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EXAMINING PERSONALITY-BASED FILTERING OF CONFLICTING TECHNICAL DATA THROUGH A HUMAN RESOURCES LENS

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Abstract
Employees in today's workplaces are often data-driven due to the continuous and sometimes competing pieces of information that are often interwoven in the workplace. Individual biases shape perceptions and prioritizations of data based on personality differences. Thus, this study aims to fill this knowledge gap by investigating personality traits with the filtering of conflicting technical data and by using the human resources (HR) lens to assess and address these cognitive and behavioral differences. A personality profiling system was created for a sample of 100 participants, which was taken from an HR and IT firm. It was also observed that the participants were placed into controlled data conflict scenarios. Their performance on these scenarios was assessed about the Big Five personality traits. The study found that higher scores on the openness and conscientiousness traits were linked to higher accuracy and confidence in the data. On the other hand, neuroticism was linked to indecisiveness and over-relying on the prevailing narratives. The results demonstrate the value of personality biases in the evaluation and interpretation of data, which highlights the need for strategic HR-driven data-aided decision-making and team composition.
Keywords: Personality Traits, Conflicting Data, Human Resources, Technical Decision-Making, Big Five Model, Cognitive Filtering, HR Interventions

INTRODUCTION

Striking a balance between interdepartmental collaboration while fulfilling all technical and operational information-seeking functions has, up until recently, relied heavily on the use of data within an organization. Though employees within an organization claim to "function through data," technical data comes with its own set of challenges where employees may data discrepancies ranging from sources to version control (Gokhale & Kaur, 2024). Employees encountering dissonant technical data due to the nature of their work often react based on their expertise and on traits such as risk tolerance, cognitive flexibility, and information processing (Mazraeh et al., 2019).
Furthermore, analyzing the extent to which data is unaware is particularly critical in sectors such as engineering, Healthcare IT, or QA due to the wide-spanning impact of miscalibrated data accuracy on prioritization within an organization. While cognitive psychology has provided insight into the reasoning behind personalities and their roles in decision-making behaviors, the manifestation of this research within organizational frameworks is extremely scarce (Sindhu, 2023).
In employing these hypotheses, the gaps previously identified within the research literature have focused on resolving strategies that employees with disparate personality profiles deploy to filter conflicting technical data. It is essential to understand the means through which human resources can help in fostering fair frameworks of decision-making through strategic gaps for all intervening, training, and assignment of team roles reserved for specified traits.

LITERATURE SURVEY

2.1 Personality and Information Processing

The components of the Big Five personality classification: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism has received a significant amount of attention due to its impact on cognition and behavior (Singhal et al., 2024). All of these traits have a bearing on how an individual interprets and responds to information within a given job role. People who score high on the openness trait tend to be more curious, imaginative, and data driven, thus helping them to be hyperlexically motivated to process unfamiliar technical information at various predictive and generative levels (Müller & Dupont, 2024). Furthermore, conscientious personality types are methodical, detail-oriented, and extremely well organized, leading them to favor definitive and algorithmic approaches to decision making, including analysis and verification of processes (Fatma & Ayşe, 2025). Factors such as extraversion and agreeableness relate to the social aspects of decision-making: for example, the use of input from other decisions or evaluative collaboration. Neuroticism, on the other hand, introduces an emotional element, along with volatility and uncertainty, which is known to distort the information process in capacitated environments (Le, 2024).

2.2 Conflicting Data in Technical Environments

In the engineering and IT sectors, modern workplaces face the problem of employees dealing with conflicting technical information due to disparate systems, asynchronous data updates, or discrepancies in report formatting. These inconsistencies can stem from redundant sources, mismatched APIs, non-uniform sensor calibrations, and even outdated protocols. In these situations, professionals need to assess which data to trust without clear data information systems and prioritization policy workflows (Trivedi et al., 2023). The problem is not only how to reconcile the inconsistencies, but how to do that while stressed, which is mentally taxing and increases the likelihood of error. The problem is not only in the conflict resolution strategy but how to handle the pressure, which often reflects deeply rooted psychological and personality-driven frameworks (Bharathi et al., 2025).

2.3 Cognitive Biases and Decision Errors

Cognitive filtering is a type of mental processing that helps users handle the overwhelming amount of information available. This filtering process is prone to biased intervention under pressure or uncertainty. For instance, highly neurotic individuals may focus primarily on negative factors or information associated with risks, which will compel them to make pessimistic or avoidant decisions (Abdullah, 2025). Extraverted individuals may display a different form of bias: overconfidence, as they will swiftly utilize dominant or well-recognized information without proper validation. In contrast, highly conscientious individuals are prone to verifying the information, biasing the focus, and reconciling details and discrepancies, which helps them avoid these filters. These biases necessitate the further need for assistance and awareness, especially when the environment is filled with contradicting information (Tran &Ngoc, 2024).

