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Assessing the Impact of Algorithmic Screening on Time-to-Productivity and Quality of Hire: A Simulation-Based Analysis

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ABSTRACT

Organizations increasingly screen job applicants with algorithmic tools, yet the evidence on what this does to how fast new hires become productive, and to the quality of those hires, remains thin. This study sets out a four-stage analysis that compares an algorithmically screened cohort with a traditionally screened cohort on two outcomes, time-to-productivity and a composite quality-of-hire index. Working from a simulated dataset of 1,000 hires built to resemble real hiring records, the analysis cleans the data and profiles it, constructs the two outcome measures, tests for group differences, and models the time until each hire reaches full productivity. Algorithmic screening was associated with a shorter time-to-productivity, 58.54 days against 67.10 days, a difference of 8.55 days (95% CI 6.16 to 10.95), $t = 7.01$, $p < .001$, with a small-to-moderate effect size (Cohen's $d = 0.45$). The quality-of-hire index was higher for the algorithmic cohort, 57.22 against 50.24 on a 0 to 100 scale, $t = 11.40$, $p < .001$, $d = 0.72$. A Cox proportional-hazards model, adjusting for role and prior experience, gave a hazard ratio of 1.68 (95% CI 1.47 to 1.92, $p < .001$) for reaching full productivity under algorithmic screening. The method is reproducible and can be applied to an organization's own hiring records once they are supplied.

Keywords: Algorithmic screening, Time-to-productivity, Quality of hire, Recruitment analytics, Survival analysis, Hypothesis testing, People analytics, Candidate selection.

INTRODUCTION

Hiring decides a large part of what an organization can do, and the cost of getting it wrong is paid over years in lost output and repeated recruitment [2], [45]. For most of the past decade the screening of applicants has moved from manual review of resumes toward tools that rank and filter candidates automatically [6], [10], [30]. Chatbots conduct first-round conversations, parsers read resumes at scale, and scoring models rank applicants before a recruiter sees them [2], [33], [38]. Adoption has been quick, and the claims made for these tools are strong, faster processing, lower cost per hire, and better matches between people and roles [32], [52].

Two outcomes sit at the center of those claims and receive less direct measurement than they deserve. The first is time-to-productivity, the span between a person's start date and the point at which they perform at the level expected of the role. The second is quality of hire, a broader judgement that folds together performance, retention, and the satisfaction of the hiring manager [8], [45]. Recruitment metrics have long leaned on what is easy to count, time-to-fill and cost-per-hire, because the outcomes that matter most are lag measures that only reveal themselves months after a person joins [45]. When screening changes, these are the outcomes that should move, and they are the ones this study measures.

The gap this paper addresses is methodological as much as empirical. Studies of algorithmic hiring tend to report model accuracy on a prediction task, or survey perceptions of fairness, rather than estimate the effect

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of screening method on downstream outcomes with the cohort as the unit of analysis [3], [19], [47]. A credible answer needs more than a single test. It needs clean data, outcome measures that are defined before they are compared, a comparison that reports effect sizes and not only p-values, and a treatment of time that respects the fact that some hires have not yet reached full productivity when the data are collected [7], [56].

This study sets out that analysis in four stages and demonstrates it on a simulated cohort of 1,000 hires. Stage one cleans and profiles the data. Stage two constructs the quality-of-hire index and the time-to-productivity measure. Stage three tests whether the two screening methods differ on these outcomes. Stage four models the time until a hire reaches full productivity, adjusting for role and prior experience. The contribution is a reproducible procedure, reported in enough detail to be run again on an organization's real hiring records, together with an illustration of the kind of evidence it produces.

LITERATURE REVIEW

The literature relevant to this study falls into six areas. Table 1 summarizes each area, the gap it leaves, and the sources, and the paragraphs below take the areas in turn.

AI and algorithmic screening in recruitment

A first body of work documents how far artificial intelligence has entered recruitment and what organizations expect from it. Accounts of chatbots acting as first-contact recruiters describe systems that answer candidate questions and conduct structured conversations at scale [2], [10]. Reviews of the adoption of these tools in software firms and service sectors report gains in speed and reductions in manual effort, alongside caution about over-reliance [6], [11], [13]. Several studies tie the use of AI in talent acquisition to employer reputation and to the willingness of candidates and managers to trust automated decisions [30], [33], [38], [39]. Others take stock of the field and ask where human judgement still belongs in a process that software now mediates [32], [51], [52].

Resume screening, parsing and candidate ranking

A second area concerns the technical task at the heart of screening, reading a resume and ranking it against a role. Work here applies natural language processing to parse free text and matches it to job requirements [15], [24], [28]. Methods range from cosine similarity between resume and job description to transformer-based sentence encoders and large language model agents that score and shortlist applicants [34], [36], [41], [43], [54]. Surveys of these mechanisms compare their accuracy and the features they rely on, and decision-support systems rank applicants to assist recruiters rather than replace them [18], [35], [40].

Quality of hire, selection and recruitment metrics

A third strand asks what a good hire is and how to measure it. Quality of hire has been called the hardest and most valuable construct in recruitment because it depends on lag measures such as performance and tenure that appear only after a person has been in post [45]. Studies connect recruitment quality to employer reputation and to the long-run value a hire delivers [8], [48]. Work on personnel selection builds multi-criteria models that weigh candidate attributes against role demands [16], [49], and research on selection ethics and the gatekeeping role of human resources sets out the standards a selection process is expected to meet [4], [20], [27].

Predicting hiring outcomes, performance and retention

A fourth area applies machine learning to predict what a hire will do after joining. Models predict employee performance from pre-hire and early-tenure data using decision trees, ensembles, and gradient boosting [3], [5], [17]. Related work predicts attrition and turnover intention so that retention effort can be directed where it matters [7], [21], [37]. Studies of hiring-outcome prediction in online labor markets and of neural models

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for predictive hiring report the features that carry the most weight, and recent work extends these methods to the detection of socially desirable responding in selection [44], [47], [56], [60].

