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ENHANCING RECRUITMENT WITH MONTE CARLO METHODS

Abstract. *The article explores the use of Monte Carlo simulations to improve recruitment processes under high uncertainty. The authors highlight challenges such as candidate availability, unpredictable timelines, varying acquisition costs and the inherent difficulty in forecasting candidate-role alignment. Traditional deterministic planning methods often fall short in such dynamic contexts, leading to missed targets, budget overruns and inefficient hiring.*

Monte Carlo methods are presented as a powerful tool for simulating probabilistic scenarios and managing risk. By repeatedly sampling values from defined probability distributions, this method enables the modeling of a wide range of possible outcomes, providing a comprehensive understanding of complex systems. Its foundation lies in the law of large numbers, which ensures convergence toward theoretical distributions over multiple iterations, supporting more reliable planning in uncertain conditions.

The article emphasizes the strategic value of incorporating Monte Carlo simulations into recruitment. This approach enables a shift from reactive problem-solving to proactive planning, enhancing resource allocation, minimizing risks and delivering competitive advantages. Recruitment is thereby elevated from an administrative task to a critical strategic function that significantly impacts organizational success.

Key words: *recruitment, Monte Carlo methods, simulation, uncertainty, risk management, strategic planning, analytics, forecasting, talent acquisition.*

Problem's statement. Traditional, deterministic approaches to planning and forecasting in recruitment often prove inadequate in capturing this inherent variability. Such methods can lead to missed targets, budget overruns, and suboptimal outcomes, as projects frequently overrun their budgets and deliver late due to insufficient initial estimations.

Monte Carlo methods are broadly characterized as statistical techniques that use sequences of random numbers to generate approximate solutions to mathematically complex optimization and simulation problems. Their two key strengths lie in the simplicity of their conceptual foundation and the solid theoretical underpinning that supports their use. According to the Law of Large Numbers, the outcomes produced by Monte Carlo simulations converge toward the true solution as the number of iterations increases. Since their initial development by Metropolis and Ulam in 1949, these methods have found extensive application across a wide range of scientific and engineering fields.

In response to these challenges, Monte Carlo simulations have emerged as a powerful analytical technique. A Monte Carlo simulation is a computerized mathematical method that enables the modelling of risk and uncertainty within quantitative analysis and decision-making processes. Its operational core involves repeatedly sampling random values for uncertain input variables from their respective probability distributions. The technique, conceived by Stanislaw Ulam and John von Neumann was initially applied to complex problems in nuclear physics. Its name, an homage to the Monte Carlo casino in Monaco, reflects the central role of chance and randomness in its methodology.

This subject has been thoroughly examined in a recent comprehensive review by Saltelli et al. (2019), as well as in earlier work by Sin et al. (2009), which focused on its application in process design. A fundamental aspect of any Monte Carlo simulation – whether for sensitivity analysis or uncertainty quantification – is the accurate identification and characterization of uncertainty sources within the defined input domain. Numerous Monte Carlo studies have shown that while the method effectively accounts for "known knowns" and "known unknowns" it remains limited in addressing "unknown unknowns".

Georgescu (2023), outlines a general approach, compatible with high-speed electronic computing systems, for determining the properties of substances modeled as assemblies of interacting individual molecules.

The strategic value of incorporating simulation techniques into modern recruitment practices is substantial. These methods facilitate a paradigm shift from reactive problem-solving to proactive, strategic planning by systematically quantifying uncertainty and allowing for the exploration of a comprehensive range of potential future scenarios. Consequently, Monte Carlo simulations provide a robust, data-driven foundation for optimizing recruitment strategies, allocating resources with greater efficacy and managing the inherent risks associated with complex hiring processes.

The aim of this study was to investigate and justify the application of Monte Carlo methods to improve recruitment processes by modeling uncertainties associated with personnel selection in order to transform recruitment from an administrative function into a strategic tool for risk and resource management.

Analysis of recent research and publications. The modeling of human decision-making processes, such as the stopping behavior in sequential search tasks described by Baumann et al. (2020), can be significantly enriched through the integration of agent-based modeling (ABM) and Monte Carlo simulation techniques. Baumann and colleagues demonstrated that a linear threshold heuristic effectively captures how individuals make stopping decisions across both experimental and real-world settings. When such heuristics are embedded within autonomous agents – following the principles outlined by Bonabeau (2002) – researchers can simulate complex, interactive environments that reflect organizational, market or behavioral dynamics.

