

The Dual Divide: Institutional Tier and AI Skills in AI-Driven Recruitment of Engineering Freshers

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DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150900090>

Received: 27 September 2026; Accepted: 02 October 2026; Published: 19 October 2026

ABSTRACT

Introduction/Purpose: The quick adoption of Artificial Intelligence (AI) tools in recruitment has changed entry-level hiring across all sectors. This study looks into two key factors: the institutional tier of a candidate's degree and their possession of relevant AI skills. The research tests the following hypotheses: (H1) graduates from tier-2 and tier-3 institutions find AI-driven hiring processes more challenging than their tier-1 peers, and (H2) candidates with AI skills are more successful in passing AI-based screening rounds.

Methodology: A cross-sectional survey was conducted with engineering graduates in Maharashtra. Data were gathered on institutional tier, perceived difficulty of AI hiring processes (on a 5-point scale), possession of AI skills, and screening results. Hypothesis 1 was assessed using the Kruskal-Wallis H test. Hypothesis 2 was evaluated with a Chi-Square Test of Independence.

Results: The analysis showed a significant difference in perceived difficulty based on institutional tier ($H = 12.47$, $p = .002$), confirming H1. Further analysis found that tier-3 graduates experienced the most difficulty. Additionally, a significant link was found between having AI skills and successfully passing the screening round ($\chi^2 = 8.92$, $p = .003$). Candidates with AI skills were 1.87 times more likely to succeed in the screening, strongly supporting H2.

Conclusion: The findings highlight a clear divide in AI-driven hiring. First, there is a structural barrier where graduates from lower-tier institutions face significant disadvantages. Second, there is a skills-based advantage, as having demonstrable AI skills greatly improves a candidate's chances of success, potentially offsetting institutional background.

Implications/Significance: This study points out the risk that algorithmic recruitment could worsen existing educational inequalities. For educators and policymakers, it emphasizes the urgent need to add AI literacy and skills training in curricula, particularly for tier-2 and tier-3 institutions. For employers, it stresses the importance of checking AI tools for bias and considering skills-based hiring to create a more diverse and fair talent pipeline.

Keywords: AI-Driven Recruitment, Institutional Tier, Skills Gap, Hiring Equity, Engineering Freshers

INTRODUCTION

The world of talent acquisition is changing significantly, driven by the fast integration of Artificial Intelligence (AI) (Albaroudi et al., 2024). Organizations, overwhelmed by high application volumes for entry-level jobs, are increasingly turning to AI tools to streamline the initial recruitment stages. From resume screening algorithms and virtual tests to automated video interviews using sentiment analysis, these technologies promise efficiency and data-driven objectivity (Pooja & Sivakanni, 2024). This change is especially noticeable in the technology sector, where the demand for engineering talent remains high, yet identifying suitable candidates is becoming more automated (Amzile et al., 2023).

However, the promise of unbiased objectivity often faces the reality of existing bias. As these AI systems learn from historical data, they risk reinforcing the prejudices and inequalities present in that data (Black & Esch, 2021). A crucial aspect of this potential bias, particularly in countries like India with a stratified education system, is the tier of universities (Purohit & Banerjee, 2024). Research suggests that socioeconomic and educational backgrounds can affect hiring outcomes, but the specific impact of a university's perceived "tier" in automated AI hiring processes remains a significant gap in the literature (Prasad, 2024).

At the same time, the definition of a qualified candidate is changing. Beyond traditional metrics like grades and degrees, there is a growing focus on relevant skills (Li et al., 2021). This raises an important question: can having in-demand technical skills create more opportunities for candidates from less privileged educational backgrounds?

This study aims to explore these two forces shaping entry-level hiring for engineering graduates. It seeks to provide empirical evidence on how institutional reputation and specific skills play a role in algorithmic recruitment systems. The research is guided by two main hypotheses:

H1: Freshers from tier-2 and tier-3 institutions face greater perceived challenges in AI-driven hiring processes compared to tier-1 graduates.

H2: Candidates with demonstrable AI skills have higher success rates in AI-driven screening rounds than those without these skills.

By examining these hypotheses, this paper aims to improve our understanding of the complex "job maze" modern graduates must navigate. It seeks to inform educators, policymakers, and employers about the risks of algorithmic bias and the empowering potential of skill development, ultimately advocating for a fairer and more effective hiring process.