Algorithmic fairness, bias and ethics in hiring

A fifth strand examines whether automated screening is fair and what follows when it is not. Experimental work measures how candidates perceive the fairness of algorithmic tools and finds that perceived fairness shapes acceptance [19], [50]. Studies test whether personality-based or other algorithms narrow or widen demographic gaps in who is selected [25], [29]. A legal and ethical literature sets out the safeguards that algorithmic human resource management should carry, from the right to work to protection against fraudulent applications [23], [55].

People analytics, HR technology and the future of work

A sixth area places screening inside the wider turn toward data-driven human resource management. Work on people analytics argues for evidence-based management of employees and reports how analytics functions are built and used [26], [59]. Studies track the effect of digital tools on recruitment and retention and on the attractiveness of the employer to job seekers [12], [46], [48], [57]. Large-scale analyses of hiring and retention networks describe the structure of labor markets at the level of whole sectors [1], [31], and broader reviews consider how automation and the changing nature of work reshape the human resource function and the civil service [9], [14], [22], [42], [53], [58].

A pattern runs through these six areas. The literature describes the tools, scores them on ranking or prediction tasks, and debates their fairness, yet it rarely measures the two outcomes that a screening change is meant to move, how fast a hire becomes productive and how good that hire turns out to be [45], [8]. Where quality of hire is discussed, it stays a construct rather than a measured, reproducible index [45], and where machine learning is applied it reports model scores rather than the effect of the screening method on the hire [3], [17], [47]. Table 1 sets out each gap against the area that leaves it. This manuscript addresses them together, with defined outcome measures, a comparison that reports effect sizes, and a survival model that respects censored time.

Table 1. Summary of the reviewed literature by theme, the gap each area leaves, and the sources.

Theme	What the literature covers	Gap addressed in this manuscript	Sources
A. AI and algorithmic screening in recruitment	Adoption of AI tools and chatbots, trust in automated decisions, and employer reputation.	These accounts report adoption and expectations but seldom measure what screening does to hire outcomes. This manuscript measures time-to-productivity and quality of hire as outcomes of the screening method.	[2], [6], [10], [11], [13], [30], [32], [33], [38], [39], [51], [52]
B. Resume screening, parsing and candidate ranking	NLP parsing, similarity scoring, and transformer or LLM ranking of applicants.	This work is judged by ranking accuracy, not by what happens after the hire. This manuscript links the screening method to post-hire productivity and quality.	[15], [18], [24], [28], [34], [35], [36], [40], [41], [43], [54]

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C. Quality of hire, selection and recruitment metrics	Defining and measuring hire quality, multi-criteria selection, and selection ethics.	Quality of hire is treated as a construct that is hard to operationalize. This manuscript builds a weighted, reproducible quality-of-hire index and tests it across the two cohorts.	[4], [8], [16], [20], [27], [45], [48], [49]
D. Predicting hiring outcomes, performance and retention	Supervised models for employee performance, attrition, and hiring outcomes.	These studies report model scores on a prediction task. This manuscript estimates the screening effect as a measured outcome, with effect sizes and covariate adjustment.	[3], [5], [7], [17], [21], [37], [44], [47], [56], [60]
E. Algorithmic fairness, bias and ethics in hiring	Perceived fairness, demographic bias, and legal or ethical safeguards.	Fairness is studied apart from downstream productivity. This manuscript gives an outcome-comparison procedure to which these fairness checks can be attached, and marks that step as needed.	[19], [23], [25], [29], [50], [55]
F. People analytics, HR technology and the future of work	People analytics practice, digital HR, and labor-market and future-of-work studies.	The framing is broad and strategic. This manuscript supplies a concrete four-stage analysis that turns hiring records into decision-relevant evidence.	[1], [9], [12], [14], [22], [26], [31], [42], [46], [53], [57], [58], [59]

Data and Methods

The analysis runs in four stages. Figure 1 shows the sequence, from the paired cohorts through to the estimated effect of screening method. Each stage is described below, with the measures and tests defined before any comparison is made.

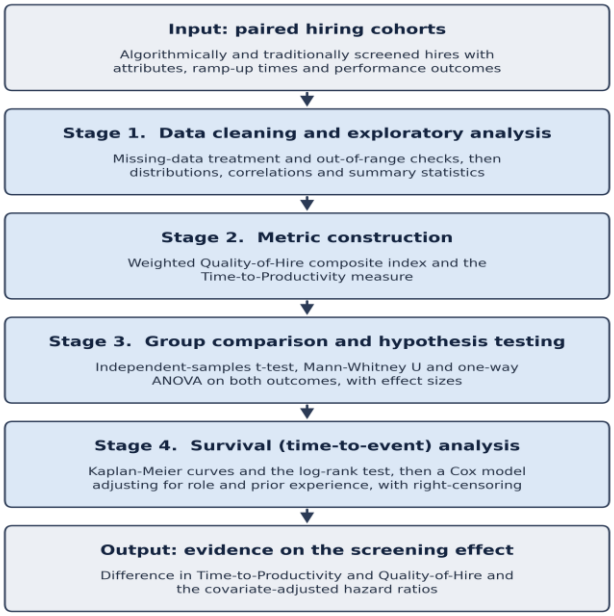


Figure 1. The four-stage analysis pipeline, from paired hiring cohorts to the estimated screening effect.

