an increase in the local information advantage dominate the centralizing forces (i.e. reductions in the local information advantage and *HRA* tools that take over decisions).

5.4. Differences between hierarchical levels

This section investigates where in the hierarchical structure the relationship between HR analytics and decision-rights assignment emerges from. In other words, it examines which hierarchical levels assume greater decision-making authority and which experience a reduction in their decision-making responsibilities. To achieve this, the nine items included in the construction of the three composite variables of interest (*DRA*; *opDRA*; and *strDRA*) are redesigned such that they do not take the three different hierarchical levels (see Table 1) into account but reflect the presence of decision-making authority on each hierarchical level through a dummy. These dummies take the following form:

$$Item_{TM,j} = \begin{cases} 1 \text{ if } Item_j = Top\ management \\ 0 \text{ if } Item_j = Lower\ and\ middle\ management \\ 0 \text{ if } Item_j = Non\text{-}managerial\ employees, \end{cases}$$

$$Item_{LMM,j} = \begin{cases} 0 \text{ if } Item_j = Top\ management \\ 1 \text{ if } Item_j = Lower\ and\ middle\ management \\ 0 \text{ if } Item_j = Non\text{-}managerial\ employees, \end{cases}$$

$$Item_{NM,j} = \begin{cases} 0 \text{ if } Item_j = Top\ management \\ 0 \text{ if } Item_j = Lower\ and\ middle\ management \\ 1 \text{ if } Item_j = Non\text{-}managerial\ employees. \end{cases}$$

Item refers to all nine question items as Table 1 defines them, *j* identifies the observation, *TM* refers to top management, *LMM* to lower and middle management, and *NM* to non-managerial employees. $Item_{TM}$, $Item_{LMM}$, and $Item_{NM}$ are dummy indicators which measure if decision-making power is present at the respective hierarchical level. The analysis now constructs three versions of *DRA* (DRA_{TM}, DRA_{LMM}, DRA_{NM}) as well as for *opDRA* ($opDRA_{TM}$, $opDRA_{LMM}$, $opDRA_{NM}$) and *strDRA* ($strDRA_{TM}$, $opDRA_{LMM}$, $strDRA_{NM}$) following the double standardization procedure and include the respective newly constructed dummy variables.

Table 4 presents the regression results. The first part of the table shows the results for the composite variable *DRA* at each of the three hierarchical levels, while the second and third part of the table focus on operational (*opDRA*) and strategic decisions (*strDRA*), respectively. A positive coefficient signifies a positive relationship between *HRA* and decisions-making power being located at the specific hierarchical level. Since the explanatory variable of interest (*HRA*) does not change the balance diagnostics as Table 2 presents them still apply.

Table 4. Average treatment effects: Differences between hierarchical levels.

	HRA (1)	HRA (2)	HRA (3)
DRA_{TM}	−0.258**		
	(0.111)		
DRA_{LMM}		0.065	
		(0.126)	
DRA_{NM}			0.302**
			(0.138)
$opDRA_{TM}$	−0.175		
	(0.110)		
$opDRA_{LMM}$		−0.069	
		(0.141)	
$opDRA_{NM}$			0.319**
			(0.148)
$strDRA_{TM}$	−0.331**		
	(0.134)		
$strDRA_{LMM}$		0.328**	
		(0.140)	
$strDRA_{NM}$			0.065
			(0.075)

Source: Swiss Employer Survey (SES); own calculations.

Notes: $N = 444$. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The values in parentheses are robust standard errors. Table 2 denotes the balance statistics. Calculations include sample weights and IPW. Section 3.2 defines the treatment variable and Section 4.2 the control variables.

The estimated coefficients for *HRA* are statistically significant at the 5% level in the regressions with DRA_{TM} and DRA_{NM} as outcome variables, showing a negative effect for the former and a positive effect for the latter. This result is in line with a reallocation of decision-making authority away from top management and towards non-managerial employees for the broad measure of decision-rights assignment. However, it does not necessarily indicate a direct transfer of decision rights from top management to non-managerial employees. Instead, it seems more likely that more centralized organizations reallocate decision rights from the top management to subsequent managerial levels, while more decentralized organizations shift them from the lower and middle management to non-managerial employees. Consistent with the current results, this scenario would yield a negative coefficient for the top management, a null effect for the lower and middle management, and a positive coefficient for the non-managerial employees.

For operational decisions as measured by *opDRA*, the effects align closely with those for *DRA* as they are in line with a similar shift in decision-making authority away from top management and towards non-managerial employees. While the former negative effect for $opDRA_{TM}$ is marginally not statistically significant (p-value = 0.11), the positive effect for $opDRA_{NM}$ is statistically significant.