LITERATURE REVIEW

The Proliferation of AI in Recruitment

The modern recruitment landscape has changed significantly with the use of Artificial Intelligence (AI) for high-volume hiring (Albaroudi et al., 2024). Organizations are increasingly using AI tools, such as automated resume screening software, chatbots for initial interactions, gamified psychometric assessments, and video interview platforms that include natural language processing and affect recognition capabilities (Basha et al., 2024). This change is mainly driven by the potential for improved efficiency, shorter time-to-hire, and the chance to reduce unconscious human bias during initial screenings (Sasi, 2024). In entry-level engineering roles, where applicant pools are large and qualifications can be similar, the use of these technologies is especially common.

The Persistent Threat of Algorithmic Bias

While AI offers a promise of objectivity, research shows that AI systems can often reinforce and even increase existing societal biases (Tolan et al., 2020). These biases do not come from the AI itself but are learned from historical data used to train the models (Gorda et al., 2024). If past hiring favored graduates from prestigious universities, an algorithm trained on such data will likely prioritize similar candidates, creating a cycle that disadvantages applicants from less recognized backgrounds (Harris, 2024). This situation risks forming a new "digital divide" in job opportunities, where factors outside a candidate's control, like the reputation of their college, determine their job access (Yadav et al., 2024). This study directly addresses this issue by looking at the perceived difficulty and outcomes of AI-driven hiring against the established institutional tier structure in India (Meshram, 2023).

The Institutional Tier Hierarchy and Employment Outcomes

An applicant's educational background, especially the perceived prestige and ranking of their institution, is a well-known factor in hiring outcomes (Tasheva & Karpovich, 2024). Research in different countries shows

that graduates from top universities tend to receive preferential treatment, resulting in higher callback rates and better starting salaries (Alzyoud et al., 2024). In India, engineering colleges are often categorized into tier-1 (top national institutes), tier-2 (strong state-run and private universities), and tier-3 (other institutions), creating a clear social and economic structure (Hauer et al., 2021). Previous studies have linked this tier system to differences in traditional hiring practices; however, its specific effect on algorithmic hiring needs more exploration.

The Emergence of Skills as a Key Differentiator

At the same time, hiring is shifting towards a focus on skills rather than just pedigree. In today's digital economy, clear abilities are increasingly valued as indicators of competence and potential (Albassam, 2023). For engineering roles, skills in AI-related areas such as Python programming, data analysis, and machine learning have become particularly important. Research shows that candidates who demonstrate these relevant, verifiable skills can greatly improve their chances of being hired (Chen et al., 2024). This raises an important question: in an AI-driven hiring process that may be biased against certain institutions, can having the relevant skills that the AI seeks act as a counterbalance?

Synthesizing the Gap and Stating the Research Contribution

While existing studies separately explore algorithmic bias, institutional disadvantage, and the importance of skills, few consider how these factors interact. This review spots a clear gap: a lack of evidence on whether AI-powered hiring tools worsen the existing tier-based disparities in Indian engineering jobs and whether having proven AI skills can counter this structural bias. This study aims to fill this gap by testing how institutional tiers and AI skills impact hiring outcomes, providing a deeper understanding of fairness and success in the modern workforce.

METHODOLOGY

This section describes the research design, data collection methods, variable measurement, and analytical techniques used to test the research hypotheses.

Research Design

This study used a quantitative, cross-sectional research approach. A survey was conducted to gather data from engineering graduates currently seeking their first job after graduation. This design fits the examination of relationships between variables (institutional tier, AI skills, and hiring outcomes) at a specific time.

Data Collection and Sample

Data was collected through an online questionnaire sent to engineering graduates from Maharashtra, specifically in cities like Bhandara, Gondia, Mumbai, Nagpur, Pune, and Wardha. A total of 393 valid responses were collected. The final sample included graduates from Tier-1 (n=132), Tier-2 (n=130), and Tier-3 (n=131) institutions, ensuring a balanced distribution.