2.4 HR's Role in Cognitive and Behavioral Calibration

Although formerly, an HR department's functions were centered around dealing with payroll and employee relations, now there is greater appreciation for their strategic contribution in optimizing behavior in the workplace (Rahimi et al., 2018). Through psychometric evaluation, for instance, the Big Five Inventory, HR can assess cognitive styles at both the individual and group levels (Salave, 2025). These results can guide role allocation, such as assigning data entry and validation tasks to people with high levels of conscientiousness, or assigning decision review tasks to those who are low neuroticism (Nejad & Fard, 2019). Furthermore, HR is able to provide bias reduction training, confidence calibration, and structured decision making to aid in bias reduction and executive functions at all levels, which are relevant to the decision-making confidence calibration bias. In this manner, HR acts as a mediator in the interaction of personality traits and the technical skills in decision-making (Prakash & Prakash, 2023).

2.5 Research Gap in HR-Personality-Tech Triad

There has been extensive research on personaility psychology and decision science; however, very little has been done on the intersection of personality, technical conflict resolution, and human resource (HR) practices. Current frameworks and models of personality focus on cognitive behavior as a singular, self-contained process, neglecting the larger organizational contexts that may influence such behaviors. This research seeks to fill that gap by harnessing human resources as active agents in shaping a personality-informed, data-driven decision-making climate in the organization.

PROPOSED METHODOLOGY

This research adopts a correlational mixed-methods approach to study the impact of personality traits on employees' filtering behaviors concerning conflicting technical information, as well as how human resources may address such behaviors. The methodology is applied to a sample of 100 employees from the engineering and information technology divisions of two multinational companies, which provides relevance from both industry and demographic perspectives.

3.1 Research Framework

Step 1: Personality Profiling

The study starts with the Big Five Inventory (BFI) being given to all participants. This psychometric device assesses the five major dimensions of personality and places respondents into a high, medium, or low score for each trait. The outcomes are treated as the independent variable in the study, giving a behavioral perspective to the biases in data interpretation and the tendency to misinterpret data. Human Resource (HR) professionals are given anonymized aggregate personality profiles, allowing organizational-level insights while safeguarding individual-level data.

Step 2: Scenario-Based Data Conflict Tasks

Every participant is given a meticulously crafted technical case scenario containing contradictory datasets, mismatched visuals, or ambiguous sensor logs. This is similar to real-world scenarios like deciding between system audit logs containing timestamp mismatches or deciphering appraisal audit reports. Each of the participants are expected to:

- Make a selection from the available options for the data source they would trust the most.
- Justify the selection given using rationale.
- Self assess their confidence regarding the above decision on a 1 to 10 scale.

Completing this exercise assists in isolating behavioral patterns related to trust, like overconfidence, indecision, and verification thoroughness.

Step 3: HR Behavior Mapping

Aligned with the assignment, trained HR specialists record participant actions using a pre-defined checklist. The taxonomy includes the following markers:

•Delegation (soliciting assistance),
•Deferral (declining to make a decision),
•Confrontation (contesting data bluntly),
•Systematic reconciliation (cross-checking every data entry).

These actions are subsequently mapped to participants' personality assessments, aiding HR in recognizing relationships and potential sabbatical design strategies.

Step 4: Outcome and Bias Analysis

As per the defined methodology, the participants' decisions accuracy (in reference to pre-defined benchmarks of accuracy), confidence congruence (the gap between confidence and accuracy), and consistency over multiple scenarios are evaluated after the task. Outcomes are clustered by levels of specific traits (in this case, personality traits) in order to map cognitive profiles. This information is leveraged to inform, in this case, human resource management actions such as customized bias mitigation training, simulation-informed onboarding, and data-informed decision audits. The approach integrates personality and simulation to underpin their utilization in technical decision support.

