

1 **Opening the Black Box of Job Satisfaction: Can**
2 **AI Tell You Why You're Dissatisfied?**

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5 A friend asked me to help with something, and while doing it I ended up reading quite a few papers.
6 In the process I wanted to understand what is actually happening at the point where HR meets
7 machine learning. The answer turned up in an unexpected place.



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10 **1. The First Question: “Can Job Satisfaction Be Predicted?”**

11 Job satisfaction is an old topic. It is a staple of organizational behavior, and any HR professional
 12 has run a survey on it at least once. Yet something is strange. After decades of studying “what
 13 influences job satisfaction?”, there is almost no research that actually predicts “**how will this**
 14 **employee’s satisfaction change next year?”**

15 Traditional analysis relies on OLS regression. When variable A goes up by one unit, job satisfaction
 16 goes up by B. Clean. A single straight line explains everything.

17 The problem is that reality is not a straight line.

18 Somers, Birnbaum, and Casal (2021) ran OLS and an artificial neural network (ANN) on the same
19 data simultaneously. The results differed. The effect of supervisor support on employee well-being
20 rose up to a certain point, and beyond that threshold it **stopped rising**. Diminishing returns.
21 OLS failed entirely to capture this bend, because a straight line has no bend.

22 Roedenbeck and Poljsak-Rosinski (2023) confirmed that an ANN achieved $R^2 > 0.75$ on data from
23 43,000 people. It clearly outperformed the OLS baseline. Schulz et al. (2026) found something even
24 more striking in longitudinal data from 509 firms. There was an **inverted U-shaped** relationship
25 between AI adoption and job satisfaction. Adopting AI raises satisfaction up to a point, but
26 adopting too much of it brings satisfaction back down.

27 This is just like a drug’s dose-response curve. The right dose heals, but an overdose becomes poison.
28 And OLS regression flattens this curve into a straight line, concluding only that the drug “has a
29 slight effect” — even though an optimal dose actually exists.

30 The first answer is this. Machine learning models can predict job satisfaction. And they do it
31 better than traditional OLS. Consistently, across multiple studies.

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33 **2. The Second Question: “But Why Do They Do Better?”**

34 This is where the story gets tangled.

35 We accept that ML models are more accurate than OLS. But we do not know **why** they are more
36 accurate. Say a random forest hits $R^2 = 0.85$. The HR professional will ask, “So what exactly am I
37 supposed to do with that?”

38 The model does not answer. It is a black box.

39 Here we run into the tension between “accurate prediction” and “explainable prediction.” Benabou
40 (2026) called this the accuracy-interpretability trade-off. Random forests and XGBoost are the most
41 accurate but the most opaque, while decision trees (CART) are transparent but less accurate.

42 When I combed through 53 papers, the number that resolved this tension was **two**. Exactly two.

43 Chaudhary (2025) used a tool called SHAP for employee turnover prediction. SHAP comes from the
44 Shapley value in game theory, and it numerically decomposes how much each variable contributed
45 to a prediction. By analogy, it is like calculating each player’s **marginal contribution** to winning
46 a soccer match. Not only the player who scored, but also the player who passed, the player who
47 blocked on defense, and the coach who set the team tactics — each one’s share of the contribution
48 is divided up precisely.

49 Sobrie (2024) combined LightGBM with SHAP in a railway traffic control setting to build a system
50 that predicts and explains workload in real time. Instead of merely telling controllers “you are
51 currently overloaded,” it became able to say, “this train-assignment pattern explains 73% of your
52 workload.”

53 What the convergence of these two studies shows is clear. SHAP-based XAI (explainable AI) can
54 open the black box. It preserves ML’s predictive power while explaining “why.”

55 But — and this is the crux — neither study targeted **job satisfaction**. One is about turnover,
56 the other about workload. As far as I have read, there is not yet a study that applies SHAP to
57 predicting job satisfaction.

58

59 **3. The Third Question: “Is Job Satisfaction a Single Thing?”**

60 This question changes everything.

61 Most existing research measures job satisfaction as a single score. “How satisfied are you with your
62 current job?” From 1 to 5. But stop and think for a moment. A person who loves the work itself
63 but is poorly paid, and a person who is paid decently but struggles with colleagues, can give the
64 same score. Behind the number 3 lie completely different stories.