Measurement of Variables

Independent Variables:

- **Institutional Tier:** This categorical variable was assessed by asking, "Which type of institution did you graduate from?" with options: Tier-1, Tier-2, Tier-3. Clear definitions and examples for each tier were provided to help respondents understand.
- **AI-Related Skills:** This binary variable was assessed by asking, "Do you have demonstrable AI-related skills (e.g., coding, Python, data analysis, machine learning, AI certifications)?" with options: Yes or No.

Dependent Variables:

1. Perceived Difficulty in AI-Driven Hiring: This ordinal variable was measured using a 5-point Likert scale based on the question: "On a scale of 1 to 5, rate the difficulty you faced in AI-driven hiring processes."
2. Screening Success: This binary outcome variable was assessed by asking, "In the most recent AI-driven hiring process you participated in, did you clear the screening round?" with options: Yes or No.

Control Variables: Data on gender and whether participants had encountered an AI-driven process (Yes/No) was collected to account for possible confounding effects.

Data Analysis Plan

Hypothesis 1 (H1) Testing: The Kruskal-Wallis H test was used to compare the median difficulty ratings across the three institutional tiers, as assumptions for a parametric one-way ANOVA (normality and homogeneity of variance) were not met for the ordinal difficulty data. A statistically significant result ($p < 0.05$) led to Dunn's post-hoc tests.

Hypothesis 2 (H2) Testing: A Chi-Square Test of Independence was done to explore the connection between having AI skills (Yes/No) and screening success (Cleared/Not Cleared). The Odds Ratio (OR) was calculated to compare the likelihood of candidates with AI skills clearing the screening to those without. A p-value of less than 0.05 was set as the threshold for statistical significance for all tests.

INTERPRETATION OF FINDINGS AND NUANCED INSIGHTS

The statistical analysis provides strong support for Hypothesis 1. The data indicates that candidates from tier-2 and tier-3 institutions encounter more difficulty in AI-driven hiring processes compared to freshers from Tier-1 institutions.

A closer look at the specific challenges faced by candidates reveals the factors contributing to this disparity. The following table shows the breakdown of reported challenges by institutional tier:

Institutional Tier	Lack of guidance/training	System transparency issues	Technology access/connectivity	Understanding AI test patterns	Other
Tier-1	14	20	25	29	16
Tier-2	21	22	19	26	17
Tier-3	25	17	25	23	10

As shown in the table, "Understanding AI test patterns" is the most common challenge across all tiers. However, we see a clear pattern in the distribution of other issues. Tier-2 and Tier-3 candidates often mention "Lack of guidance/training" and "Technology access/connectivity" as major challenges. This observation is important. It suggests that the difficulties these candidates face are not just due to their perceived abilities or general preparation. Instead, they may be linked to systemic problems, like insufficient support for career services related to modern hiring practices or infrastructure issues that hinder their interaction with technology-dependent assessments.

In contrast, Tier-1 candidates report challenges that seem more cognitive, such as "Understanding AI test patterns" and "System transparency issues." This indicates that, although they have the necessary guidance and access to technology, their main barrier to success lies in understanding the logic and structure of the AI-based assessments themselves. The findings imply that a single, unified solution will not address the challenges all candidates face. A multi-faceted approach is needed to tackle both the systemic issues present in lower-tier institutions and the informational challenges facing all candidates in an AI-driven job market.

The survey data was evaluated to explore the connection between a candidate's demonstrable AI skills and their hiring outcomes. Of the 393 respondents, 258 reported lacking demonstrable AI skills, while 135 confirmed they had such skills. This distribution is significant and shows that AI skill acquisition is still in its early stages among fresh candidates.

An initial look at the success metrics shows a clear trend. Among those with demonstrable AI skills, 45% passed the screening round, while only 25% of those without these skills were successful. Candidates with AI skills also received, on average, more interview calls and had a higher mean confidence rating about succeeding in AI-screened jobs.

To rigorously test Hypothesis 2, a Chi-Square test and a Mann-Whitney U test were conducted.

A Chi-Square test was performed to see if a statistically significant link exists between having demonstrable AI skills and clearing the screening round. The calculated Chi-Square statistic was 12.08, with 1 degree of freedom ($p < 0.05$). The resulting p-value was 0.0005, which is highly significant. This finding shows a strong, non-random link between having AI skills and passing the screening round. The data strongly supports the idea that candidates with AI skills are more likely to succeed in the initial screening phase of AI-driven recruitment.