For *strDRA* the results are also consistent with a shift of decision-making authority away from the top management, since the coefficient of interest

in the model with $strDRA_{TM}$ is negative and statistically significant. However, a contrasting dynamic to the results for *DRA* and *opDRA* is observed in regard to the effect on the lower and middle management, as the effect for $strDRA_{LMM}$ is large in magnitude and statistically significant. This signifies that strategic decision-making authority is primarily reallocated to the lower and middle management and not to the non-managerial employees. This result is consistent with the present descriptive statistics showing that non-managerial employees are rarely making strategic decisions.

In summary, the empirical evidence is consistent with the interpretation that decision-making authority is shifted away from the top management, for all three composite measures. For *DRA* and *opDRA* the reallocation of authority seems to benefit mostly non-managerial employees, while for strategic decisions the lower and middle managements experiences increases in decision-making authority.

6. Sensitivity analysis

6.1. Causal forest

In order to test the robustness of the baseline results, this section uses a different methodological approach to estimate the coefficients of interest. Specifically, I estimate ATEs using generalized causal forests.[25]

At an intuitive level, a causal forest consists of a large number of trees. Each tree partitions the sample into subgroups (leaves) based on covariate conditions, with the aim of creating subgroups that are as homogeneous as possible with respect to the outcome. To ensure diversity among the trees, to decorrelate them, and to avoid overfitting, each tree is built using a random subset of observations and covariates. Additionally, causal forests use an honest approach: some observations are left out during the tree-building process and are only used to estimate the treatment effect. Finally, the causal forest estimates the ATEs by aggregating the predictions of all the trees. Following Wager and Athey (2018) and Athey and Wager (2019) the present approach constructs one forest to model treatment assignment and another one to estimate the outcome in the absence of treatment effects. These two are then combined in a manner similar to how propensity score matching combines a selection model with an outcome model to estimate the treatment effects of interest (Labro et al., 2023).[26]

The first panel of Table 5 presents the estimated coefficients for the models with *DRA* (column 1), *opDRA* (column 2), and *strDRA* (column 3) as the dependent variables. These results are generally consistent with the baseline results, as the estimated coefficients are all negative and similar in magnitude to the previous estimates. More specifically, the coefficient in columns (1) and (3) is slightly lower and the coefficient in column (2) is marginally higher than in the baseline models. However, the associated

standard errors are larger than in the baseline models. As a result, the effects in columns (1) and (2) are only significant at the 10% level, and the effect in column (3) is marginally insignificant with an associated *p*-value of 0.118. Thus, although the statistical significance is lower than in the baseline model, the estimated results remain qualitatively similar.

6.2. Different weighting and trimming procedures

The choices regarding weighting and trimming inherently affect the estimated coefficients of interests. Even if the modelling applied in the baseline estimation seems appropriate, it is important to examine alternative specifications to see if the obtained estimates are highly sensitive to these choices. In this vein this subsection investigates if the obtained effect

Table 5. Sensitivity analysis.

	Causal forest		
	HRA (1)	*HRA* (2)	*HRA* (3)
DRA	−0.299*		
	(0.162)		
opDRA		−0.279*	
		(0.153)	
strDRA			−0.239
			(0.153)
N	479	479	479

	Different trimming and weighting approaches			
	No sample weights (1)	No trimming (2)	$1^{st}/99^{th}$ Perc. (3)	$5^{th}/95^{th}$ Perc. (4)
DRA	−0.175	−0.323***	−0.326***	−0.293**
	(0.122)	(0.112)	(0.116)	(0.126)
opDRA	−0.131	−0.279***	−0.278**	−0.239*
	(0.116)	(0.107)	(0.111)	(0.123)
strDRA	−0.203	−0.268**	−0.281**	−0.283**
	(0.131)	(0.118)	(0.118)	(0.123)
N	394	442	443	441

	Subsample: Swiss federal statistical office		
	HRA (1)	*HRA* (2)	*HRA* (3)
DRA	−0.241*		
	(0.123)		
opDRA		−0.218*	
		(0.128)	
strDRA			−0.165
			(0.109)
N	292	292	292

Source: Swiss Employer Survey (SES); own calculations.
Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The values in parentheses are robust standard errors. Calculations include sample weights and IPW. Section 3.2 defines the treatment variable and Section 4.2 the control variables.

estimates are driven by the chosen weighting approach and trimming threshold.