Sadeghi Dastaki and Afrazeh (2018) introduce a manpower planning model tailored for production departments, incorporating both individual and hierarchical skill levels, along with the possibility of skill substitution. Recognizing that workforce demand is inherently uncertain, the authors develop a two-stage stochastic programming model to address this variability. To evaluate the model's robustness and performance under different demand scenarios, Monte Carlo simulation can be integrated, allowing for the generation of numerous possible future states and supporting better-informed, risk-aware planning decisions. This approach enhances the model's practical utility by aligning manpower planning with real-world operational uncertainties.

Shonkwiler and Mendivil (2024) provide a concise historical overview of the Monte Carlo method, highlighting its development and diverse applications across scientific fields. To illustrate its fundamental principles, they work through the classic Buffon's needle problem as a means of estimating π, demonstrating how randomness and repeated sampling underpin the method's power. The authors also show how tools such as histograms and sample paths can be used to visualize and analyze the outcomes of Monte Carlo simulations, making abstract probabilistic concepts more tangible and emphasizing the method's educational and practical value.

Gölbaşi and Sahiner (2024) present a research study focused on developing a continuous-event simulation algorithm designed to optimize the configuration and allocation of maintenance crews in production environments characterized by diverse failure mode clusters across multiple equipment operations. The proposed algorithm not only supports optimal crew deployment but also dynamically assesses the potential for reallocating currently engaged crews to overlapping maintenance tasks that demand comparable technical expertise.

Huffcutt, A. I., Culbertson, S. S. and Weyhrauch, W. S. (2013) conducted a study aimed at updating the evidence on the interrater reliability of employment interviews. One key implication of their findings is that professionals involved in conducting interviews should avoid forming conclusions about the psychometric quality of their interview processes based solely on interrater reliability estimates that fail to incorporate all three relevant sources.

Both studies by Gölbaşi and Sahiner (2024) and Huffcutt et al. (2013) emphasize the importance of robust, data-driven evaluation methods in complex decision-making environments. Gölbaşi and Sahiner developed a continuous-event simulation algorithm – potentially enhanced through Monte Carlo methods – to optimize maintenance crew allocation by simulating various failure and reassignment scenarios in dynamic production settings. Similarly, Huffcutt et al. stress the need for comprehensive data inclusion when evaluating interrater reliability in employment interviews, cautioning against conclusions based on partial metrics. Integrating Monte Carlo simulation into the context of interview assessment, much like in maintenance planning, could provide a more nuanced understanding of variability and reliability across different conditions, ultimately leading to more informed and accurate decision-making processes.

Komar et al. (2008) conducted a Monte Carlo simulation study to examine how applicant faking affects the criterion-related validity of conscientiousness in predicting supervisory ratings of job performance. Drawing from existing faking research, the authors manipulated six key parameters – magnitude of faking, proportion of fakers, variability in faking, and the relationships between faking and both conscientiousness and job performance, along with the selection ratio – resulting in 4,500 unique faking scenarios. This extensive simulation approach allowed for a detailed understanding of how different faking conditions can distort the predictive power of personality measures in personnel selection contexts.

Lee, Joo, and Fyffe (2019) addressed a notable gap in the literature by using Monte Carlo simulation to investigate how different faking conditions – such as the prevalence of fakers, the percentage of items faked, and the magnitude of faking – impact the construct validity of Big Five personality measures. Their findings reveal that motivated faking during testing can significantly distort the underlying structure of personality assessments, thereby threatening their construct validity. The study underscores the practical implications for selection processes and highlights the need for further research on mitigating the effects of faking in high-stakes assessment contexts.

Ock and Oswald (2018) used Monte Carlo simulation to explore the trade-offs between compensatory and multiple-hurdle selection models, particularly in terms of selection utility and cost-reliability dynamics. Their simulations demonstrated that compensatory selection models generally yielded higher expected criterion performance among selected applicants and achieved greater overall selection utility across a range of conditions. This study highlights the practical advantages of compensatory approaches in personnel selection when balancing predictive accuracy with resource constraints.

Paxton et al. (2001) highlight the growing use of Monte Carlo simulations in structural equation modeling (SEM) for empirically evaluating statistical estimators, while noting the lack of clear guidance for researchers. To address this gap, they outline a comprehensive nine-step framework for planning and conducting Monte Carlo analyses: formulating a theoretically grounded research question, building a valid model, designing experimental conditions, specifying population parameters, selecting appropriate software, running the simulations, managing data storage, troubleshooting and verifying simulation accuracy and interpreting and summarizing results. Through a detailed example, they illustrate how Monte Carlo methods can be effectively applied in SEM to assess model behavior under various controlled conditions.

