

Personality-Informed Recruitment for Technical Teams: A Practical Application of the Myers-Briggs Type Indicator (MBTI)



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Abstract

Recruitment for technical teams still leans, more often than not, on credentials and skills tests — a sensible starting point, perhaps, but one that says little about whether a candidate will actually work well alongside the people already in the room. This study set out to explore whether the Myers-Briggs Type Indicator (MBTI) could offer something more: a practical, if imperfect, lens for aligning candidates with roles based on cognitive-function fit rather than resume alone. Fifteen employees across an existing technical department's hierarchy — from Head of Department down to Junior Executive — completed MBTI assessments, and their results were compared against a reference population of 1,439 personality-labeled records drawn from a public dataset. A rule-based classification pipeline, built in Python and grounded in established cognitive-function and team-effectiveness literature, mapped candidates onto four broad role categories, isolating 879 records meeting an "ideal" configuration for benchmarking purposes. The comparison revealed a fairly uneven deviation between the department's current composition and this ideal distribution, with some MBTI types considerably underrepresented relative to expectation. From this, role-specific personality profiles were generated to guide future recruitment and internal development decisions. Taken together, the findings

suggest that MBTI, applied carefully and not in isolation, may offer HR practitioners a workable heuristic for improving role-fit within technical teams — though the small organizational sample and the reliance on a non-proprietary assessment platform mean these results should be treated as a starting point rather than a settled conclusion.

Keywords

Myers-Briggs Type Indicator; technical recruitment; team composition; cognitive functions; human resource management

1. Introduction

Personality, in one form or another, has always shaped who gets hired, who gets promoted, and who ends up quietly miserable in a job that never fit them to begin with. The Myers-Briggs Type Indicator (MBTI) is one of the more enduring attempts to put some structure around that messy reality. It sorts people into sixteen personality types, each built from four preference pairs — Extraversion or Introversion, Sensing or iNtuition, Thinking or Feeling, and Judging or Perceiving — and in doing so, it tries to say something meaningful about how a person

Significance | Offers HR practitioners a practical, evidence-informed heuristic for aligning candidate personality with technical team roles beyond conventional skills-based screening.

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actually processes the world around them: how they take in information, how they decide, how they recharge. The instrument traces back to Isabel Briggs Myers and her mother, Katharine Cook Briggs, who spent decades adapting the psychological type theory first proposed by the Swiss psychiatrist Carl Jung (Jung, 1988) into something practical enough for ordinary use. That lineage matters, because it explains why MBTI reads less like a rigid diagnostic tool and more like a framework for noticing patterns — patterns in communication, in decision-making, in the way two people can look at the same problem and arrive at entirely different solutions.

It would be easy to dismiss MBTI as a workplace fad, the kind of thing HR departments roll out once and then forget. The numbers suggest otherwise. Roughly 80% of Fortune 500 companies, and 89 of the Fortune 100 specifically, still use the instrument in some capacity to understand employee personalities and, ideally, match people to roles where they're more likely to thrive (Business Insider, 2014). That's a striking figure for a tool that's often criticized in academic circles for lacking strong psychometric validity — and yet organizations keep reaching for it, presumably because even an imperfect lens is better than guessing. Beyond the corporate world, MBTI has found a comfortable home in career counseling, personal development, team-building workshops, and even relationship counseling, largely because it gives people a shared vocabulary for talking about differences that are otherwise hard to name (Tieger et al., 2014).

None of this happens in a vacuum, of course. Recruitment itself is a notoriously difficult problem, and not just because resumes are unreliable and interviews are biased. Breaugh, Macan, and Grambow (2008) point out that the recruitment process involves a tangle of decisions — where to source candidates, how to attract the right ones, how to evaluate fit — each of which carries its own set of assumptions about what "fit" even means. Traditional hiring pipelines tend to lean heavily on technical skills and credentials, which makes sense on the surface, but skill alone rarely predicts whether someone will function well inside a team. Papla, Balnur, and Pak (2022) go further, arguing that contemporary recruitment and selection practice hasn't kept pace with what organizations actually need.

This gap becomes especially visible once you zoom in on technical teams, the kind found in software engineering and product development. Team effectiveness

researchers have been circling this problem for decades. Sundstrom, De Meuse, and Futrell (1990) laid out foundational thinking on what makes work teams effective, and Campion, Medsker, and Higgs (1993) tied specific group characteristics to measurable outcomes. Chen and Lin (2004) took this further into engineering contexts specifically, modeling how individual team member characteristics could be matched to form better multifunctional teams for concurrent engineering work.