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Study design and simulated data

The unit of analysis is the individual hire. Two cohorts are compared, one screened with an algorithmic tool and one screened by traditional manual review. Because hiring records carry personal data and are rarely open, the demonstration uses a simulated dataset of 1,000 hires generated to resemble the structure of real records. Each record holds the screening method, the role (Engineering, Sales, Operations, or Support), prior experience in years, education level, the hiring manager, the time-to-productivity in days, ramp-up in weeks, tenure in months, a performance rating on a 1 to 5 scale, manager satisfaction on the same scale, and a twelve-month retention flag. The generating process gives algorithmic screening a modest advantage in ramp-up and performance, and lets role and experience shift the time-to-productivity, so that the covariate adjustment in stage four has something to adjust for. The cohort holds 523 algorithmically screened hires and 477 traditionally screened hires.

Stage one: data cleaning and exploratory data analysis

Cleaning came before any analysis. Missing values were present in three fields, prior experience (40 records), performance rating (30 records), and manager satisfaction (60 records), and one performance rating fell outside the valid 1 to 5 range and was set to missing. Missing numeric values were filled with the column median, a treatment that leaves the center of the distribution undisturbed. After this step no missing values remained. Profiling then described each variable by screening method and examined the distributions and the correlation structure among the numeric fields, which guided the choice of tests in the later stages.

Stage two: constructing the outcome measures

Two outcomes were defined. Time-to-productivity is the number of days between a hire's start date and the point at which performance reaches the level expected of the role. The quality-of-hire index is a weighted composite of four components, the performance rating, retention measured by tenure, ramp-up speed, and manager satisfaction. Each component was placed on a common 0 to 1 scale by min-max normalization,

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

so that a value of 0 marks the lowest observed score and 1 the highest. The index for hire i is the weighted sum of the four normalized components, scaled to a 0 to 100 range,

$$QoH_i = 100\,(w_p z_{perf} + w_r z_{ret} + w_u(1 - z_{ramp}) + w_m z_{mgr})$$

where z denotes the normalized component and ramp-up enters as (1 minus its normalized value) because a shorter ramp-up is better. The weights reflect the relative importance commonly placed on each component, 0.35 for performance, 0.25 for retention, 0.20 for ramp-up, and 0.20 for manager satisfaction, and they sum to one. Table 3 lists them. The weighting is a modelling choice, and the procedure allows an organization to set its own weights.

Stage three: group comparison and hypothesis testing

The two screening methods were compared on each outcome. The null hypothesis in each case is that the two cohorts share the same mean. Because the two cohorts differ in size and need not share a variance, the Welch form of the independent-samples t-test was used,

$$t = \frac{\bar{x}_A - \bar{x}_T}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_T^2}{n_T}}}$$

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where A and T index the algorithmic and traditional cohorts. The Mann-Whitney U test was run alongside it as a check that does not assume normal distributions.

The practical size of each difference was reported with Cohen's d, the mean difference divided by the pooled standard deviation,

$$d = \frac{\bar{x}_A - \bar{x}_T}{s_p}$$

A one-way analysis of variance across the four roles tested whether the outcomes varied by role, using the ratio of between-group to within-group mean squares,

$$F = \frac{MS_{between}}{MS_{within}}$$

Stage four: survival analysis of time-to-productivity

Treating time-to-productivity as a simple average discards information about the hires who had not yet reached full productivity when the data were collected. Survival analysis keeps that information through right-censoring. The event of interest is reaching full productivity, and the observation window was set to 90 days. A hire who reached full productivity within the window and before leaving contributes an event. A hire who left, or who had not reached full productivity by day 90, is censored at that point. The survival function, the probability that a hire has not yet reached full productivity by time t, was estimated with the Kaplan-Meier product-limit estimator,

$$\hat{S}(t) = \prod_{t_i \le t} \frac{n_i - d_i}{n_i}$$

where n sub i is the number of hires still at risk just before time t sub i and d sub i is the number reaching full productivity at that time. The two cohorts' curves were compared with the log-rank test. A Cox proportional-hazards model then estimated the effect of screening method on the rate of reaching full productivity while adjusting for role and prior experience,

$$h(t \mid x) = h_0(t) \exp(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p)$$

where h sub 0 is the baseline hazard and the exponentiated coefficients are hazard ratios. A hazard ratio above one for algorithmic screening means a higher instantaneous rate of reaching full productivity, which is a shorter time-to-productivity. All analyses were carried out in Python with pandas, numpy, scipy, and lifelines.

RESULTS

Data profile and exploratory analysis

The cleaned cohort held 1,000 hires across the four roles, Engineering (310), Sales (269), Operations (222), and Support (199). Table 2 reports the descriptive statistics by screening method. The algorithmic cohort showed a lower time-to-productivity and a higher performance rating, higher manager satisfaction, and longer tenure, while prior experience was close to balanced across the two groups, 5.32 years against 5.10 years. Figure 2 shows the distributions and the correlation structure. Time-to-productivity correlated with ramp-up by construction, and both performance and manager satisfaction moved together, which informed the weighting in the quality-of-hire index.

Table 2. Descriptive statistics by screening method, reported as mean (standard deviation).