Recruitment is accompanied by numerous uncertainties: fluctuations in candidate availability, timing, costs, recruitment efficiency. Traditional approaches are often inadequate - leading to budget overruns and delays. Monte Carlo methods allow you to simulate these uncertainties, building probabilistic scenarios and allowing you to make more accurate forecasts. The use of simulations moves recruitment from reactive management to strategic planning. The increasing availability of these methods due to new software solutions (such as Crystal Ball, EnForeSys etc.) is also emphasized. Thus, the article aims to demonstrate that the use of Monte Carlo methods in recruiting allows for more informed decisions, more effective resource planning, and reduced risks – which brings recruiting to the level of strategic management.

Przysucha et al. (2024) demonstrate that Monte Carlo simulation can outperform simpler techniques like averaging, especially when dealing with uncertainty and randomness. Their findings highlight the superior capability of Monte Carlo methods to model complex, variable conditions, leading to more accurate demand forecasting. This improvement in predictive accuracy has significant practical implications, as it enhances the ability of businesses to optimize operations such as inventory management, resource allocation, and supply chain planning. Their study reinforces the value of simulation-based approaches in decision-making processes where uncertainty is a critical factor.

Lombardi, van den Berg, and Vikström (2021) extend the Empirical Monte Carlo simulation framework developed by Huber et al. (2013) to evaluate the estimation accuracy of Timing-of-Events (ToE) models. Using detailed Swedish data on unemployed job seekers, the researchers simulate placebo treatment durations to mimic participation in a training program. This approach allows them to identify which covariates act as critical confounders and should be included in selection models to ensure valid causal inference. Their work highlights the power of Monte Carlo methods in uncovering biases and improving model specification in applied labor economics research.

Mangino and Finch (2021) employed a Monte Carlo simulation to evaluate the predictive performance of several advanced multilevel classification algorithms under diverse data conditions. Their comparative analysis focused on the accuracy of prediction, revealing that the panel neural network and the Bayesian generalized mixed effects model (multilevel Bayes) consistently outperformed other models across nearly all simulated scenarios. The study demonstrates the effectiveness of simulation-based evaluation in identifying robust predictive models, especially in complex multilevel data contexts.

Tilahun and Levinson (2013) introduce ABODE, an agent-based model designed for Origin-Destination (OD) demand estimation, particularly focused on modeling work trip distributions. The model incorporates residential and workplace locations as fixed inputs and simulates the dynamic interactions between workers and firms to form job-worker matches, leading to commute patterns that reflect real-world behavior. To enhance the robustness and variability analysis of ABODE, Monte Carlo simulation can be integrated. By repeatedly running the model under different stochastic configurations – such as variations in job offers, worker preferences or commuting constraints – researchers can assess the sensitivity of outcomes and better understand the probabilistic distribution of commuting patterns. This combination strengthens the model's predictive capabilities and supports more data-informed transportation planning under uncertainty.

Banack, Hayes-Larson, and Mayeda (2021) describe methods that can be applied to investigate the potential influence of various biases, including confounding bias, selection bias (such as collider stratification bias) and information bias.

The results of the research and their discussion. Monte Carlo methods allow you to model and evaluate these complex processes, taking into account: the probability of successfully completing each stage (feedback → selection → interview → offer), delays at each stage, the effectiveness of candidate recruitment channels (job boards, recruitment agencies, social networks, etc.), changing external conditions that affect the labor market. Thus, there is a clear scientific and practical connection between the application of Monte Carlo methods in HR recruitment. It is about optimizing processes that have a multi-stage structure, depend on probabilistic events and are accompanied by a high level of uncertainty.

At its core, employing Monte Carlo simulation in recruitment modeling involves the development of a mathematical or logical framework that mirrors the recruitment process. This framework accounts for variables characterized by uncertainty – such as candidate response rates or the likelihood of job offer acceptance. The simulation operates by executing a large number of iterations, where each run draws random values for these uncertain variables from their respective probability distributions.

In the specific case of trial recruitment, such simulations are used to estimate expected recruitment durations, assess the number of participants likely to enroll within a given timeframe and evaluate the risk of delays. Scholars such as Concato and Feinstein have recognized the value of Monte Carlo techniques, emphasizing their potential to help researchers address multifaceted challenges. Further contributions by Abbas et al. expanded on this by exploring simulation models under both continuous and discrete time scenarios, specifically tailored for patient recruitment in trials.