Software development, in particular, seems to attract this kind of scrutiny. Constantine (1995) wrote at length about the sociology of peopleware, and Hohmann (1997) made a similar case, framing software development as fundamentally a social activity dressed up in technical clothing. Communication breakdowns across cross-functional teams have been documented by Smart and Barnum (2000), while Klein and Jiang (2001) explored how consonance among team members and stakeholders tends to predict whether projects go smoothly. Project management style itself needs to be matched to the type of project at hand, according to Shenhar and Wideman (2000). Reel (1999) identified critical success factors for software projects, and, further back, both Gallagher (1998) and Stinson (1990) were already writing about how much friction in engineering work comes down to interpersonal mismatch rather than technical shortfall. MacDonald, Krendl, Deichman, and Miller (1986) made a comparable observation in interdisciplinary research settings, and Prince, Brannick, Prince, and Salas (1992) pushed the conversation toward measurement. Allen's (1986) work on organizational structure and R&D productivity, alongside Amabile, Conti, Coon, Lazenby, and Herron's (1996) study of the conditions that foster workplace creativity, both suggest the environment surrounding a team matters as much as the individuals inside it.

So where does MBTI fit into all this? Perhaps as a bridge. Otto Kroeger Associates (1985) formalized much of the practical guidance around applying MBTI in organizational settings, and platforms like 16Personalities have since made type-based self-assessment accessible to millions (16Personalities, 2024). More recently, Amirhosseini and Kazemian (2020) explored whether personality types could be predicted computationally from text data, an approach whose relevance is easy to see given datasets like the one compiled by Die9origephit on Kaggle (Die9origephit, 2024). Figure 1 illustrates how each of the sixteen MBTI types maps onto a distinct configuration of

cognitive functions, with background color denoting each type's dominant function and text color marking its auxiliary function (Amirhosseini & Kazemian, 2020).

Taken together, this body of work points toward a clear, if underexplored, opportunity: using MBTI not just as a diagnostic curiosity handed out at onboarding, but as an active input into how technical teams are built. That's the gap this research tries to address — building a recruitment approach that uses MBTI upfront to identify which candidates are likely to occupy which team roles effectively. Given the practical constraints of this study, the scope has been narrowed: what follows is primarily an analysis of existing resources rather than a full-scale deployment across a live hiring pipeline.

2. Methodology

2.1 Study Design and Rationale

This study is best described, honestly, as an applied simulation exercise rather than a controlled experiment — there was no manipulation of variables in the traditional sense, no randomized assignment of employees to conditions. What we set out to do instead was build a rule-based classification pipeline that could take a candidate's MBTI-derived cognitive function profile, as summarized in Figure 1, and compare it in a fairly structured way against the personality composition of an existing technical department. The logic underlying this design draws on the premise, established in earlier work on team effectiveness (Campion et al., 1993; Sundstrom et al., 1990) and on engineering team formation specifically (Chen & Lin, 2004), that certain configurations of individual characteristics tend to co-occur with better team functioning. Rather than test that premise directly, we operationalized it — turning it into an explicit set of decision rules that could be applied consistently to any personality profile, following the pipeline outlined in Figure 2, which is, admittedly, a simplification of something psychologically messier, but a necessary one if the method is to be reproducible.

2.2 Data Sources

Two distinct data sources were used, and it's worth being precise about how each was obtained, since the reproducibility of the whole pipeline depends on it.

Organizational sample. Fifteen employees from a single technical department of the organization under study participated voluntarily in MBTI assessment. Participants

were distributed across four hierarchical tiers — Head of Department, Manager, Executive, and Junior Executive — which reflects the department's existing organizational structure. No compensation or incentive was offered beyond routine workplace participation, and personality results were self-reported directly from the assessment platform rather than inferred or estimated by the research team. **Reference dataset.** To contextualize the organizational sample against a broader population, a publicly available dataset of 1,439 MBTI-labeled records was obtained from Kaggle (Die9origephit, 2024). This dataset served as the comparison population against which the department's personality distribution could be benchmarked — the idea being that deviations between the two would surface where the current team composition diverges from what the broader personality landscape would predict as "ideal" for each role category.