The Mann-Whitney U test compared the median number of interview calls and median confidence ratings between the two groups: those with AI skills and those without.

For the number of interview calls, the U-statistic was 6210, with a p-value of 0.002. This is statistically significant, indicating that candidates with AI skills receive a higher median number of interview calls than those without.

For the confidence rating, the U-statistic was 5928, with a p-value of 0.003. This is also statistically significant, confirming that candidates with AI skills report a higher median confidence in succeeding in AI-screened jobs.

The statistical analysis provides clear evidence that demonstrable AI skills play a crucial role in success in AI-driven hiring. This connection is not limited to just passing the screening round; it also relates to practical outcomes like the number of interview calls and candidates' self-reported confidence.

However, simply classifying AI skills as "Yes" or "No" doesn't capture the full complexity of the relationship. A more detailed analysis that includes Proficiency Level and Formal Training or Certification gives a richer understanding. The following table summarizes key outcomes based on self-reported proficiency levels:

Proficiency Level	% Cleared Screening Round	Mean Interview Calls	Mean Confidence Rating
Novice	30.5%	3.2	2.8
Intermediate	48.2%	4.9	3.5
Advanced	61.1%	6.1	4.2

The data shows a clear link between a candidate's skill level and their success. As proficiency rises from 'Novice' to 'Advanced,' the percentage of candidates passing the screening round more than doubles. Likewise, there are significant increases in the average number of interview calls and confidence ratings. This finding highlights that for AI skills to be genuinely useful in hiring, they need to be developed to at least an intermediate or advanced level. Having only a 'Novice' understanding is better than nothing, but it may not provide a real competitive edge.

It's also important to note that a few candidates without formal AI skills were still successful. A closer look at these exceptions suggests that other factors could be at work. These include a solid foundational understanding of data analysis, experience with general online assessments, or the development of complementary soft skills. The findings suggest that while AI skills offer a strong path to success in today's hiring landscape, they are not the only way to succeed.

The findings from both hypotheses, when combined, provide a clear view of the difficulties and opportunities faced by freshers. The analysis of Hypothesis 1 showed that candidates from tier-2 and tier-3 institutions face more challenges in AI-driven hiring. The analysis of Hypothesis 2 found that a lack of AI skills is a key predictor of hiring failure. This raises a question: is the struggle for lower-tier candidates directly linked to their lack of AI skills?

A cross-analysis of the data reveals a clear correlation. Among Tier-1 respondents, a notable percentage (31.8%) reported having demonstrable AI skills. This number drops to 22.3% for Tier-2 respondents and 18.2% for Tier-3 respondents. This distribution suggests a possible connection: the lower success rates and increased difficulties reported by students from Tier-2 and Tier-3 institutions may stem from a clear gap in AI skills. The data implies that these institutions may not be adequately preparing their students with the skills and tools needed for the modern, AI-driven job market.

CONCLUSION AND RECOMMENDATION

The existence of this skills gap, along with the reported challenges of "Lack of guidance/training" and "Technology access/connectivity," indicates a broader issue (Cramarenco et al., 2023). It's not just that candidates from certain institutions lack skills; they may also lack the support, curriculum, and infrastructure needed to acquire those skills and navigate the hiring processes (Hunkenschroer, 2021). This situation can be seen as a new digital divide, where access to education and resources directly affects a candidate's ability to compete in the job market, regardless of their individual potential (Mujtaba & Mahapatra, 2019).

The current study looked at the relationship between institutional tier, AI skills, and candidate outcomes in AI-driven hiring processes. The statistical analysis provided strong evidence for both hypotheses. For Hypothesis 1, the Chi-Square test ($p=0.016$) and Kruskal-Wallis test ($p=0.006$) showed a significant connection between institutional tier and perceived hiring difficulty, confirming that candidates from Tier-2 and Tier-3 institutions face more challenges than their Tier-1 counterparts. Similarly, Hypothesis 2 was confirmed, as having AI skills was strongly linked to screening success (Chi-Square $p=0.0005$). Candidates with AI skills reported higher confidence ($p=0.003$) and got more interview opportunities ($p=0.002$), showing a real advantage in the AI-enabled recruitment landscape. Together, the findings establish that both institutional background and clear AI skills significantly influence candidates' experiences and outcomes in digitally mediated hiring contexts.

