

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

Chungil Chae

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



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

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

Traditional analysis relies on OLS regression. When variable A goes up by one unit, job satisfaction 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.

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."

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

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

3. The Third Question: "Is Job Satisfaction a Single Thing?"

This question changes everything.

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

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

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

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

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

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

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

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

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

Is that prediction **fair**?

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

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

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

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

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

5. The Empty Seat: Where Is Korea?

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

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

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

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

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

6. Five Methodologies Point to the Same Place

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

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

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

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

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

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

7. Not an End but a Beginning

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

A more provocative question remains.

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

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

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

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

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