2.3 Instrumentation

MBTI type was determined using the freely available online assessment hosted by 16Personalities (16Personalities, 2024), which classifies respondents along the four canonical MBTI dichotomies and additionally reports a cognitive-function ordering (dominant, auxiliary, tertiary, inferior) consistent with Jungian typological theory (Jung, 1988). We opted for this platform rather than administering a proprietary or paper-based instrument for two reasons: first, it is the same instrument that generated the reference dataset, which preserves comparability between the two samples; second, it returns cognitive-function data directly, which our classification rules depend on rather than the raw four-letter type alone.

It should be acknowledged — and this is a limitation worth flagging up front rather than burying in the discussion — that 16Personalities is not identical to the proprietary MBTI instrument published by The Myers-Briggs Company, and its psychometric properties have not been validated to the same standard. We proceeded with it anyway, in keeping with prior applied work that has used the same platform for similar purposes (Amirhosseini & Kazemian, 2020), largely on grounds of accessibility and cost.

2.4 Role-Function Mapping

Before any data processing occurred, we needed a defensible way of linking cognitive function pairs to team roles. This mapping was not derived empirically from the data itself; it was constructed a priori, drawing on the

descriptive literature on MBTI cognitive functions (Amirhosseini & Kazemian, 2020) together with recruitment and role-fit considerations discussed by Tieger et al. (2014), Breaugh et al. (2008), and Papla et al. (2022). The resulting rule set specifies, for each of four role categories, which pairs of dominant/auxiliary functions were treated as indicative of role suitability:

Technical roles: (Ni + Te), (Ni + Se), or (Te + Se)

Sales roles: (Ne + Ti), (Ne + Se), or (Ti + Se)

Managerial roles: (Ne + Te), (Si + Te), or (Ne + Si)

Head of Department roles: (Ni + Ne), (Ni + Se), (Ni + Te), (Ne + Te), or (Ne + Se)

We want to be upfront that these mappings represent one reasonable interpretation of the literature rather than the only possible one; a different research team working from the same sources might have drawn the boundaries slightly differently. We would encourage anyone attempting to replicate or extend this work to treat the mapping itself as a tunable parameter rather than a fixed truth.

2.5 Data Processing Pipeline

All data processing was implemented in Python (version 3.x), using the NumPy library for array-based operations (full code provided in Appendix A). The pipeline proceeded through four discrete steps: Ingestion. Both the reference dataset and the organizational sample were formatted as comma-separated value (CSV) files with a consistent schema: role label, overall personality type, and the four cognitive functions (first through fourth) associated with that type. Files were read using `numpy.genfromtxt`, with the header row skipped and all fields read as string type to preserve the alphanumeric function codes (e.g., "Ni", "Te").

Randomization for reference simulation. Because the Kaggle dataset (Die9origephit, 2024) was not originally organized by role, records were randomly shuffled and then partitioned to simulate a plausible "ideal" population against which the organizational data could be compared. This step is, admittedly, a simulation rather than a direct empirical measurement, and we flag that limitation explicitly in Section 4. Rule application. For each record, a custom function (`check_conditions`) evaluated whether the pair of cognitive functions present in that record satisfied the role-specific criteria defined in Section 2.4. Records

satisfying the relevant condition were labeled "ideal"; all others were labeled "not ideal." This function was applied row-wise across both datasets using a list comprehension, producing an additional results column that was subsequently concatenated back onto the original array via `numpy.column_stack`.

Output generation. The final labeled array — comprising role, personality type, all four cognitive functions, and the ideal/not-ideal classification — was written to a new CSV file (`output_tec_sales_man_hst.csv`) using `numpy.savetxt`, preserving a full audit trail from raw input to final classification.

2.6 Comparative Analysis

Once both datasets had been passed through the classification pipeline, the organization's 15 employee records were compared against the 879 records from the reference dataset that satisfied the "ideal" criterion (out of the original 1,439). To keep the main text concentrated on the paper's central argument, this comparison is illustrated here with two summary figures (Figures 3 and 4) and one representative type-by-type example (Figure 5); the complete set of fifteen deviation charts, one per MBTI type, is provided as Supplementary Figures S2–S15. In the same spirit, the role-specific recommendations that follow from these deviations are illustrated with one representative profile (Figure 6), with the remaining five role profiles provided as Supplementary Figures S16–S20. Readers interested in the full, type-by-type and role-by-role detail should consult the Supplementary Materials alongside this section.