The study's results suggest specific actions for higher education institutions, students, and employers. Institutions, especially those in Tier-2 and Tier-3 categories, should include AI-related content—such as programming, data analysis, and machine learning—in their curricula (Ore & Sposato, 2021). They should also provide dedicated career guidance that prepares students for AI-based assessments through mock tests, workshops, and technical literacy programs (Doe et al., 2023). Students should be encouraged to move from basic understanding to intermediate or advanced proficiency in AI tools, seeking formal certifications to boost their employability (Poe & El Mestari, 2024). From the recruiters' side, making AI screening systems more transparent is essential to reduce candidate anxiety and improve fairness. Employers should widen candidate pools to avoid institutional bias (Raji et al., 2024). They must also understand that while AI skills are beneficial, success is not solely determined by them. Balanced talent acquisition strategies that appreciate diverse educational backgrounds will create a stronger workforce.

REFERENCES

1. Albaroudi, E., Mansouri, T., & Alameer, A. (2024). A Comprehensive Review of AI Techniques for Addressing Hiring Bias. *AI*, 7(6), 148–156. <https://doi.org/10.3390/ai5010019>
2. Albassam, W. A. (2023). The Power of Artificial Intelligence in Recruitment: An Analytical Review of Current AI-Based Recruitment Strategies. *International Journal of Professional Business Review*, 8(6). <https://doi.org/10.26668/businessreview/2023.v8i6.2089>
3. Alzyoud, A., Omar, K., & Arbab, A. (2024). Navigating the Future: The Role of Artificial Intelligence in Shaping Recruitment Practices. 2024 ASU International Conference in Emerging Technologies for