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Variable	Algorithmic (n = 523)	Traditional (n = 477)
Time to productivity (days)	58.54 (18.77)	67.10 (19.74)
Ramp-up (weeks)	8.36 (2.68)	9.58 (2.82)
Tenure (months)	30.00 (10.56)	26.20 (10.95)
Performance rating (1-5)	3.56 (0.69)	3.35 (0.66)
Manager satisfaction (1-5)	3.58 (0.67)	3.16 (0.66)
Prior experience (years)	5.32 (3.46)	5.10 (3.34)
Quality-of-Hire index (0-100)	57.22 (10.03)	50.24 (9.33)

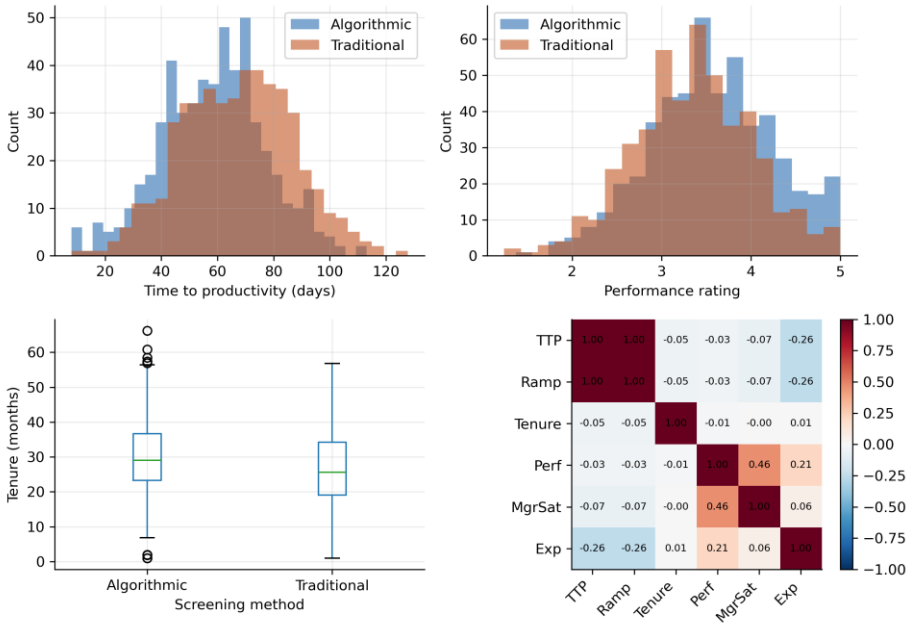


Figure 2. Exploratory analysis. Distributions of time-to-productivity and performance rating by screening method, tenure by method, and the correlation matrix of the numeric variables (TTP, Ramp, Tenure, Perf, MgrSat, Exp).

The constructed outcome measures

The quality-of-hire index combined the four components with the weights in Table 3. The index ranged across the full 0 to 100 scale and had a higher mean in the algorithmic cohort, which the next section tests. Time-to-productivity was carried forward in days as defined in stage two.

Table 3. Components and weights of the Quality-of-Hire composite index.

Component	Direction	Weight
Performance rating (normalized)	Higher is better	0.35
Retention, measured by tenure (normalized)	Higher is better	0.25

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Ramp-up speed (normalized, inverted)	Shorter is better	0.20
Manager satisfaction (normalized)	Higher is better	0.20

Group comparison and hypothesis testing

Algorithmic screening was associated with a shorter time-to-productivity. The algorithmic cohort reached full productivity in 58.54 days on average (SD 18.77) against 67.10 days (SD 19.74) for the traditional cohort, a difference of 8.55 days (95% CI 6.16 to 10.95). The Welch t-test rejected the null hypothesis of equal means, $t = 7.01$, $p < .001$, and the Mann-Whitney U test agreed, $U = 94{,}442$, $p < .001$. The effect size was small to moderate, Cohen's $d = 0.45$. The quality-of-hire index told the same story more strongly. The algorithmic cohort scored 57.22 (SD 10.03) against 50.24 (SD 9.33), a difference of 6.98 points (95% CI 5.78 to 8.18), $t = 11.40$, $p < .001$, $U = 173{,}187$, $p < .001$, with a moderate effect size, $d = 0.72$. The one-way analysis of variance across roles was significant for both outcomes, $F = 81.63$, $p < .001$ for time-to-productivity and $F = 6.45$, $p < .001$ for quality of hire, which confirmed that role is a source of variation worth adjusting for in the survival model. Table 4 collects these results, and Figure 3 shows the group distributions.

Table 4. Group comparison of algorithmic versus traditional screening on the two outcomes.

Group / outcome	Mean (SD)	Difference [95% CI]	t, p	Cohen's d
TTP, algorithmic	58.54 (18.77)			
TTP, traditional	67.10 (19.74)	−8.55 [−10.95, −6.16]	7.01, $p < .001$	0.45
QoH, algorithmic	57.22 (10.03)			
QoH, traditional	50.24 (9.33)	6.98 [5.78, 8.18]	11.40, $p < .001$	0.72

Note. TTP = time-to-productivity (days); QoH = quality-of-hire index (0 to 100). Mann-Whitney U confirmed both differences at $p < .001$.

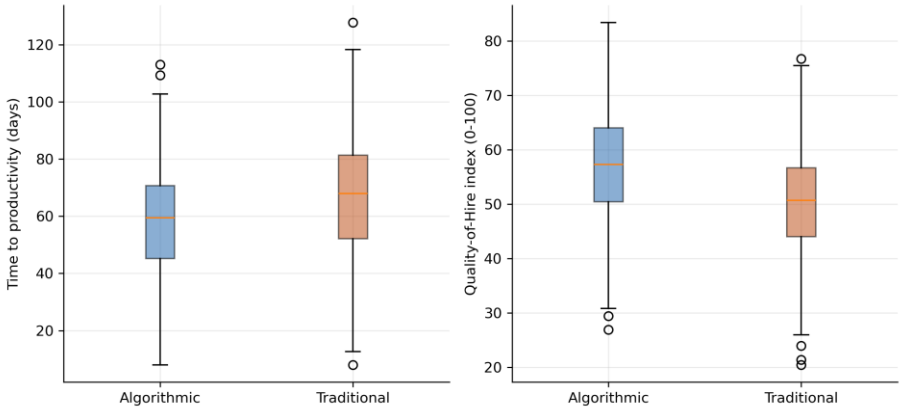


Figure 3. Group comparison. Time-to-productivity and the quality-of-hire index by screening method.