2.7 Reproducibility Statement

To support replication, the complete analysis code is provided in Appendix A, and the reference dataset is publicly accessible through Kaggle (Die9origephit, 2024). The 16Personalities assessment (16Personalities, 2024) used to type both the organizational sample and, by extension, the broader public data underlying the Kaggle set, is freely available online at no cost to future researchers. We would note, however, that the organizational sample itself — the 15 employee records — is not publicly released, for reasons of participant confidentiality; researchers seeking to replicate this specific case study would need to substitute their own organizational sample while retaining the same instrumentation, role-function mapping, and classification code described above.

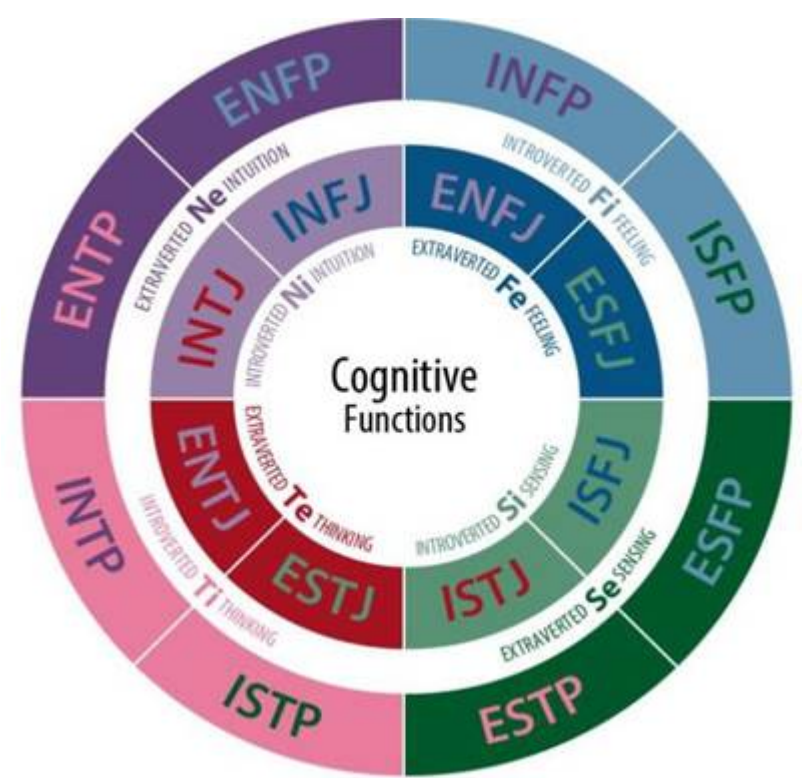


Figure 1. Chart of the eight Jungian cognitive functions underlying each of the 16 MBTI types, with background color marking each type's dominant function and text color marking its auxiliary function (Amirhosseini & Kazemian, 2020).



Figure 2. Flowchart of the study's methodology, from data ingestion and role-function classification through comparison of the organization's personality composition against the reference population.

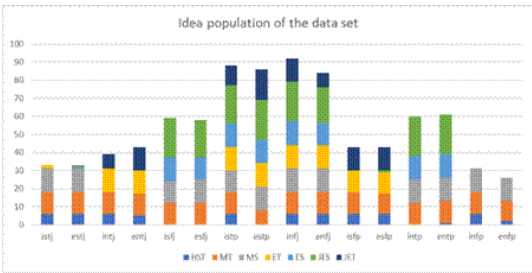


Figure 3. Bar chart of the 1,439 reference-dataset records (Die9origephit, 2024) split into those meeting the "ideal" role-function criterion (879) versus "not ideal" (560).

3. Results

3.1 Overview of the Analytic Sample

Before getting into the deviations themselves, it's worth

pausing on the raw numbers, because they frame everything that follows. The organization's technical department contributed 15 employees across its existing hierarchy — Head of Department, Manager, Executive, and Junior Executive — each of whom completed the MBTI assessment voluntarily (16Personalities, 2024; Figure 4). Against this relatively small, real-world sample sat the reference dataset of 1,439 personality-labeled records drawn from Kaggle (Die9origephit, 2024), which, once passed through the role-function classification rules described in Section 2.4, narrowed down to 879 records meeting the "ideal" criterion (Figure 3). That's a fairly steep filtering ratio — well under two-thirds of the original dataset survived — and it's a first hint, before any direct comparison has even happened, that the criteria being applied are not trivially easy to satisfy.