Markov models – also known as Markov chains – are mathematical frameworks used to represent systems that transition between distinct states according to defined probabilities. A fundamental feature of these models is the Markov property, which asserts that the likelihood of moving to a future state depends solely on the current state, rather than on the path taken to reach it. In recruitment contexts, Markov models offer a structured way to map the journey of candidates through sequential stages such as initial contact, screening, evaluation, job offer, and eventual hiring or enrollment.

In their research, Abbas et al. applied Monte Carlo simulation in conjunction with Markov models to design and analyze various recruitment strategies for trials. This integration of methods is particularly effective in examining how to maximize participant enrollment within a fixed timeframe.

Markov Chain Monte Carlo (MCMC) methods represent a more sophisticated extension of this concept. These algorithms are used to draw samples from complex probability distributions, particularly when direct sampling is not feasible. While the literature primarily highlights the use of "Monte Carlo simulation Markov models", MCMC methods build on the same principles – using purposefully constructed Markov chains to generate samples for Monte Carlo-based estimation. Introductions to MCMC emphasize its utility in numerically approximating uncertainties in model parameters through chains of random samples.

The frequent combination of Monte Carlo simulation with Markov modeling is not incidental – it reflects a powerful methodological synergy. Monte Carlo methods are adept at handling uncertainty through repeated random sampling, while Markov models excel at describing systems that progress through probabilistic stages. Recruitment, by nature, is a multi-phase process: a pipeline where individuals move from awareness or application through filtering mechanisms such as interviews and assessments, toward final selection.

Markov models effectively capture the probabilistic structure of this progression, while Monte Carlo simulations introduce realism by accounting for variability in candidate flow and transition success rates at each stage. By combining the two, researchers and practitioners gain a more dynamic and nuanced view of recruitment performance. This approach enables the identification of bottlenecks, estimation of throughput rates, and prediction of timeframes for achieving recruitment goals – surpassing the limitations of simplified aggregate models that, for example, treat total hires as a single stochastic output.

Recruitment simulation models can be structured using either discrete or continuous time frameworks, each offering different perspectives and analytical depth. Discrete time models divide recruitment activity into fixed intervals – such as tracking the number of patients enrolled per week or employees hired per month. Continuous time models, on the other hand, treat recruitment as a fluid process in which events (like patient arrivals or candidate applications) can occur at any moment. This approach enables more detailed analysis of time-sensitive aspects of recruitment.

Effectively applying Monte Carlo simulations in the context of recruitment requires a structured, methodical approach that integrates domain-specific expertise with robust statistical techniques. Baumann, Singmann, Gershman, and von Helversen (2020) introduce a model of human stopping behavior in sequential decision-making tasks, grounded in a linear threshold heuristic. Their first two studies reveal that this model provides a superior fit to participant behavior compared to existing models, effectively capturing patterns of search behavior across varying environments. A third study further demonstrates the model's applicability to a real-world scenario, marking a significant advancement in the understanding of human sequential decision-making processes.

Conclusions and prospects of further research. This article provides a comprehensive analysis of the potential of Monte Carlo and Markov models for optimizing recruitment processes, in the general HR context. The conclusions drawn show that these mathematical and statistical approaches are extremely useful in modelling, forecasting, and improving multifactorial processes characterized by a high level of uncertainty and variability.

In particular, Monte Carlo methods allow for the creation of numerous scenarios based on random samples from established probability distributions, which makes them a powerful tool in situations where classical analytical methods lose accuracy or cannot be applied at all. Combined with Markov models that describe probabilistic transitions between successive states of the system (for example, candidate selection stages), these simulation tools allow not only to predict possible outcomes, but also to actively influence the structure of the recruitment process.

In the field of research, these methods have already demonstrated their effectiveness. As shown in a number of studies, in particular in the works of Abbas et al., Monte Carlo Markov-type models allow not only to predict the timing of patient recruitment, but also to minimize these times by simulating testing of various strategies: expanding the number of recruitment centres, changing the inclusion criteria, or optimizing administrative procedures.

In HR recruitment, the situation is similar: recruitment processes are also multi-stage, with a large number of probabilistic variables, such as the response rate of candidates, interview pass rate, probability of accepting the offer, etc. Monte Carlo methods help to model not only the final result (number of hires), but also to identify specific bottlenecks in the recruitment "funnel", predict the workload on recruiters, calculate the effectiveness of various recruitment channels and reduce the risks of not achieving KPIs.