65 Job satisfaction has at least three **sub-dimensions**.

- 66 • **Satisfaction with the work content:** Is the work itself meaningful?
- 67 • **Pay satisfaction:** Is the compensation fair?
- 68 • **Interpersonal satisfaction:** Are relationships with the people you work with good?

69 Are the factors that determine these three the same? Intuitively they differ. Yet no study has
70 predicted them separately with ML and compared the key drivers of each dimension using SHAP.

71 This is where Job Demands-Resources (JD-R) theory enters. The theory was originally created to
72 explain burnout and motivation. Job resources (autonomy, supervisor support, growth opportuni-
73 ties) raise motivation, while job demands (overload, time pressure, emotional labor) deplete energy.
74 It is a simple but powerful frame.

75 Applying this theory by **twisting** it onto the sub-dimensions of job satisfaction makes interesting
76 predictions possible. For satisfaction with work content, the core drivers would be autonomy
77 and competence development among the job resources. Pay satisfaction would be dominated by
78 compensation fairness. Interpersonal satisfaction would be determined by social support and team
79 cohesion.

80 This is a theoretical conjecture. It has not yet been empirically demonstrated. But if SHAP
81 analysis supports this prediction, we gain two things at once: an answer to **why** the ML model
82 predicts as it does, and empirical evidence that JD-R theory operates even at the sub-dimension
83 level.

84

85 **4. The Fourth Question: “Is the Prediction Fair?”**

86 ML can predict job satisfaction. Good. SHAP can explain the reasons. Even better. But one thing
87 remains.

88 Is that prediction **fair**?

89 Fabris et al. (2024) issues a direct warning. AI-based hiring systems can reproduce structural
90 discrimination against particular groups. If there is a model that predicts highly educated men to
91 be “more satisfied,” that is not prediction — it is the automation of prejudice.

92 Zheng et al. (2025) identified four “shadow experiences” of AI-HRM systems: erosion of interper-
93 sonal autonomy, surveillance-induced precarity, the algorithmic bias dilemma, and personalized
94 dissatisfaction. It is the paradox that AI, introduced to help HR, can instead gnaw away at
95 employees’ autonomy.

96 Yet Deng et al. (2025)’s finding offers a counterweight to this pessimism. Algorithmic monitoring can
97 **improve** employee well-being through perceptions of organizational fairness. There is a condition,
98 however. **When it is transparent.** When employees can understand why the algorithm reached
99 the judgment it did.

100 SHAP is precisely the tool for this transparency. “Your pay satisfaction is predicted to be low
101 mainly because of your compensation level relative to the same job family (contribution 42%)
102 and the transparency of performance evaluation (contribution 28%).” If you can explain it this
103 way, employees do not treat the algorithm as an enemy. Instead they accept it as a tool for
104 understanding their own situation.

105 It is like a medical checkup. Saying only “your cholesterol is high” makes you anxious. But saying,
106 “your LDL is 160, mainly driven by saturated-fat intake (contribution 45%) and lack of exercise
107 (contribution 30%), and it can be improved within three months through dietary control,” leads to
108 action. A SHAP-based explanation of job satisfaction is, in effect, the organizational version of a
109 medical checkup report.

110

111 **5. The Empty Seat: Where Is Korea?**

112 There was corporate data from Europe, North America, Southeast Asia, and the Middle East.
113 Korea was absent.

114 To be precise, there was **not a single** ML-based job satisfaction prediction study using Korea’s
115 Human Capital Corporate Panel (HCCP) data. Kim (2025) analyzed job-portal text from the
116 Korean food-service industry, but that is text data, not the multidimensional survey structure of
117 the HCCP.

118 There is a reason this gap is not merely an unexamined area.

119 Korean organizations are different. Within a culture of high power distance and hierarchy, the
120 quality of the supervisor-subordinate relationship may be a far stronger predictor than in Western
121 contexts. Within the dual structure of regular and non-regular employment, employment type may
122 be a key boundary condition that determines pay satisfaction. With the MZ generation and the
123 baby-boom generation working in the same office, the very structure of job satisfaction may differ
124 across generations.

125 There is no guarantee that patterns confirmed in the West will be reproduced in Korea. In the
126 pathway “AI HR analytics → job crafting → resilience” proposed by Xiao, Yan, and Bamber (2025),
127 the cultural acceptability of the act of job crafting — actively redesigning one’s own job — may be
128 lower in high-power-distance Korean organizations than in the West. This cultural moderating
129 effect is a distinctive question that cannot be tested except through HCCP-based research.