3.2 Role-Function Classification Outcomes

Applying the function-pairing logic outlined earlier produced four broad classification categories, one per role type. Technical roles were treated as consistent with the cognitive pairings (Ni + Te), (Ni + Se), or (Te + Se); sales roles with (Ne + Ti), (Ne + Se), or (Ti + Se); managerial roles with (Ne + Te), (Si + Te), or (Ne + Si); and Head of Department roles with any of (Ni + Ne), (Ni + Se), (Ni + Te), (Ne + Te), or (Ne + Se). These groupings weren't arbitrary — they were built from the descriptive cognitive-function literature (Amirhosseini & Kazemian, 2020) and the broader recruitment and role-fit reasoning found in Tieger et al. (2014), Breaugh et al. (2008), and Papla et al. (2022). Still, it's fair to say the mapping represents an interpretation of that literature rather than a settled fact, and readers should keep that caveat in mind while looking at what follows.

3.3 Deviation Between the Organization and the Reference Population

The central finding of this study — if there is one single finding worth naming — is the gap between what the department currently looks like, personality-wise, and what the "ideal" reference population would suggest it should look like. Figure 5 illustrates this pattern for a representative type, INTJ, comparing its proportion in the department against its proportion in the ideal reference

population, by hierarchical role. The same comparison was repeated for all fifteen MBTI types represented in the sample — ISTJ, ESTJ, ENTJ, ISFJ, ESFJ, ISTP, ESTP, INFJ, ENFJ, ESFP, INTP, ENTP, INFP, and ENFP — and the complete set of charts is provided as Supplementary Figures S2–S15 for readers who want the full type-by-type breakdown. Rather than one uniform pattern, what emerges across these figures is something closer to a patchwork — some types are noticeably underrepresented in the department relative to what the reference distribution would predict, while a handful sit close enough to expected proportions that little correction seems warranted there. We won't pretend the deviation is evenly distributed across every type; it isn't, and that unevenness is, in a sense, the whole point of running the comparison in the first place.

Taken together, these figures suggest that the department's current composition leans toward certain cognitive-function combinations more heavily than the reference population would recommend, particularly in relation to the technical-role pairings described above — which, on reflection, is perhaps unsurprising for a technical department, but the degree of the skew is still worth flagging for HR planning purposes.

3.4 Recommended Personality Profiles for Recruitment and Development

Once the deviations were mapped, the next step was translating them into something more directly usable — concrete suggestions about who might be worth recruiting, or developing internally, going forward. Figure 6 sets out proposed profiles for heads of the sales team as a representative example of this output. The same recommendation logic was applied to produce profiles for technical-team managers, technical-team executives, sales-team executives, sales-team junior executives, and technical-team junior executives, all of which are provided as Supplementary Figures S16–S20. Each of these recommendations follows directly from the role-function logic established earlier (Section 2.4), rather than from any post-hoc judgment about who "seems like" a good fit — the intention being that a hiring manager could, in principle, use these profiles as a starting checklist when screening future candidates for these specific positions.

It's worth being honest, too, about what these figures do not show. They aren't performance predictions, and they don't claim that a candidate matching one of these profiles

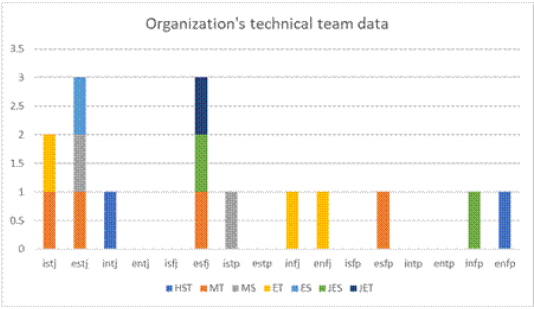


Figure 4. Bar chart of the organization's 15 technical-department employees broken down by MBTI type and hierarchical role (Head of Department, Manager, Executive, Junior Executive).