In addition, the differences between the discrete and continuous approaches to time modelling in recruitment were highlighted. Although discrete models are easier to implement, it is the continuous approach that provides higher accuracy and allows you to detect hidden time delays that accumulate at the micro level, but significantly affect the overall time to close vacancies or enrol patients in a trial.

It is also worth noting that Monte Carlo methods are not the only possible model for recruitment simulations. For example, Poisson mixture models are also used to model variable recruitment rates. However, the combination of Monte Carlo and Markov models provides exceptional flexibility, allowing you to simultaneously model randomness and the dynamics of transitions between stages.

Therefore, we can say that simulation modelling of recruitment processes using Monte Carlo methods is not only a forecasting tool, but also a platform for strategic resource management, adaptive planning, time and cost optimization. The use of these methods is especially appropriate in cases where recruitment is critical to achieving target indicators, has a high level of variability, or is costly.

Future research prospects include expanding modelling by integrating real-time data (e.g., from ATS or CRM systems), combining simulations with machine learning to automatically adjust model parameters, and adapting models to the specifics of different labour markets, industries, or cultural contexts.

Thus, the application of Monte Carlo methods in recruiting is an important step towards transforming traditional personnel selection into an analytically driven, flexible, and predictive function that meets the challenges of the modern world.

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The authors declare that there are no conflicts of interest that could affect the objectivity or results of this study. All stages of the study, including planning, execution, and preparation of the article, were conducted independently, without external influence or bias.

REFERENCES

Arthur, W. Jr. & Villado, A. J. (2008). The importance of distinguishing between constructs and methods when comparing predictors in personnel selection research and practice. *Journal of Applied Psychology*, *93*, 435–442. URL: https://doi.org/10.1037/0021-9010.93.2.435

Banack, H. R., Hayes-Larson, E., & Mayeda, E. R. (2021). *Monte Carlo Simulation Approaches for Quantitative Bias Analysis: A Tutorial.* Epidemiologic Reviews, 43(1), 183–192. URL: https://doi.org/10.1093/epirev/mxab012

Baumann, C., Singmann, H., Gershman, S. J., & von Helversen, B. (2020). *A linear threshold model for optimal stopping behavior.* Proceedings of the National Academy of Sciences of the United States of America, 117(23), 12750–12755. URL:https://doi.org/10.1073/pnas.2002312117

Bonabeau, E. (2002). *Agent-based modeling: Methods and techniques for simulating human systems.* Proceedings of the National Academy of Sciences of the United States of America, 99(Suppl 3), 7280–7287. URL:https://doi.org/10.1073/pnas.082080899

Georgescu, I. The early days of Monte Carlo methods. *Nat Rev Phys* **5**, 372 (2023). URL:https://doi.org/10.1038/s42254-023-00608-w

Gölbaşi, O., & Sahiner, S. F. (2024). *Simulation-based optimization of workforce configuration for multi-division maintenance departments.* Computers & Industrial Engineering, 188, 109880. URL: https://doi.org/10.1016/j.cie.2024.109880

Huffcutt, A. I., Culbertson, S. S. & Weyhrauch, W. S. (2013). Employment interview reliability: New meta-analytic estimates by structure and format. *International Journal of Selection and Assessment*, *21*, 264–276. URL:https://doi.org/10.1111/ijsa.12036

Huber M., Lechner M., Wunsch C. (2013). The performance of estimators based on the propensity score Journal of Econometrics, volume 175, issue 1, p. 1 – 21 URL:https://api.semanticscholar.org/CorpusID:54996557

Komar, S., Brown, D. J., Komar, J. A., & Robie, C. (2008). *Faking and the validity of conscientiousness: A Monte Carlo investigation.* Journal of Applied Psychology, 93(1), 140–154. URL:https://doi.org/10.1037/0021-9010.93.1.140

Lee, P., Joo, S.-H., & Fyffe, S. (2019). *Investigating faking effects on the construct validity through the Monte Carlo simulation study.* Personality and Individual Differences, 150, 109491. URL:https://doi.org/10.1016/j.paid.2019.07.001

Lombardi, Stefano and van den Berg, Gerard J. and Vikström, Johan. (2021). Empirical Monte Carlo Evidence on Estimation of Timing-of-Events Models. IZA Discussion Paper No. 14015, Available at SSRN: URL:https://ssrn.com/abstract=3762885