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Survival analysis of time-to-productivity

Within the 90-day window, 904 of the 1,000 hires reached full productivity, an event rate of 0.904, and the rest were censored. The Kaplan-Meier curves separated early and stayed apart, with a median time to full productivity of 59.4 days for the algorithmic cohort against 67.0 days for the traditional cohort (Figure 4). The log-rank test rejected the hypothesis of equal survival, chi-square = 42.68, $p < .001$. The Cox proportional-hazards model, adjusting for role and prior experience, estimated a hazard ratio of 1.68 for algorithmic screening (95% CI 1.47 to 1.92, $p < .001$), meaning algorithmic hires reached full productivity at 1.68 times the rate of traditional hires once the covariates were held constant. Prior experience carried a hazard ratio of 1.09 per year (95% CI 1.07 to 1.11, $p < .001$). Role mattered as the earlier analysis of variance suggested, with Support, Operations, and Sales roles reaching productivity faster than the Engineering baseline. The model's concordance was 0.69. Table 5 reports the full model.

Table 5. Cox proportional-hazards model for reaching full productivity (reference role: Engineering).

Covariate	Hazard ratio [95% CI]	p
Algorithmic screening	1.68 [1.47, 1.92]	< .001
Prior experience (per year)	1.09 [1.07, 1.11]	< .001
Role: Sales	2.31 [1.93, 2.75]	< .001
Role: Operations	1.78 [1.48, 2.14]	< .001
Role: Support	3.88 [3.20, 4.72]	< .001

Note. A hazard ratio above one indicates a faster time to full productivity. Model concordance = 0.69.

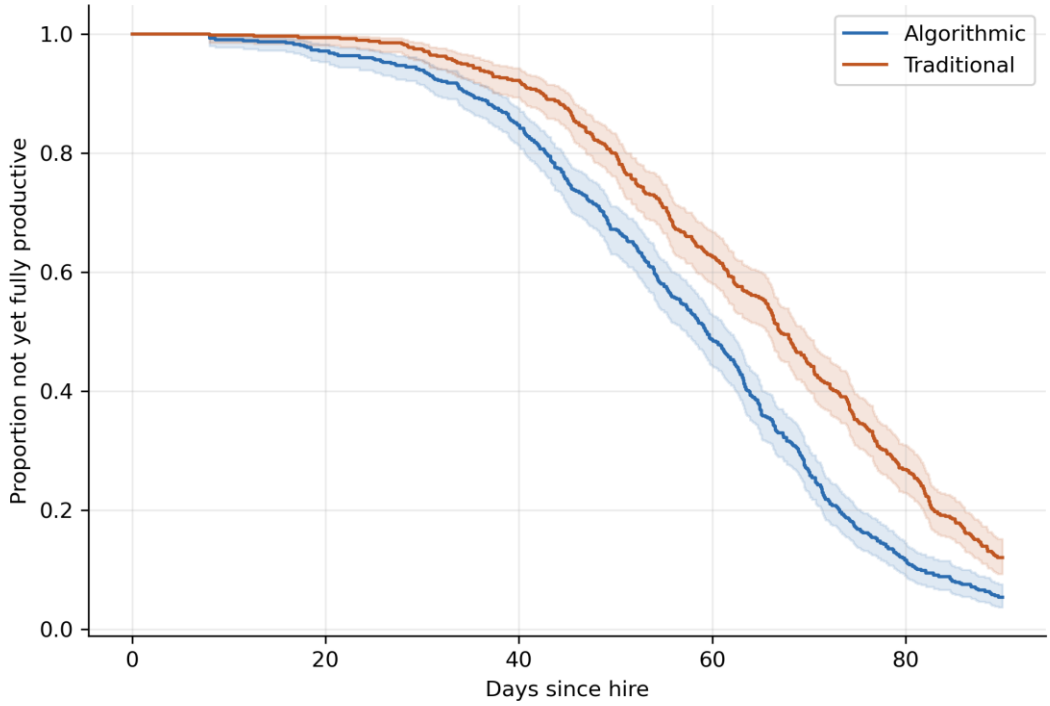


Figure 4. Kaplan-Meier curves for the proportion of hires not yet fully productive, by screening method. Shaded bands are 95% confidence intervals.

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DISCUSSION

The results point one way across all four stages. Hires screened by the algorithmic tool reached full productivity sooner and scored higher on the composite quality measure, and the advantage held after role and prior experience were accounted for. The size of the effect is worth reading carefully. A difference of 8.55 days in time-to-productivity is small for any single hire, yet at the scale of a large recruiting operation it compounds into real savings in the period when a new hire costs more than they return [8], [48]. The quality-of-hire difference, with an effect size of 0.72, is the stronger of the two findings and is the one that speaks most directly to the value a screening change delivers [45].

These findings sit well with the wider literature. Studies that predict performance and retention from early-tenure data report that the signal captured at screening carries forward into how a hire performs [3], [5], [17], and the present analysis shows that signal expressed as a measured outcome rather than a model score. The survival result adds something that an average cannot, a view of when the two groups diverge. The curves separate inside the first month, which suggests the screening advantage shows up early in the ramp rather than building slowly [7], [44].

The analysis also speaks to the fairness literature. A screening method that shortens time-to-productivity is attractive to an employer, yet speed and quality are not the only tests a selection process must pass [19], [23]. The procedure set out here can be extended with the disparate-impact and demographic checks that other work has developed [25], [29], and reporting the outcome difference without that check would be incomplete in a real deployment [50], [55]. Set inside a people-analytics function, this four-stage analysis is one input to a hiring decision rather than the whole of it [26], [59].