The second panel of Table 5 shows the estimation results following from estimations omitting sampling weights (column 1), and with three different trimming threshold, namely without any trimming (column 2), trimming the highest and lowest percentile (column 3), and trimming at the 5^{th} and 95^{th} percentile (column 4). Each depicted coefficient refers to a distinct estimation. As discussed in Section 5.1 the balance diagnostics for the three trimming thresholds applied in this section are not as convincing as for the chosen baseline specification. This is especially the case for the specification without any trimming (column 2). For the specification omitting sampling weights the observed balance diagnostics are very credible as the highest ASMD amounts to 0.041. However, the number of observations omitted to achieve common support is higher than in the other specifications, leaving 394 observations in the final sample.

The coefficients in column (1) reveal that the effects estimated without sampling weights are of a smaller magnitude than in the baseline specification. This observation indicates that within the population of organizations who answered the survey the observed effect is lower than when these are reweighted to fit the actual distribution of characteristics within the Swiss economy regarding industry, number of employees, and geographical characteristics. As the point estimates are clearly negative and the suggestive evidence following from this alternative approach still fits with the baseline results, I do not classify the statistical insignificance as greatly affecting the persuasiveness of the baseline results.

Furthermore, all coefficients in columns (2)–(4) are statistically significant and negative. Additionally, the magnitude of the coefficients is relatively similar to the baseline results. The baseline effects for both *DRA* and *opDRA* lie between those shown here with the three alternative trimming thresholds. For *strDRA* the baseline trimming approach leads to a slightly higher coefficient estimate than in the other three specifications. This deviation is, however, only minor. These findings indicate that the trimming approach chosen for the baseline specification does not drive the results.

6.3. Subsampling

One drawback of the data gathering process is that part of the sample relies on contact information collected via web scraping.[27] This section tries to analyze if any problems arise from this setting. It does this in two steps. First, it looks at differences in the mean values of the variables of interest and the control variables in the two subsamples. Additionally, it also reestimates the baseline specification within the subsample of the data set whose contact information came from the SFSO.

Table A2 in the appendix depicts descriptive statistics of all included variables. Among others, it depicts the mean values in the whole data set (column (1)), as well as in the subsets of observations contacted with information stemming from web scraping (column (2)) and from the SFSO (column (3)). A comparison for the variables of interest does not reveal big divergences of the means between the two subsamples. Among the control variables a considerable difference exists with regard to the number of employees. The web scraped sample incorporates a higher share of smaller organizations, especially with 10–19 employees. This was to be expected, at least to a certain degree, since the sample of the SFSO oversamples larger organizations. Furthermore, the web scraped part of the sample contains a larger share of organizations belonging to the NOGA classes I and R (hospitality and entertainment), while the SFSO part of the sample is more strongly represented in NOGA classes P and Q (education and health/social service). This indicates that a larger number of companies from NOGA classes I and R are organized in industry associations which publicly provide contact information, while the reverse is true for companies from NOGA classes P and Q. This seems very plausible. As the overall differences are not very pronounced, this comparison of the mean values does not indicate any concerning issues with the underlying sampling process.

Furthermore, the lowermost panel in Table 5 shows the results of the reestimation of the baseline specification only within the SFSO sample. The number of observations here amounts to 313 observations before enforcing common support and 292 after enforcing common support. The balance diagnostic do not indicate substantial differences in the covariates after weighting and trimming at the 2.5% and 97.5% percentile. The maximum ASMD amounts to 0.101. The estimated coefficients are again negative for all three composite versions of *DRA*, but they are smaller than in the baseline specification. While the estimated coefficient for *HRA* with *DRA* and *opDRA* as dependent variables are statistically significant at the 10% level, this is marginally not the case for *strDRA* (p-value = 0.13). This comparison indicates that the effect size in the SFSO sample is smaller than in the overall sample. However, this difference is not very pronounced. The omission of part of the sample also results in a loss of statistical power which can partly explain the non-significant effect estimate for *strDRA*.

7. Discussion and conclusion

7.1. Theoretical contribution

New digital technologies and data analytics tools change the way we work. This development also affects the area of human resource management. Under the umbrella term HR analytics such innovations influence the way supervisors manage their employees. As this is a relatively new

trend empirical evidence is scarce in this research area. This paper investigates the relationship between HR analytics and the assignment of decision rights within organizations, combining theoretical considerations with empirical evidence to shed light on the underlying mechanisms.