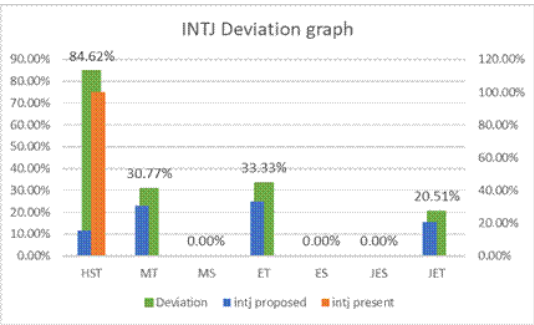


Figure 5. Bar chart comparing the proportion of INTJ employees in the organization's technical department against the proportion of INTJ in the "ideal" reference population, by hierarchical role. Presented here as a representative example; the equivalent charts for all fifteen sampled MBTI types are provided as Supplementary Figures S2–S15.



Figure 6. Recommended MBTI personality profiles for future candidates to the Head of Sales Team role, derived from the role-function criteria in Section 2.4. Presented here as a representative example; the corresponding profiles for the remaining five roles are provided as Supplementary Figures S16–S20.

will necessarily outperform a candidate who doesn't. What they offer is narrower and more modest: a personality-based heuristic, derived from the reference population's own successful classifications, that organizations can weigh alongside — not instead of — the more conventional criteria already built into their hiring process.

3.5 Summary of Findings

Pulling the threads together, three observations stand out. First, the organization's existing technical department shows a measurable, if uneven, deviation from the personality distribution that the reference dataset (Die9origephit, 2024) suggests would be "ideal" for its role structure. Second, that deviation is not uniform across MBTI types — some categories are close to expected proportions, others considerably less so, as the type-by-type breakdown (Figure 5; Supplementary Figures S2–S15) makes clear. And third, the classification pipeline yields role-specific personality recommendations (Figure 6; Supplementary Figures S16–S20) that, while grounded in the cognitive-function literature (Amirhosseini & Kazemian, 2020; Tieger et al., 2014), should be read as a decision-support tool rather than a definitive hiring rule. Whether these deviations translate into meaningful gains in team performance is, admittedly, a question this study can gesture toward but not fully answer — a limitation taken up more directly in the discussion that follows.

4. Discussion

4.1 Interpreting the Deviation

So, what do we actually make of the gap uncovered in Section 3 — the mismatch between the department's current personality composition and the "ideal" reference distribution (Figure 5; Supplementary Figures S2–S15)? At the most basic level, it tells a fairly straightforward story: the organization's technical department, as it stands, is not assembled the way the reference data would suggest it should be if role-fit were optimized purely along cognitive-function lines. But it would be a mistake, we think, to read that gap as evidence of some organizational failure. More likely, it simply reflects how most technical departments actually come together in practice — hired one role at a time, over years, against whatever candidate pool happened to be available at the moment, rather than assembled deliberately around a personality-balanced blueprint. Sundstrom, De Meuse, and Futrell (1990) made a similar point decades ago: effective teams rarely emerge by accident, and the traits that predict good team

functioning are seldom the same ones that dominate a typical hiring shortlist. Seen that way, the deviation documented here isn't really a criticism of the department — it's closer to a diagnostic snapshot of a fairly ordinary hiring history.

4.2 What the Deviation Might Mean for Productivity and Team Composition

Assuming the deviation is real and not just an artifact of sample size — and with only 15 employees, that caveat deserves to be said plainly rather than buried — the implication seems to be that assembling a workforce with a wider spread of personality types could plausibly support better organizational outcomes. This tracks with Campion, Medsker, and Higgs (1993), whose work tied specific group compositional characteristics to measurable gains in team effectiveness, and with Chen and Lin's (2004) modeling of team member characteristics in engineering-specific contexts, which is arguably the closest analogue to the technical setting examined here. There's also a softer, harder-to-quantify piece of this: understanding how different MBTI types tend to approach problems may help management value employees more accurately — not necessarily in terms of who works "harder," but in terms of who contributes which kind of cognitive labor to a shared task. Whether that translates into better retention or morale is a separate question this study can't directly answer, but it seems a reasonable inference given the broader literature on team dynamics (Klein & Jiang, 2001; Smart & Barnum, 2000).