Limitations

The clearest limitation is that the data are simulated. The numbers reported here describe a dataset built to resemble real hiring records, and they are an illustration of what the method produces, not an estimate of the effect of any real tool. The generating process also builds in a screening advantage, so the significance of the comparison reflects that design and should not be read as evidence about algorithmic screening in general. A second limitation is that the comparison is observational in form. Even with role and experience held constant in the Cox model, hires are not randomly assigned to a screening method in practice, and unobserved differences between the cohorts could carry part of the effect [7]. A third limitation is the quality-of-hire index itself. Its weights are a reasonable choice rather than a measured truth, and a different organization might weight retention above performance and reach a different ranking [45], [16]. The procedure makes those weights explicit so they can be debated and changed.

CONCLUSION

This study set out a four-stage procedure for measuring what algorithmic screening does to time-to-productivity and quality of hire, and showed it on a simulated cohort of 1,000 hires. Cleaning and profiling prepared the data, two outcome measures were defined before any comparison, hypothesis tests established that the cohorts differed, and a survival model estimated the screening effect while adjusting for role and experience. On these data the algorithmic cohort reached full productivity about 8.55 days sooner and scored about 7 points higher on the quality index, with the survival model giving a hazard ratio of 1.68. The value of the procedure lies in its reuse. Supplied with an organization's real hiring records, the same four stages produce the same evidence, and that evidence can inform whether a screening change earns its place. A natural next step is to apply it to real cohorts and to add the fairness checks that a responsible deployment requires [29], [55].

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REFERENCES

1. Wapman, K.H., Zhang, S., Clauset, A.J., & Larremore, D.B. (2022). Quantifying hierarchy and dynamics in US faculty hiring and retention. Nature. https://doi.org/10.1038/s41586-022-05222-x
2. Nawaz, N., & Mary, A.I. (2019). Artificial Intelligence Chatbots are New Recruiters. International Journal of Advanced Computer Science and Applications. https://doi.org/10.14569/ijacsa.2019.0100901
3. Qutub, A., Al-Mehmadi, A., Al-Hssan, M., Aljohani, R., & Alghamdi, H.S. (2021). Prediction of Employee Attrition Using Machine Learning and Ensemble Methods. International Journal of Machine Learning and Computing. https://doi.org/10.18178/ijmlc.2021.11.2.1022
4. Nikolaou, I. (2021). What is the Role of Technology in Recruitment and Selection?. The Spanish Journal of Psychology. https://doi.org/10.1017/sjp.2021.6
5. Hasan, M.R., Ray, R.K., & Chowdhury, F.R. (2024). Employee Performance Prediction: An Integrated Approach of Business Analytics and Machine Learning. Journal of Business and Management Studies. https://doi.org/10.32996/jbms.2024.6.1.14
6. Rąb-Kettler, K., & Lehnervp, B. (2019). Recruitment in the Times of Machine Learning. Management Systems in Production Engineering. https://doi.org/10.1515/mspe-2019-0018
7. Park, J., Feng, Y., & Jeong, S. (2024). Developing an advanced prediction model for new employee turnover intention utilizing machine learning techniques. Scientific Reports. https://doi.org/10.1038/s41598-023-50593-4
8. Kot, S., Hussain, H.I., Bilan, S., Haseeb, M., & Mihardjo, L.W. (2021). THE ROLE OF ARTIFICIAL INTELLIGENCE RECRUITMENT AND QUALITY TO EXPLAIN THE PHENOMENON OF EMPLOYER REPUTATION. Journal of Business Economics and Management. https://doi.org/10.3846/jbem.2021.14606
9. Ajayi, F.A., & Udeh, C.A. (2024). Innovative recruitment strategies in the IT sector: A review of successes and failures. Magna Scientia Advanced Research and Reviews. https://doi.org/10.30574/msarr.2024.10.2.0057
10. Nawaz, N. (2019). Artificial Intelligence interchange human intervention in the recruitment process in Indian Software Industry. International Journal of Advanced Trends in Computer Science and Engineering. https://doi.org/10.30534/ijatcse/2019/62842019
11. Vedapradha, R., Hariharan, R., & Shivakami, R. (2019). Artificial Intelligence: A Technological Prototype in Recruitment. Journal of Service Science and Management. https://doi.org/10.4236/jssm.2019.123026
12. Zainal, N.S.B., Wider, W., Lajuma, S.B., Khadri, M.W.A.B.A., Taib, N.M., & Joseph, A. (2022). Employee Retention in the Service Industry in Malaysia. Frontiers in Sociology. https://doi.org/10.3389/fsoc.2022.928951
13. Mahieu, J., Melillo, F., Reichstein, T., & THOMPSON, P.W. (2019). Shooting stars? Uncertainty in hiring entrepreneurs. Strategic Entrepreneurship Journal. https://doi.org/10.1002/sej.1339
14. Campello, M., Kankanhalli, G., & Muthukrishnan, P. (2023). Corporate Hiring Under COVID-19: Financial Constraints and the Nature of New Jobs. Journal of Financial and Quantitative Analysis. https://doi.org/10.1017/s0022109023000522
15. Gan, C., Zhang, Q., & Mori, T. (2024). Application of LLM Agents in Recruitment: A Novel Framework for Automated Resume Screening. Journal of Information Processing. https://doi.org/10.2197/ipsjjip.32.881

ISSN No. 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV Issue XI November 2026