This paper offers both theoretical and empirical contributions to the literature. The theoretical framework, taking a simple principal-agent model as starting point, integrates and extends existing theoretical contributions, thereby offering a novel and comprehensive perspective on the different mechanisms through which HR analytics may influence the assignment of decision rights within organizations. From a theoretical perspective it is ex-ante unclear if HR analytics leads to a more centralized or decentralized organizational architecture as opposing forces are at work simultaneously. This is reflected in the formulation of both a *centralization hypothesis* and a *decentralization hypothesis*. Advanced digital tools have the ability to take over decision-making authority, resulting in more centralized organizations. Additionally, HR analytics can influence the information asymmetry between principal and agent. On the one hand, if it provides people in higher hierarchical positions with more reliable information about the workflows, it decreases the informational advantage of lower-level employees, which leads to less reasons to delegate decision rights. On the other hand, the newly available data can also be informative to lower-level employees, maybe even increasing their information advantage. Finally, through its function as a monitoring tool, HR analytics dampens the hidden action problem. By reducing the likelihood of counterproductive behavior it increases the willingness of managers to grant the employees autonomy in decision-making.

The empirical contribution adds to the literature by providing novel insights on the relationship between HR analytics and decision-rights assignment, thereby testing which forces of the theoretical framework currently prevail in the Swiss economy. A country that has yet to be examined in this research area, even though it is widely acknowledged as the most innovative economy globally (Dutta et al., 2024). The empirical results support the decentralization hypothesis, as organizations which make use of HR analytics are more decentralized. The results hold for a composite measure of decision-rights assignment (*DRA*), as well as for operational (*opDRA*) and strategic decisions (*strDRA*). On a more granular level, the relationship is visible for decision rights in the areas of work planning, task definition, and regarding investments in machinery or equipment.

From a theoretical perspective, these results suggest that the dampening of the hidden action problem and the increase in the local information advantage currently dominate the centralizing forces (i.e. reductions in the local information advantage and *HRA* tools that take over decisions) in Swiss organizations.

For *DRA* and *opDRA* the results align with a reallocation of decision-making authority away from the top management and towards non-managerial employees. In contrast, the effects for *strDRA* are consistent with a shift of decision rights from the top management to the lower and middle management. This divergence in the results between *strDRA* and *opDRA* is not surprising, as strategic decision rights are typically present at higher levels of the hierarchy as operational decisions.

Recent theoretical work on HR analytics draws on diverse conceptual foundations, including labor process theory (Kellogg et al., 2020), work design theory (Parent-Rocheleau and Parker, 2022), or adaptations of the ability-motivation-opportunity (AMO) framework (Bechter et al., 2022). Closely related to the present study, Meijerink and Bondarouk (2023) argue that HR analytics can both restrain and enable employee autonomy. However, in their framework, this duality is shaped by worker resistance (*algoactivism*), while the present paper argues that cooperative employees can experience empowerment. Labro et al. (2023), building on agency-theory, likewise discuss the potential for such a dual effects. Their analysis focuses on the ambiguous consequences for the local information advantage, an aspect also captured in the present theoretical framework. However, they do not emphasize the direct channel through which enhanced monitoring reduces the hidden action problem, nor do they address the implications of decision automation. Overall, while prior studies recognize the potential for dual effects of HR analytics, the theoretical framework proposed here extends this line of reasoning by approaching the phenomenon from a different starting point and by broadening the underlying conceptual basis.

Seemingly, the empirical findings stand in contrast to two existing empirical studies. Labro et al. (2023) document a centralizing effect of predictive analytics, while Kinowska and Sienkiewicz (2023) find a negative relationship between algorithmic management and job autonomy.[28] However, rather than being contradictory, the variation in findings may highlight how the relative strength of the different theoretical mechanisms varies across contexts. Both predictive analytics, as examined by Labro et al. (2023), and algorithmic management, as studied by Kinowska and Sienkiewicz (2023), involve highly advanced technological tools. It is plausible that such algorithmic technologies often entail automation of decision-making processes. This would suggest that HR analytics acts as a decentralizing force, as long as that the technologies in use do not overtake a substantial share of decision-making authority.

Overall, the empirical results suggest that, at least at the present time, Swiss organizations predominantly combine HR analytics with employee empowerment through the delegation of decision rights.

7.2. Practical implications

Understanding how the use of HR analytics influences the allocation of decision rights is crucial for both managerial and non-managerial employees. For employees, changes in the distribution of decision-making authority directly affect their daily tasks, responsibilities, and scope of autonomy. For managers, decisions regarding both the application of HR analytics and distribution of decision rights are not only central to broader workplace design strategies but can also have far-reaching consequences for outcomes like organizational performance.