130

131 **6. Five Methodologies Point to the Same Place**

132 When you gather the patterns together, a remarkably consistent picture emerges.

133 **First convergence:** ML predicts better than OLS. ANN (Somers, Birnbaum, and Casal 2021),
134 large-scale ANN (Roedenbeck and Poljsak-Rosinski 2023), GBM/XGBoost (Seo 2026), random
135 forest (Gupta et al. 2023), multimodal deep learning (Yang 2025). The algorithms differ and the
136 data differ, but the conclusion is the same. Nonlinear models capture the complex dynamics of job
137 satisfaction more accurately.

138 **Second convergence:** SHAP can open the black box. Turnover prediction (Chaudhary 2025),
139 workload prediction (Sobrie 2024). In different domains and on different models, SHAP generated
140 explanations that HR practitioners can trust.

141 **Third convergence:** Transparency builds trust. Organizational fairness research (Deng et al.
142 2025), platform labor research (Jabagi 2025), decision-support experiments (Langer, Koenig, and
143 Busch 2021). When an algorithm is explainable, employees’ perceptions of fairness and their
144 acceptance rise.

145 The three streams of research converge on a single conclusion. **Explainable prediction is the**
146 **condition for trustworthy HR decision-making.**

147 Yet no one has yet integrated these three streams within a single study. ML prediction + SHAP
148 interpretation + JD-R theory + job satisfaction sub-dimensions + the Korean context. When
149 these five puzzle pieces fit together, we can predict “why an employee is dissatisfied” in numbers,
150 explain the reasons, and propose intervention strategies by dimension.

151

152 7. Not an End but a Beginning

153 There is a temptation to wrap up this piece neatly. “ML is good, SHAP is needed, Korean research
154 is urgent.” True enough, but not sufficient.

155 A more provocative question remains.

156 In a world where ML models have come to predict job satisfaction accurately, what becomes of HR’s
157 role? What is a manager to do upon receiving the prediction that “this employee’s satisfaction will
158 decline within six months”? And if that intervention nullifies the model’s prediction — if satisfaction
159 did not decline thanks to the intervention — is the model “wrong,” or has it “succeeded”?

160 This is the paradox of prediction. The best prediction is the one that makes itself wrong.

161 And one final question. When SHAP shows that “pay explains 42% of satisfaction,” will the
162 organization actually raise pay? When data tells an uncomfortable truth, will the decision-maker
163 follow the data, or turn off the dashboard?

164 It is not a problem of technology. What explainable AI ultimately poses is a question about the
165 organization’s **will**.

166 Benabou, Samira. 2026. “Optimising HRM Practices in Call Centres: Predicting and Explaining
167 Employee Turnover Intention Using Classification and Regression Trees.” *International Journal
168 of Organizational Analysis*. <https://doi.org/10.1108/IJOA-12-2024-5117>.

169 Chaudhary, Rashmi. 2025. “An Integrated Model to Evaluate the Transparency in Predicting
170 Employee Churn Using Explainable Artificial Intelligence.” *Journal of Innovation & Knowledge
171 10*: 100700. <https://doi.org/10.1016/j.jik.2025.100700>.

172 Deng, Huiying, Yang Lu, Di Fan, Wei Liu, and Yucheng Xia. 2025. “The Power of Precision:
173 How Algorithmic Monitoring and Performance Management Enhances Employee Workplace
174 Well-Being.” *New Technology, Work and Employment* 40 (3): 390–403. [https://doi.org/10.
175 1111/ntwe.12328](https://doi.org/10.1111/ntwe.12328).

176 Fabris, Alessandro, Natalia Brunner Wska, Matthew J. Dennis, David Graus, and Philipp Hacker.
177 2024. “Fairness and Bias in Algorithmic Hiring: A Multidisciplinary Survey.” *ACM Transactions
178 on Intelligent Systems and Technology* 16 (1): Article 54. <https://doi.org/10.1145/3696457>.

179 Gupta, Aman, Aarushi Chadha, Vijay Tiwari, Arup Varma, and Vijay Pereira. 2023. “Sustainable
180 Training Practices: Predicting Job Satisfaction and Employee Behavior Using Machine Learning
181 Techniques.” *Asian Business & Management* 22 (5): 1913–36. [https://doi.org/10.1057/s41291-
182 023-00234-5](https://doi.org/10.1057/s41291-023-00234-5).