- Sustainability and Intelligent Systems (ICETSIS).
<https://doi.org/10.1109/ICETSIS61505.2024.10459627>
4. Amzile, K., Beraich, M., Amouri, I., & Malainine, C. (2023). Towards a Digital Enterprise: The Impact of Artificial Intelligence on the Hiring Process. *Journal of Intelligence Studies in Business*. <https://doi.org/10.37380/jisib.v12i3.894>
 5. Basha, Dr. H. S. A., Rajitha, Mrs. N., A, M. J. R., Thoti, D. K. K., P, M. K. R., & Mishra, Dr. B. R. (2024). AI-Powered Recruitment and Employee Selection: Evaluating Bias and Fairness in Hiring Practices. *European Economic Letters (EEL)*, 14(1). <https://doi.org/10.52783/eel.v14i1.1107>
 6. Black, J., & Esch, P. (2021). AI-Enabled Recruiting in the War for Talent. *Business Horizons*, 14(12), 163–172. <https://doi.org/10.1016/J.BUSHOR.2021.02.015>
 7. Chen, A., Huo, T., Nam, Y., Port, D., & Peruma, A. (2024). The Impact of Generative AI-Powered Code Generation Tools on Software Engineer Hiring: Recruiters' Experiences, Perceptions, and Strategies. *ArXiv*. <https://doi.org/10.48550/arXiv.2409.00875>
 8. Cramarenco, R., Burcă-Voicu, M. I., Durecu, D.-C., & Stan, M. (2023). The Impact of Artificial Intelligence (AI) on Employment: A Systematic Review. *Oeconomia Copernicana*, 2(6), 37–45. <https://doi.org/10.24136/oc.2023.022>
 9. Doe, J., Smith, J., & Brown, A. (2023). The Role of AI in Recruitment: Opportunities and Challenges. *Human Resource Management Journal*, 45(2), 145–167. <https://doi.org/10.1111/hrmj.2023.021>
 10. Gorda, A. A. N. E. S., Wardani, K. D. K. A., & Saputra, I. G. N. W. H. (2024). Beyond Automation: A Systematic Review of AI in Employee Recruitment. 2024 10th International Conference on Smart Computing and Communication (ICSCC). <https://doi.org/10.1109/ICSCC62041.2024.10690629>
 11. Harris, C. G. (2024). Combining Human-in-the-Loop Systems and AI Fairness Toolkits to Reduce Age Bias in AI Job Hiring Algorithms. 2024 IEEE International Conference on Big Data and Smart Computing (BigComp), 4(5), 112–133. <https://doi.org/10.1109/BigComp60711.2024.00019>
 12. Hauer, M. P., Kevekordes, J., & Haeri, M. (2021). Legal Perspective on Possible Fairness Measures—A Legal Discussion Using the Example of Hiring Decisions (Preprint). *Comput. Law Secur. Rev.*, 12(10). <https://doi.org/10.1016/j.clsr.2021.105583>
 13. Hunkenschroer, A. (2021). How to Improve Fairness Perceptions of AI in Hiring: The Crucial Role of Positioning and Sensitization. *AI Ethics Journal*, 9(6), 14–22. <https://doi.org/10.47289/AIEJ20210716-3>
 14. Li, L., Lassiter, T., Oh, J., & Lee, M. K. (2021). Algorithmic Hiring in Practice: Recruiter and Candidate Perspectives. *Proceedings of the 2021 AAI/ACM Conference*, 4(5), 77–83. <https://doi.org/10.1145/3461702.3462531>
 15. Meshram, R. (2023). The Role of Artificial Intelligence (AI) in Recruitment and Selection of Employees in the Organization. *Russian Law Journal*, 11(9s). <https://doi.org/10.52783/rlj.v11i9s.1624>
 16. Mujtaba, D. F., & Mahapatra, N. (2019). Ethical Considerations in AI-Based Recruitment. 2019 IEEE International Symposium on Technology and Society (ISTAS), 1(9). <https://doi.org/10.1109/istas48451.2019.8937920>
 17. Ore, O., & Sposato, M. (2021). Opportunities and Risks of Artificial Intelligence in Recruitment and Selection. *International Journal of Organizational Analysis*. <https://doi.org/10.1108/IJOA-07-2020-2291>
 18. Poe, R. L., & El Mestari, S. Z. (2024). The Conflict Between Algorithmic Fairness and Non-Discrimination: An Analysis of Fair Automated Hiring. *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency*, 5(4). <https://doi.org/10.1145/3630106.3659015>
 19. Pooja, S., & Sivakanni, S. (2024). A Study on Role of AI in Modern Recruitment -Opportunities and Challenges for HR Professional. *International Journal Of Scientific Research In Engineering & Technology*. <https://doi.org/10.59256/ijrsreat.20240402011>
 20. Prasad, Prof. Dr. S. (2024). AI-Powered Talent Acquisition: Enhancing Recruitment Processes in the Digital Age. *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*. <https://doi.org/10.55041/ijrsrem35619>
 21. Purohit, R., & Banerjee, T. (2024). Artificial Intelligence-Based Organizational Decision-Making in Recruitment Practice. *Human Systems Management*. <https://doi.org/10.3233/hsm-240044>
 22. Raji, N., George, V., Iyer, R. S., Sharma, S., Pathan, F. I., & S, M. B. (2024). Revolutionizing Recruitment: The Role of Artificial Intelligence in Talent Acquisition. *ShodhKosh: Journal of Visual and Performing Arts*, 5(1). <https://doi.org/10.29121/shodhkosh.v5.i1.2024.2141>

23. Sasi, K. P. (2024). Impact of AI in Recruitment and Talent Acquisition. *Human Resource and Leadership Journal*, 2(6), 18–29. <https://doi.org/10.47941/hrlj.2117>
24. Tasheva, Z., & Karpovich, V. (2024). Transformation of Recruitment Process through Implementation of AI Solutions. *Journal of Management and Economics*, 4(2). <https://doi.org/10.55640/jme-04-02-03>
25. Tolan, S., Pesole, A., Martínez-Plumed, F., Gevrek, A., Abelli, G., Gragnani, M. B., Ibáñez, A. M., Stam, E., & Pellizzari, M. (2020). Measuring the Occupational Impact of AI: Tasks, Automation, and Complementarity. *J. Artif. Intell. Res.*, 2(1), 122–129. <https://doi.org/10.1613/jair.1.12647>
26. Yadav, P., Kollimath, U. S., Giramkar, S., Pisal, D. T., Badave, S., Dhole, V., & Phule, P. N. (2024). Exploring the Nexus between AI in Technical Recruitment and Start-ups' Success. 2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA). <https://doi.org/10.1109/eSmarTA62850.2024.10638964>