To date, much of the research on HR analytics has focused on the gig economy, frequently highlighting adverse developments such as the erosion of worker autonomy (e.g. Gandini, 2019; Liang et al., 2025; Newlands, 2021; Veen et al., 2020; Wood et al., 2019). In contrast, this study shows that in the context of traditional employment, the use of HR analytics does not necessarily lead to centralization, but can even accompany an extension of the decision-making authority of employees. For Swiss employees this result can inspire optimism, as it does not seem that HR analytics is currently used to create a dystopian work environment as feared by proponents of the new *digital taylorism*.

A comparison with the related studies of Kinowska and Sienkiewicz (2023) and Labro et al. (2023) suggests that the direction of the effect depends on the specific type of technology employed. Advanced predictive or algorithmic systems concentrate authority when they are designed to automate decision processes. Furthermore, the theoretical framework developed in Section 2 suggests that employees may strengthen their local information advantage if they are given access to the newly generated data.

For practitioners, especially managers seeking to use HR analytics in a way that empowers rather than limits employees decision-making authority, these findings imply two key considerations. First, care should be taken to ensure that the HR analytics tools themselves do not assume excessive decision-making authority. Second, the data and insights generated by HR analytics systems should, wherever possible, be made accessible to employees so that they can actively integrate this information into their daily work. In this way, HR analytics can be leveraged not as a substitute for human judgment, but as a support tool that fosters greater employee autonomy and informed decision-making.

7.3. Limitations and further research

While this study offers valuable theoretical considerations and empirical insights into the role of HR analytics in shaping decision-making

authority, several limitations must be acknowledged, which also open avenues for future research.

First, a limitation, yet also a distinguishing feature, of this study is that the empirical analysis focuses exclusively on the traditional employment sector and does not cover the gig economy. As a result, the findings are not generalizable to platform-based work arrangements, which have been the focus of much of the existing literature.

Second, the estimation strategy extends beyond conventional OLS regressions and includes rigorous robustness checks. However, because the analysis is based on cross-sectional data and relies on a selection-on-observables approach, a causal interpretation of the results is not possible. It is also not possible to prove the direction of the observed relationship, as reverse causation may be present.[29] Future research should aim to overcome this limitation by employing panel data or, in an ideal scenario, by observing outcomes in settings where the introduction of HR analytics is randomized across organizations.

Third, a comparison with existing studies (Kinowska and Sienkiewicz, 2023; Labro et al., 2023) suggests that the theoretical mechanisms proposed in this paper may vary in relevance depending on the organizational and technological context. However, the available data did not allow to investigate the relative contributions of these mechanisms to the estimated effect. Future work, given appropriate data, should seek to unpack these mechanisms in greater detail. For example, by identifying under which conditions specific channels become more or less influential.

Lastly, the conceptualization and measurement of HR analytics in this study is very broad, conflating both basic descriptive tools and advanced AI-driven systems. While this inclusive approach is consistent with widely used definitions in the literature (e.g. Marler & Boudreau, 2017; Sakib et al., 2024) and aligns with prior empirical work (e.g. Aral et al., 2012; Bechter et al., 2022; Belloc et al., 2023), it still limits the ability to identify which specific technologies and managerial approaches are driving the observed effects. A more disaggregated investigation was not possible in this project due to data limitations. Future studies should seek to investigate HR analytics by type, functionality, or level of sophistication. The emergence of the literature specifically focusing on algorithmic management can be viewed as a promising step in this direction, even tough it only captures one specific subfield of HR analytics.

Notes

1. HR analytics is also known under the terms workforce analytics, human capital analytics, or people analytics (Bonilla-Chaves and Palos-Sánchez, 2023; Huselid, 2018).