4.3 Reconsidering Compensation, Recognition, and Retention

One thread that came up almost as an aside during this work, but that probably deserves more attention than it initially got, concerns compensation. If certain personality profiles are disproportionately valuable to a given role — the recommended profiles (Figure 6; Supplementary Figures S16–S20) imply as much — then it stands to reason that employees who match those profiles particularly well might reasonably expect recognition or compensation that reflects that fit, rather than being evaluated on the same generic scale as everyone else in their title. This isn't a novel idea exactly; Amabile, Conti, Coon, Lazenby, and Herron (1996) argued something adjacent when they examined how organizational conditions either support or suppress creative output, suggesting that recognition systems calibrated to actual

contribution — rather than tenure or title alone — tend to sustain better performance over time. We raise this cautiously, though, because "better fit" is not the same as "better performer," and conflating the two risks turning a modest personality heuristic into something it was never meant to be.

4.4 Practical Implications for HR and Team Development

Beyond recruitment itself, there's a developmental angle worth drawing out. Employees who don't match the "ideal" profile for their current role aren't, by that fact alone, poor fits for the organization — they may simply be underdeveloped in the specific skills or working styles their role rewards. Additional technical training, cross-functional exposure, or structured workshops could, in principle, narrow that gap over time, an idea broadly consistent with Hohmann's (1997) framing of software development as a fundamentally social and developmental process rather than a purely technical one. HR teams might reasonably use the deviation figures (Figure 5; Supplementary Figures S2–S15) less as a hiring filter and more as a coaching map — a rough guide to where internal development effort would be best spent, department by department, role by role.

4.5 Limitations

It would be dishonest not to spend real space on this. The organizational sample is small — fifteen employees is not a number that supports strong statistical claims, and readers should resist the temptation to generalize these specific deviation patterns (Figure 5; Supplementary Figures S2–S15) beyond this one department, let alone this one organization. The reference dataset (Die9origephit, 2024), while considerably larger at 1,439 records, was randomized to simulate an "ideal" population rather than independently validated against actual team-performance outcomes — which means the comparison, however useful as a heuristic, is still a simulation layered against real-world data rather than a true experimental benchmark. The role-function mapping itself (Section 2.4) was constructed from the descriptive literature (Amirhosseini & Kazemian, 2020; Tieger et al., 2014) rather than derived empirically from this organization's own performance records, so it necessarily carries the interpretive judgment of the researchers rather than objective ground truth. And finally, the assessment instrument used throughout, 16Personalities

(16Personalities, 2024), while convenient and freely accessible, is not psychometrically identical to the proprietary MBTI instrument, a distinction that matters more than it might first appear given how central cognitive-function labeling is to the entire classification pipeline.

4.6 Directions for Future Work

None of this is to say the approach isn't worth pursuing further — quite the opposite, really. Future work could usefully incorporate employees' actual work experience and technical training history as additional variables alongside personality type, which might sharpen the precision of the role-fit predictions considerably. It would also be worth testing whether the recommended profiles (Figure 6; Supplementary Figures S16–S20) actually correlate with measurable performance or retention outcomes once implemented, rather than resting solely on the theoretical grounding provided by Breaugh, Macan, and Grambow (2008) and Papla, Balnur, and Pak (2022). A longitudinal design — tracking a department's personality composition and performance metrics over several hiring cycles — would go a long way toward answering the question this study can only gesture at: not just whether the deviation exists, but whether closing it actually improves anything that matters to the organization.

5. Conclusion

This study set out with a fairly modest ambition — to see whether MBTI could meaningfully inform how technical teams are recruited and organized — and, on balance, the evidence gathered here suggests it can, at least as a supplementary tool rather than a standalone solution. By comparing an organization's existing personality composition against a broader reference population, clear and, in places, fairly pronounced deviations emerged, pointing toward specific gaps in the department's current makeup. These gaps translated into concrete, role-specific recommendations that HR teams could reasonably use when screening future candidates or planning internal development. It's worth being honest, though: this isn't a finished framework so much as a proof of concept, one built on a fairly small organizational sample and a set of interpretive assumptions about which cognitive functions suit which roles. Even so, the approach seems promising enough to warrant further refinement, and it offers a genuinely usable starting point for organizations looking to move recruitment for technical roles beyond skills

checklists alone. The main figures presented here (Figures 1–6) summarize the core logic and headline evidence; the full type-by-type and role-by-role detail is available in the accompanying Supplementary Materials (Figures S1–S20).

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