183 Jabagi, Naomi. 2025. “Do Algorithms Play Fair? Analysing the Perceived Fairness of HR-Decisions
184 Made by Algorithms and Their Impacts on Gig-Workers.” *International Journal of Human
185 Resource Management*. <https://doi.org/10.1080/09585192.2024.2441448>.

186 Kim, Seonghyeon. 2025. “A Comparative Analysis of Job Satisfaction Prediction Models Using
187 Machine Learning: A Mixed-Method Approach.” *Data Technologies and Applications*. <https://doi.org/10.1108/DTA-10-2023-0697>.

189 Langer, Markus, Cornelius J. Koenig, and Verena Busch. 2021. “Changing the Means of Managerial
190 Work: Effects of Automated Decision Support Systems on Personnel Selection Tasks.” *Journal
191 of Business and Psychology* 36 (5): 751–69. <https://doi.org/10.1007/s10869-020-09711-6>.

- 192 Roedenbeck, Marc, and Petra Poljsak-Rosinski. 2023. “Artificial Neural Network in Soft HR
193 Performance Management: New Insights from a Large Organizational Dataset.” *Evidence-Based*
194 *HRM: A Global Forum for Empirical Scholarship* 11 (3): 519–37. [https://doi.org/10.1108/](https://doi.org/10.1108/EBHRM-07-2022-0171)
195 [EBHRM-07-2022-0171](https://doi.org/10.1108/EBHRM-07-2022-0171).
- 196 Schulz, Christian, David Bendig, Alexander Braunche, and Bastian Kindermann. 2026. “Curse or
197 Blessing: Investigating the Influence of Firms’ Artificial Intelligence Adoption on Employee Job
198 Satisfaction.” *Journal of Management Studies* 63 (2): 561–95. [https://doi.org/10.1111/joms.](https://doi.org/10.1111/joms.70004)
199 [70004](https://doi.org/10.1111/joms.70004).
- 200 Seo, Jihye. 2026. “Using Machine Learning in HRD Research: Applications to Advance AI-Driven
201 Organizational Analytics.” *Human Resource Development International*. [https://doi.org/10.](https://doi.org/10.1080/13678868.2025.2541367)
202 [1080/13678868.2025.2541367](https://doi.org/10.1080/13678868.2025.2541367).
- 203 Sobrie, Olivier. 2024. “Explainable Real-Time Predictive Analytics on Employee Workload in
204 Digital Railway Control Rooms.” *European Journal of Operational Research* 312 (3). [https:](https://doi.org/10.1016/j.ejor.2023.09.016)
205 [//doi.org/10.1016/j.ejor.2023.09.016](https://doi.org/10.1016/j.ejor.2023.09.016).
- 206 Somers, Mark J., Dee Birnbaum, and Jean Casal. 2021. “Supervisor Support, Control over
207 Work Methods and Employee Well-Being: New Insights into Nonlinearity from Artificial
208 Neural Networks.” *International Journal of Human Resource Management* 32 (7): 1620–42.
209 <https://doi.org/10.1080/09585192.2018.1540442>.
- 210 Xiao, Qian, Jinpei Yan, and Greg J. Bamber. 2025. “How Does AI-Enabled HR Analytics Influence
211 Employee Resilience: Job Crafting as a Mediator and HRM System Strength as a Moderator.”
212 *Personnel Review* 54 (3): 824–43. <https://doi.org/10.1108/PR-03-2023-0198>.
- 213 Yang, Xiao. 2025. “Enhancing Employee Satisfaction and Retention via Multimodal Deep Learning
214 in Dynamic Human Resources Decision-Making.” *Journal of Organizational and End User*
215 *Computing* 37 (1). <https://doi.org/10.4018/JOEUC.389080>.
- 216 Zheng, Jie, Jie Zhen Zhang, Muhammad Mustafa Kamal, Xiaobei Liang, and Essam A. Alzeiby.
217 2025. “Unpacking Human-AI Interaction: Exploring Unintended Consequences on Employee
218 Well-Being in Entrepreneurial Firms Through an in-Depth Analysis.” *Journal of Business*
219 *Research* 196: 15. <https://doi.org/10.1016/j.jbusres.2025.115406>.