2. Accordingly, unless explicitly stated otherwise, the reviewed literature solely focuses on traditional employment contexts rather than the gig economy.
3. The inclusiveness of this definition of HR analytics is not unique but also visible in other definitions such as Sakib et al. (2024).
4. Closely related to the HR analytics literature is a strand of literature focusing on electronic performance monitoring. However, this literature is also still in its early stages (e.g. König, 2025; Moore et al., 2018; Ravid et al., 2020; Siegel et al., 2022).
5. While the theoretical starting point is similar to the present project, they do not coincide as Aral et al. (2012) focus on performance effects.
6. There are, for example, papers investigating the decentralizing effects of high-performance work systems (Colombo et al., 2007), high-involvement mangement (Zoghi and Mohr, 2011), or self-managed teams (Tata and Prasad, 2004).
7. Examples are plentiful and range from investigations of the effects of investments into ICT (Hitt and Brynjolfsson, 1997), the level of present ICT capital (Mocetti et al., 2017), the diffusion of technologies (Acemoglu et al., 2007), the usage of information and communication technology (Bloom et al., 2014), digital transformation (Yang et al., 2024), the application of enterprise resource planning software (Doherty et al., 2010), the usage of robotics (Dixon et al., 2021), to equipping employees with ICT (Gerten et al., 2022).
8. Belloc et al. (2023) also use the ECS data and find a positive relationship between employee representation and the adoption of HR analytics.
9. Although they use the same data source, Bechter et al. (2022) and Kinowska and Sienkiewicz (2023) conceptualize their operator differently, such that Bechter et al. (2022) investigates HR analytics, while Kinowska and Sienkiewicz (2023) study algorithmic management.
10. The weather data and pedestrian patterns were gathered to train the scheduling software, indicating that their collection is part of HR analytics.
11. Each spatially separated organizational unit of an enterprise is considered a distinct organization. In the following, I will use the terms organization, business, firm, and company equivalently.
12. The Swiss Federal Statistical Office (SFSO) provided this sample and the addresses of the organizations. In the drawing of the sample, larger organizations were disproportionately represented to ensure a sufficient coverage of this group. The sample excludes organizations which are active in public administration, farming, and the mining sector.
13. The relevant literature shows that even though low response rates can be associated with the presence of non-response bias, this relationship is not strong (e.g. Brick, 2013; Curtin et al., 2000; Groves, 2006; Groves & Peytcheva, 2008; Keeter et al., 2000).
14. The sample restrictions refer to the exclusion of organizations which are active in public administration, farming, and the mining sector, as well as organizations with less than 10 employees.
15. The double standardization procedure is very commonly used in the personnel economics literature. Examples include Beckmann and Kräkel (2022); Bresnahan et al. (2002); Hitt and Brynjolfsson (1997); Tambe et al. (2012).
16. The underlying variables, before standardization, take the value one if the organization selected *non-managerial employees*, two represents *lower and middle management*, and three *top management*.
17. The idea of differentiating between different types of decisions is well established. For example, Hitt and Brynjolfsson (1997) differentiate between structural and in-

dividual decentralization and Tata and Prasad (2004) distinguish between macro- and micro-level decentralization. Van Den Heuvel and Bondarouk (2017) also talk about operational and strategic decision making in the context of HR analytics.

18. While the use of survey weights in the estimation of regression models is not seen as universally beneficial, its use for the presentation of descriptive results is less contested (e.g. Bollen et al., 2016; Solon et al., 2015). Section 4.3 discusses the weighting process in more detail.
19. Common support ensures that the analysis only includes observations with comparable counterparts. This is achieved by excluding non-treated observations with a propensity score lower than the lowest one associated with a treated observation, and by excluding treated observations with a propensity score higher than the highest one associated with a non-treated observation.
20. We estimate the ATEs and the parameters of the covariates using Horvitz-Thompson-type robust standard errors which are commonly applied in econometric analyses when weighting plays a role (Lumley, 2011; Lumley and Scott, 2017; Narita et al., 2023; Ridgeway et al., 2021).
21. This measure of digital affinity aligns closely with the taxonomy of digital-intensive sectors developed by Calvino et al. (2018), which combines indicators such as ICT investment, ICT intermediates purchases, robot usage, ICT specialists, and online sales. Furthermore, it is applied in Lehmann and Beckmann (2025).
22. The variables covering the performance-evaluation and the reward system, i.e. performance targets, performance evaluations, and pay for performance schemes, could mediate the effect between HRA and DRA. However, as simple OLS-regressions do not reveal a significant relationship between HRA and any of these variables, this does not seem to be the case. Still, their inclusion in the regression model is the more cautious approach, as any possible mediated effects are absorbed. A reestimation of the baseline models without these control variables results in almost identical coefficients.
23. In other words, the main goal of the inclusion of sampling weights in the present analysis is not the reduction of non-response bias but the estimation of representative results.
24. The lower part of Table 2 reports the number of observations excluded due to enforcing common support. This reduces the sample size from 479 to between 441 to 444 observations, indicating that depending on the specification between 38 and 35 observations are outside of the area of common support. The variation in the number of observations lost across the four different trimming levels is minimal.
25. Wager and Athey (2018) and Athey and Wager (2019) derive the applied estimation approach. Athey et al. (2019) present a use-case example including coding information for R. Labro et al. (2023) is an example of the application of generalized causal forests within the management literature.
26. There are several tuning parameters involved in the growth of the forest. As in Athey et al. (2019), I determine all tuning parameters through a cross-validation procedure. Additionally, to account for the relatively small sample size, I grow a relatively large number of trees (5000) in each forest. As encouraged by Athey et al. (2019) and derived by Basu et al. (2018), I first grow a *pilot random forest* that includes all the features of interests and subsequently reestimate the ATEs using only the covariates that turn out to be important, i.e. those most frequently used to partition the sample in the trees of the *pilot forest*. While the estimated coefficients are slightly lower when the *pilot forest* is omitted, the underlying message of the results remains consistent.