16. Chuang, Y., Hu, S., Liou, J.J., & Tzeng, G. (2020). A DATA-DRIVEN MADM MODEL FOR PERSONNEL SELECTION AND IMPROVEMENT. Technological and Economic Development of Economy. https://doi.org/10.3846/tede.2020.12366
17. Adeniyi, J.K., Adeniyi, A.E., Oguns, Y.J., Egbedokun, G.O., Ajagbe, K.D., Obuzor, P.C., & Ajagbe, S.A. (2022). Comparison of the Performance of Machine Learning Techniques in the Prediction of Employee. ParadigmPlus. https://doi.org/10.55969/paradigmplus.v3n3a1
18. Najjar, A., Amro, B., & Macedo, M. (2021). An Intelligent Decision Support System For Recruitment: Resumes Screening And Applicants Ranking. Informatica. https://doi.org/10.31449/inf.v45i4.3356
19. Hilliard, A., Guenole, N., & Leutner, F. (2022). Robots are judging me: Perceived fairness of algorithmic recruitment tools. Frontiers in Psychology. https://doi.org/10.3389/fpsyg.2022.940456
20. Villegas, S.G., Lloyd, R.A., Tritt, A., & Vengrouskie, E.F. (2019). Human Resources as Ethical Gatekeepers: Hiring Ethics and Employee Selection. Journal of Leadership Accountability and Ethics. https://doi.org/10.33423/jlae.v16i2.2024
21. Jayadi, R. (2019). Employee Performance Prediction using Naïve Bayes. International Journal of Advanced Trends in Computer Science and Engineering. https://doi.org/10.30534/ijatcse/2019/59862019
22. Tsiskaridze, R., Reinhold, K., & Järvis, M. (2023). Innovating HRM Recruitment: A Comprehensive Review Of AI Deployment. Marketing and Management of Innovations. https://doi.org/10.21272/mmi.2023.4-18
23. Capasso, M., Arora, P., Sharma, D., & Tacconi, C. (2024). On the Right to Work in the Age of Artificial Intelligence: Ethical Safeguards in Algorithmic Human Resource Management. Business and Human Rights Journal. https://doi.org/10.1017/bhj.2024.26
24. [24] Saatçi, M., Kaya, R., & Ünlü, R. (2024). Resume Screening With Natural Language Processing (NLP). Alphanumeric Journal. https://doi.org/10.17093/alphanumeric.1536577
25. Kubiak, E., Efremova, M.I., Baron, S., & Frasca, K.J. (2023). Gender equity in hiring: examining the effectiveness of a personality-based algorithm. Frontiers in Psychology. https://doi.org/10.3389/fpsyg.2023.1219865
26. Alshamrani, M.A., Alharthi, S., Helmi, M.A., & Alwadei, T. (2023). Determinants of Employee Retention in Pharmaceutical Companies: Case of Saudi Arabia. Journal of Business and Management Studies. https://doi.org/10.32996/jbms.2023.5.2.2
27. Lamjid, A., Ariss, A., Ennejjai, I., Mabrouki, J., & Ziti, S. (2024). Enhancing the hiring process: A predictive system for soft skills assessment. Data & Metadata. https://doi.org/10.56294/dm2024.387
28. Deshmukh, A., & Raut, A.B. (2024). Enhanced Resume Screening for Smart Hiring Using Sentence-Bidirectional Encoder Representations from Transformers (S-BERT). International Journal of Advanced Computer Science and Applications. https://doi.org/10.14569/ijacsa.2024.0150825
29. Agbasiere, C.L., & Nze-Igwe, G.R. (2025). Algorithmic Fairness in Recruitment: Designing AI-Powered Hiring Tools to Identify and Reduce Biases in Candidate Selection. Path of Science. https://doi.org/10.22178/pos.116-10
30. Parasa, S.K. (2024). Impact of AI in Recruitment and Talent Acquisition. Human Resource and Leadership Journal. https://doi.org/10.47941/hrlj.2117
31. Grohsjean, T., Dokko, G., & Yang, P.Q. (2024). Can You Go Home Again? Performance Assistance Between Boomerangs and Incumbent Employees. Organization Science. https://doi.org/10.1287/orsc.2022.16685
32. Manthena, S.R.L. (2021). Impact of Artificial Intelligence on Recruitment and its Benefits. International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences. https://doi.org/10.37082/ijirmps.2021.v09si05.013

ISSN No. 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV Issue XI November 2026

33. Hmoud, B., & Várallyai, L. (2021). Artificial Intelligence In Talent Acquisition, Do we Trust It?. Journal of Agricultural Informatics. https://doi.org/10.17700/jai.2021.12.1.594
34. Tayal, S., Sharma, T., Singhal, S., & Thakur, A. (2024). Resume Screening using Machine Learning. International Journal of Scientific Research in Computer Science Engineering and Information Technology. https://doi.org/10.32628/cseit2410275
35. Onukwugha, C.G., Ofoegbu, C., Aliche, O., & Betrand, C.U. (2024). Resume Optimization Model Using Machine Learning Techniques. International Journal of Intelligent Information Systems. https://doi.org/10.11648/j.ijiis.20241305.12
36. Chavan, P.R., Chandurkar, Y., Tidake, A., Lavankar, G., Gaikwad, S., & Chavan, R. (2024). Enhancing recruitment efficiency: An advanced Applicant Tracking System (ATS). Industrial Management Advances. https://doi.org/10.59429/ima.v2i1.6373
37. V, B.A.D., & Rajeev, H. (2024). Employee Attrition Prediction. Indian Journal of Data Mining. https://doi.org/10.54105/ijdm.a1636.04010524
38. Sharma, S.A.R.P.G. (2025). The Role of Artificial Intelligence in Recruitment and Talent Acquisition-An Empirical Study. Journal of Informatics Education and Research. https://doi.org/10.52783/jier.v5i1.2007
39. Asif, A. (2024). Integrating AI in Recruitment: A Review of Perceptions, Acceptance, Adoption and Ethical Considerations of AI Usage. Frontiers in Business Economics and Management. https://doi.org/10.54097/c759fx45
40. Harsha, T.M., Moukthika, G.S., Sai, D.S., Pravallika, M.N.R., & Anamalamudi, S. (2022). Survey on Resume Screening Mechanisms. International Journal of Computer Science and Engineering. https://doi.org/10.14445/23488387/ijcse-v9i4p103
41. Anand, S., & Giri, A.K. (2024). Optimizing Resume Design for ATS Compatibility: A Large Language Model Approach. International Journal on Smart & Sustainable Intelligent Computing. https://doi.org/10.63503/j.ijssic.2024.33
42. Mamuli, L.C., Mukabi, F.E.K., & Kagucia, C. (2025). Leveraging AI and Automation in HR Practices for Enhanced Employee Performance in Kenyan Organizations: Opportunities, Challenges and the Future Work Outlook. International Journal of Academic Research in Business and Social Sciences. https://doi.org/10.6007/ijarbss/v15-i1/23498
43. [Author(s) unavailable] (2023). A COSINE SIMILARITY-BASED RESUME SCREENING SYSTEM FOR JOB RECRUITMENT. International Research Journal of Modernization in Engineering Technology and Science. https://doi.org/10.56726/irjmets35945
44. Ma, Y., Zhang, Z., & Ihler, A. (2020). A Deep Choice Model for Hiring Outcome Prediction in Online Labor Markets. International Journal of Computers Communications & Control. https://doi.org/10.15837/ijccc.2020.2.3760
45. Dutta, D., & Vedak, C. (2023). Determining quality of hire, the holy grail of recruitment: A structuration perspective. Human Resources Management and Services. https://doi.org/10.18282/hrms.v5i2.3373
46. Duong, N.T., & Thi, T.D.P. (2022). How does AI recruitment influence satisfaction among student job-seekers? The role of self-efficacy as a moderator and mediator. The Education and science journal. https://doi.org/10.17853/1994-5639-2022-8-64-94
47. Yassine, T.K., & Achchab, S. (2024). Predictive Hiring and AI: Elevating Recruitment with Optimized Neural Networks and Gradient Descent. International Journal of Intelligent Information Systems. https://doi.org/10.11648/j.ijiis.20241306.11