Mangino, A. A., & Finch, W. H. (2021). *Prediction With Mixed Effects Models: A Monte Carlo Simulation Study.* Educational and Psychological Measurement, 81(6), 1118–1142. URL: https://surl.li/manynf

Metropolis, N., & Ulam, S. (1949). The Monte Carlo Method. *Journal of the American Statistical Association*, *44*(247), 335–341. URL:https://doi.org/10.1080/01621459.1949.10483310

Ock, J., & Oswald, F. L. (2018). *The Utility of Personnel Selection Decisions: Comparing Compensatory and Multiple-Hurdle Selection Models.* Journal of Personnel Psychology, 17(4), 172–182. URL: https://doi.org/10.1027/1866-5888/a000205

Paxton, P., Curran, P. J., Bollen, K. A., Kirby, J., & Chen, F. (2001). *Monte Carlo experiments: Design and implementation.* Structural Equation Modeling, 8(2), 287-312. URL:https://doi.org/10.1207/S15328007SEM0802_7

Przysucha, B., Bednarczuk, P., Martyniuk, W., Golec, E., Jasieński, M., & Pliszczuk, D. (2024). *Monte Carlo Simulation as a Demand Forecasting Tool.* European Research Studies Journal, XXVII(Special Issue 2), 103-113. URL:https://doi.org/10.35808/ERSJ/3391

Sadeghi Dastaki, M., & Afrazeh, A. (2018). *A two-stage skilled manpower planning model with demand uncertainty.* International Journal of Intelligent Computing and Cybernetics, 11(1), 2-20. URL: https://doi.org/10.1108/IJICC-04-2018-0048

Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., et al. (2019). Why so many published sensitivity analyses are false: a systematic review of sensitivity analysis practices. *Environ. Model. Softw.* 114, 29–39. URL: https://surl.li/manynf

Sin, G., Gernaey, K. V., Neumann, M. B., van Loosdrecht, M. C., and Gujer, W. (2009). Uncertainty analysis in WWTP model applications: a critical discussion using an example from design. *Water Res.* 43, 2894–2906. URL:https://doi.org/10.1016/j.watres.2009.03.048

Shonkwiler, R.W., Mendivil, F. (2024). Introduction to Monte Carlo Methods. In: Explorations in Monte Carlo Methods. Undergraduate Texts in Mathematics. Springer, Cham. URL:https://doi.org/10.1007/978-3-031-55964-8_1

The Editors of Encyclopaedia Britannica (2025). Monte Carlo method. Encyclopedia Britannica. URL:https://www.britannica.com/science/Monte-Carlo-method

Tilahun, N., & Levinson, D. (2013). *An Agent-Based Model of Origin Destination Estimation (ABODE).* The Journal of Transport and Land Use, 6(1), 73–88. URL: https://www.jstor.org/stable/26202649

ОПТИМІЗАЦІЯ ПРОЦЕСУ НАБОРУ ПЕРСОНАЛУ ЗА ДОПОМОГОЮ МЕТОДІВ МОНТЕ-КАРЛО

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Анотація. *В статті подано обґрунтування застосування методів Монте-Карло для вдосконалення процесів підбору персоналу шляхом моделювання невизначеностей, пов'язаних із прийняттям рішень у сфері добору кадрів, з метою трансформації рекрутингу з адміністративної функції на стратегічний інструмент управління ризиками та ресурсами. У статті запропоновано симуляційну модель, яка ґрунтується на використанні численних стохастичних ітерацій для аналізу ключових параметрів процесу найму, зокрема часу відгуку, коефіцієнтів конверсії, відповідності кандидатів профілю вакансії та пов'язаних* *витрат. Результати дослідження свідчать про те, що застосування методів Монте-Карло дозволяє покращити прогнозованість процесів найму, ідентифікувати критично важливі фактори впливу та підвищити ефективність розподілу ресурсів. Симуляційний підхід дає змогу HR-аналітикам і управлінцям моделювати альтернативні сценарії добору персоналу, оцінювати ризики та обґрунтовувати кадрові рішення на базі кількісних оцінок. Отримані результати мають практичне значення для вдосконалення стратегічного управління персоналом у динамічному та конкурентному середовищі.*

Ключові слова: *рекрутинг, методи Монте-Карло, симуляція, невизначеність, управління ризиками, стратегічне планування, аналітика, прогнозування, підбір персоналу.*

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