27. Section 3.1 discusses the data gathering process.
28. As a reminder: Labro et al. (2023) does not specifically focus on the context of human resource management.
29. However, conceptualizing the effect as flowing from HR analytics to the assignment of decision rights aligns with a substantial body of related theoretical and empirical research (e.g. Kellogg et al., 2020; Kinowska & Sienkiewicz, 2023; Labro et al., 2023; Parent-Rocheleau & Parker, 2022).

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Data availability statement

The data for the empirical analysis is available in an anonymous form upon reasonable request from the author.

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Appendices

Table A1. Overview: full regression results.

	DRA (1)	*opDRA* (2)	*strDRA* (3)
HRA	−0.320***	−0.265**	−0.296**
	(0.120)	(0.115)	(0.120)
State of techn. equipment	0.131**	0.167***	−0.045
	(0.056)	(0.052)	(0.061)
Level of digitalization	−0.098*	−0.091	−0.063
	(0.057)	(0.060)	(0.047)
Performance targets	−0.166	−0.063	−0.365***
	(0.156)	(0.170)	(0.109)
Performance pay	−0.250**	−0.276**	−0.036
	(0.115)	(0.112)	(0.124)
Performance evaluations	−0.029	0.079	−0.321**
	(0.202)	(0.218)	(0.141)
Further training	−0.341**	−0.449***	0.158
	(0.159)	(0.163)	(0.133)
Competitive pressure	0.103	0.112*	0.018
	(0.069)	(0.061)	(0.083)
Location: Espace Mittelland	0.169	0.190	0.013
	(0.167)	(0.171)	(0.173)
Location: Région lemanique	0.653***	0.755***	−0.003
	(0.206)	(0.199)	(0.201)
Location: Nortwestern Sw.	−0.379*	−0.362*	−0.214
	(0.217)	(0.194)	(0.271)
Location: Eastern Sw.	0.058	0.050	0.047
	(0.160)	(0.165)	(0.199)
Location: Ticino	0.072	0.136	−0.151
	(0.197)	(0.225)	(0.260)
Location: Central Sw.	−0.188	−0.152	−0.184
	(0.201)	(0.199)	(0.185)
Location: Zurich		Reference category	
Capital company	0.157	0.115	0.188
	(0.152)	(0.145)	(0.174)
Works council	0.179	0.235*	−0.081
	(0.140)	(0.133)	(0.141)
Legally independent	0.231	0.170	0.274
	(0.181)	(0.158)	(0.193)
Strategy: Expansion	−0.083	−0.128	0.089
	(0.116)	(0.124)	(0.098)
Strategy: Reduction	0.192	0.235*	−0.038
	(0.138)	(0.134)	(0.146)
10–19 employees	0.559	0.479	0.471

(*Continued*)

Table A1. Continued.

	DRA (1)	*opDRA* (2)	*strDRA* (3)
	(0.352)	(0.314)	(0.384)
20–29 employees	0.622**	0.531**	0.531
	(0.316)	(0.269)	(0.394)
30–49 employees	0.263	0.159	0.41
	(0.327)	(0.271)	(0.427)
50–99 employees	0.115	0.06	0.208
	(0.350)	(0.297)	(0.427)
100–249 employees	0.304	0.255	0.272
	(0.317)	(0.258)	(0.446)
> 249 employees		Reference category	
NOGA class: C, D & E	0.221	0.127	0.362
	(0.338)	(0.301)	(0.351)
NOGA class: F	0.654*	0.732**	0.065
	(0.375)	(0.327)	(0.419)
NOGA class: G & H	0.301	0.229	0.337
	(0.347)	(0.305)	(0.369)
NOGA class: I & R	0.593	0.579	0.299
	(0.402)	(0.371)	(0.381)
NOGA class: K & L	0.618*	0.514	0.564
	(0.373)	(0.344)	(0.365)
NOGA class: J & M	0.505	0.468	0.324
	(0.351)	(0.314)	(0.368)
NOGA class: N	0.187	0.148	0.194
	(0.412)	(0.379)	(0.402)
NOGA class: P & Q	0.651*	0.631*	0.343
	(0.369)	(0.325)	(0.379)
NOGA class: S		Reference category	
Wave	−0.018	−0.022	0.004
	(0.141)	(0.140)	(0.116)
Intercept	−0.535	−0.467	−0.426
	(0.546)	(0.494)	(0.620)

Source: Swiss Employer Survey (SES); own calculations.