ISSN No. 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV Issue XI November 2026

48. [48] Habachi, M., Nouira, Z., Malainine, C., & Hajaji, O. (2022). Impact of digitalization on the attractiveness of employee recruitment and retention in Moroccan companies. Problems and Perspectives in Management. https://doi.org/10.21511/ppm.20(3).2022.02
49. Illiash, I., & Babiak, H. (2023). MODERN TECHNOLOGIES IN THE FIELD OF PERSONNEL RECRUITMENT. Regional'ni aspekti rozvitku produktivnih sil Ukraïni. https://doi.org/10.35774/rarrpsu2023.28.112
50. Ilham, R. (2025). Examining the Effect of Algorithmic Hiring, Perceived Fairness, and HR Tech Literacy on Recruitment Acceptance. International Journal of Business Law and Education. https://doi.org/10.56442/ijble.v6i1.1106
51. Dodda, S., Volikatla, H., & Vummadi, J.R. (2025). Exploring the Role of AI-Enhanced Chatbots in Automating Recruitment Processes in Human Capital Management Systems. International Journal of Emerging Trends in Computer Science and Information Technology. https://doi.org/10.63282/3050-9246.ijetcsit-v6i3p104
52. M, K.K., & Elangovan, R. (2021). To Study Impact of Artificial Intelligence on HR Practices. ComFin Research. https://doi.org/10.34293/commerce.v9i4.4134
53. Goncharuk, N., Bilokudria, A.V., Kovalchuk, M., Suray, I., & Komarova, K. (2025). KEY AREAS OF DEVELOPMENT OF THE HUMAN RESOURCE MANAGEMENT ECOSYSTEM OF THE CIVIL SERVICE OF UKRAINE IN THE CONTEXT OF DIGITAL TECHNOLOGIES AND GREEN PUBLIC MANAGEMENT. International Journal of Ecosystems and Ecology Science (IJEES). https://doi.org/10.31407/ijees15.418
54. [Navarro, G. (2025). Fair and Ethical Resume Screening: Enhancing ATS with JustScreen the ResumeScreeningApp. Journal of Information Technology Cybersecurity and Artificial Intelligence. https://doi.org/10.70715/jitcai.2024.v2.i1.001
55. Ussher-Eke, D., James, U.U., & Okoh, O.F. (2024). Zero Trust Onboarding in HR Tech Safeguarding Applicant Tracking Systems against Deepfake Resumes and Credential Fraud. International Journal of Scientific Research in Humanities and Social Sciences. https://doi.org/10.32628/ijsrssh243565
56. Lee, T.C., & Ziegler, M.D. (2025). Leveraging deep learning for the detection of socially desirable tendencies in personnel selection: A proof-of-concept. PLoS ONE. https://doi.org/10.1371/journal.pone.0329205
57. Shrestha, P.S., & Prajapati, D.K. (2023). Human Resource Management Practices and Employee Retention. Journal of Balkumari College. https://doi.org/10.3126/jbkc.v12i1.60415
58. Kiswantoro, A., Susanto, D.R., Hikmawati, M.M., Rohman, N., & Pradini, G. (2023). Review Dampak dan Tantangan dalam Penerapan HR Analytics untuk Meningkatkan Performa Perusahaan. Ideas Jurnal Pendidikan Sosial dan Budaya. https://doi.org/10.32884/ideas.v9i4.1519
59. Jasni, N.N., Mahadi, N.B., Yaakop, A.Y., & Baskaran, S. (2022). People Analytics: An Evidence-Based Approach in Managing Employees. International Journal of Academic Research in Progressive Education and Development. https://doi.org/10.6007/ijarped/v11-i3/15086
60. Karthika, M., & Meyyappan, T. (2020). Employee Performance Prediction Using EPP Framework. International Journal of Scientific Research in Computer Science Engineering and Information Technology. https://doi.org/10.32628/cseit206654