3.2 Flowchart of Methodology

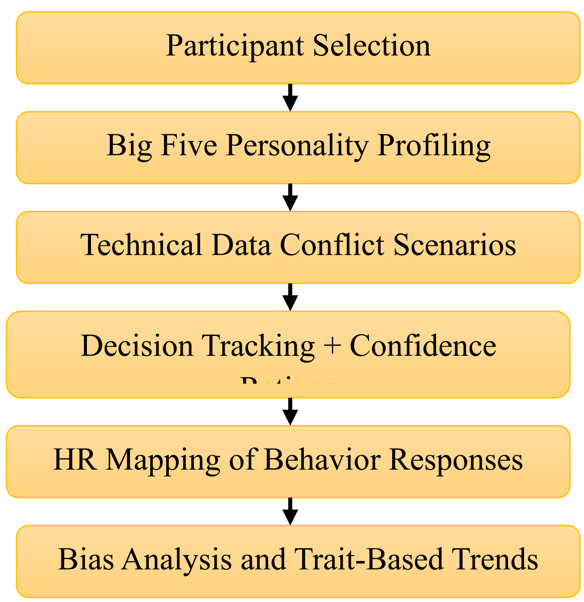

Figure 1: Methodology Flow

The methodology utilized for the study is illustrated in Figure 1. It starts with the participant selection, then entails personality assessment through the Big Five Inventory (BFI) for classification along the salient personality dimensions. Thereafter, participants are shown scenario-based conflicting technical data for decision-making in which both the decisional confidence and the confidence are tracked. Concurrently, human resources (HR) personnel monitor behavioral responses to the decision-making processes, for example, socially desirable responding (i.e. answering in a way to appear more favorable) and socially undesirable responding (i.e., answering in a way deemed less favorable). Eventually, and after performing the crucial synthesis, the remaining data is treated through bias and performance analysis to reveal analysis gaps that indicate personality-driven tendencies to data filtration. Assuredly, through this method, the correlation is fully reliable between the personality profiles and the behavior-based decision making as seen through the HR analytical framework.

RESULTS AND DISCUSSION

4.1 Accuracy Rates

Table 1: Trait-wise Decision Accuracy Rates

Personality Trait	High Group Accuracy (%)	Low Group Accuracy (%)
Conscientiousness	88.5	62.3
Openness	85.7	59.4
Neuroticism	51.2	77.6 (low = better)

As illustrated in Table 1, there are differences in accuracy of decisions made by people with both high and low levels of specific personality traits. Those participants high in both openness and conscientiousness evidenced much greater accuracy in interpreting discordant information, while high Neuroticism scored significantly lower in accuracy, supporting the view that emotional instability disrupts data interpretation.

4.2 Level Comparison

Table 2: Confidence Levels vs Accuracy

Confidence Band	Average Accuracy (%)	Dominant Trait Group
High	71.2	Extraversion
Medium	78.5	Conscientiousness
Low	60.1	Neuroticism

As indicated in Table 2, the correlation between self-rated confidence levels and actual decision-making accuracy is illustrated for each trait-dominant group. Extraverts, for example, reported high confidence levels; however, their accuracy in decision-making remained at only moderate levels. This suggests that their confidence in their abilities is overestimated. On the other hand, the conscientious group showed a more balanced profile, exhibiting both high accuracy and moderate confidence, which suggests a more calibrated judgment.

4.3 HR-Observed Behavior Styles

Table 3: HR-Observed Behavior Styles During Conflict Tasks

Trait Dominance	Common Behavior Pattern	HR Observation Notes
Openness	Information Exploration	Tends to request additional data
Neuroticism	Emotional Withdrawal	Avoids decision finality
Conscientiousness	Structured Reconciliation	Verifies all data before choice

Table 3: Through direct observation, HR noted behaviors that matched specific personality traits. Openness was characterized by seeking further context and curiosity, while neuroticism displayed emotional withdrawal and indecisive behaviors. Conscientiousness displayed adherence to processes with checklists. These behaviors have tangible implications for training and role assignment aimed at HR-driven team dynamics.

4.4 Intervention Format

Table 4: Preferred Intervention Format by Trait

Personality Trait	Preferred HR Intervention	Acceptance Rate (%)
Openness	Scenario-Based Simulation	85.1
Conscientiousness	Structured Workflow Training	89.3
Neuroticism	1-on-1 Coaching & Reflection	91.4

The preferred types of interventions are categorized by personality traits and rates of acceptance in Table 4. Those high in openness preferred scenario-based simulations, those high in conscientiousness preferred structured training, and those high in neuroticism best responded to 1-on-1 coaching. Thus, it can be concluded that HR interventions are more successful when they are customized to personal preferences based on personality traits and associated learning styles.

CONCLUSION

The current research shows that personality characteristics have an impact on how people interpret and resolve technical discrepancies. Conscientiousness and openness facilitate reasonable evaluations, whereas neuroticism introduces emotional interference that undermines the perceived dependability of a decision. A human resources department can structurally improve an organization's data interpretation efficiency by assigning roles within teams, conducting decision audits and planning training on a proactive basis through personality profiling. The study suggests that personality profiling should be part of the human resource analytics toolbox for continuous monitoring and adjustment of roles and data-driven decisions in interdisciplinary teams.

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