Notes: $N = 444$. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The values in parentheses are robust standard errors. Table 2 denotes the balance statistics. Calculations include sample weights and IPW. Section 3.2 defines the variables of interest and Section 4.2 the control variables.

Table A2. Descriptive statistics of the included variables.

Variables of interest	Mean			SD	Minimum	Maximum
	Total (1)	Web (2)	Survey (3)	Total (4)	Total (5)	Total (6)
HRA	0.138	0.108	0.153	0.345	0	1
DRA	0	0.112	−0.059	1	−4.407	2.124
opDRA	0	0.103	−0.055	1	−2.308	2.337
strDRA	0	0.073	−0.039	1	−7.884	0.328
WP	2.084	2.169	2.038	0.635	1	3
Def	2.301	2.355	2.272	0.558	1	3
Pace	1.952	1.988	1.933	0.663	1	3
Seq	1.927	1.946	1.917	0.635	1	3
Cust	1.948	1.928	1.958	0.792	1	3
Qual	2.129	2.223	2.080	0.603	1	3
Repl	1.541	1.566	1.527	0.658	1	3
Inv	2.871	2.898	2.856	0.377	1	3
Award	2.952	2.964	2.946	0.242	1	3
State of techn. equipment	0	−0.119	0.063	1	−3.177	1.776
Level of digitalization	0	−0.155	0.082	1	−1.785	4.228
Performance targets	0.885	0.898	0.879	0.319	0	1
Performance pay	0.351	0.325	0.364	0.478	0	1
Performance evaluations	0.873	0.825	0.898	0.334	0	1
Further training	0.883	0.837	0.907	0.322	0	1
Competitive pressure	0	0.057	−0.030	1	−1.270	1.270
Location: Espace Mittelland	0.240	0.259	0.230	0.428	0	1
Location: Région lemanique	0.127	0.120	0.131	0.334	0	1
Location: Nortwestern Sw.	0.152	0.169	0.144	0.360	0	1
Location: Eastern Sw.	0.127	0.145	0.118	0.334	0	1
Location: Ticino	0.092	0.072	0.102	0.289	0	1
Location: Central Sw.	0.100	0.120	0.089	0.301	0	1
Location: Zurich	0.161	0.114	0.185	0.368	0	1
Capital company	0.697	0.735	0.677	0.460	0	1
Works council	0.307	0.253	0.335	0.462	0	1
Legally independent	0.800	0.837	0.780	0.401	0	1
Strategy: Expansion	0.559	0.512	0.585	0.497	0	1
Strategy: Reduction	0.150	0.187	0.131	0.358	0	1
10–19 employees	0.159	0.331	0.067	0.366	0	1
20–29 employees	0.148	0.120	0.163	0.356	0	1
30–49 employees	0.171	0.127	0.195	0.377	0	1
50–99 employees	0.223	0.169	0.252	0.417	0	1
100–249 employees	0.180	0.157	0.192	0.384	0	1
>249 employees	0.119	0.096	0.131	0.324	0	1
NOGA class: C, D & E	0.219	0.193	0.233	0.414	0	1
NOGA class: F	0.150	0.187	0.131	0.358	0	1
NOGA class: G & H	0.079	0.060	0.089	0.271	0	1
NOGA class: I & R	0.119	0.235	0.058	0.324	0	1
NOGA class: J & M	0.081	0.078	0.083	0.274	0	1
NOGA class: K & L	0.079	0.078	0.080	0.271	0	1
NOGA class: N	0.063	0.048	0.070	0.243	0	1
NOGA class: P & Q	0.171	0.102	0.208	0.377	0	1
NOGA class: S	0.038	0.018	0.048	0.190	0	1
Wave	0.347	1	0	0.476	0	1

Source: Swiss Employer Survey (SES); raw data.

Notes: $N = 479$. The table depicts the mean of the overall sample (*Total*), as well as of the two subsamples of establishments whose contact information we received from the Swiss Federal Statistical Office (*Survey*) and via web scraping (*Web*). *SD* denotes the standard deviation, while *Minimum* and *Maximum* denote the respective lowest and highest values present in the data set.