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# TRUST CALIBRATION IN HUMAN AI SURVEILLANCE TEAMS SUPPORTED BY A PSYCHOMETRIC FRAMEWORK FOR HR DECISIONS

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**Abstract**
trust calibration in human-AI surveillance teams, but it is very dependent on calibrated trust between the human agent and the AI system. Mis-calibrated trust, such as hyper-reliance or hyper-scepticism, can degrade the quality of decisions, response times, and overall effectiveness of those teams in a mission. This paper develops a psychometric framework to support trust calibration in human-AI surveillance teams based on psychological theory and organizational decision-making models. Based on the TPMAP (Trust, Personality, Mission Alignment, and Performance) framework, we utilize cognitive and affective psychometric indicators (e.g., risk perceptions, personality traits, mood) to illuminate and propose ways to predict each individual's trust threshold. Our research will be applied to assist HR decision-making (e.g., selecting the right cadre of employees, establishing adaptive supervision and in-depth assessments of high consequence/dynamic risk interactions between surveillance personnel) which is why we include psychometric assessments for trust during training selection, supervisory oversight, and risk detection and evaluation of high consequence surveillance conditions in situations where bad actors threaten national interest, public safety, or developing regional catastrophe [5]. By matching teams and tasks to the psychometrically matched trust profile of the team, this process will lead to adaptive calibration mechanisms from contexts suited to match human and AI to manage functioning and trust under varied operations. This model will optimally improve the cohesiveness of the unit and resilience of the surveillers, coupled with transparency, accountability, and ethical compliance in an AI-enhanced or co-support surveillance system. This research links psychological profiling with human-AI system engineering while providing strategic avenues for HR departments and the workplace more broadly to increase performance, manage operational risk, and foster a culture of psychologically informed AI integration.

**Keywords:**Trust calibration, Psychometric profiling, Human-AI collaboration, Surveillance teams, TPMAP framework, HR decision-making, Cognitive traits.

## I. INTRODUCTION

Artificial intelligence (AI) is becoming embedded in decision-making systems in surveillance products, changing how people conduct surveillance and making real-time monitoring, threat detection, and field data analysis more efficient and accurate [3] [15]. Human-AI teams operate in complex, dynamic, and highly uncertain environments where the outcome of a mission is dependent upon more than just correctness; it is dependent upon the ability to collaborate (team structure) and calibrate trust (socio-cognitive relationship) with AI. Trust calibration, in the psychological study of trust and mistrust, indicates an alignment of trust with the actual capability of the AI. Calibrating trust is not just about human-AI relationships, but a human-technology relationship, and a process of calibration that could lead to over-trust or under-trust. Using too much trust in the AI can lead to 'assisted blind trust' and produce outcomes as if a human wore blinders, while too little trust can lead to a situation where the efficacy of the AI system is ignored and human users fail to take advantage of helpful recommendation system output [6].
Further, trust does not have uniform levels as trust can be specific to individuals based on individual differences, including personality, emotional regulation, experiences, and biases. Psychometric assessments can yield critical

foundational knowledge on cognitive and affective determinants or perceptions of trust by facilitating understanding of how likely a person is to trust or distrust an AI system [8]. For example, through personality inventories or aptitude tests, organizations can identify an individual's proclivity to distrust, instead of trusting a system. Pointing to the individual's level, or their mental mapping of their trust systems, provides clarity around propensity before deployment [14].

In consideration of previous research in the realm of psychometric assessment, we present a psychometric framework employing the TPMAP model (Trust, Personality, Mission Alignment, and Performance) that we hope can add value to human resource (HR) decisions. By integrating psychology into trust management, the framework supports better task assignment, team design, and adaptive interventions that enhance collaboration, accountability, and operational safety [2].

**Psychometric Foundations of Trust: Cognitive and Affective Determinants**

Trust in any AI system, including in high-stakes environments such as surveillance, is based on cognitive and emotional factors. Psychologically, trust requires evaluating the system's dependability, making sense of uncertainty, and managing emotional reactions to risk and trust in automation [11]. The way users approach AI systems is influenced by trait dimensions of personality, including openness to experience, conscientiousness, and neuroticism. For example, a high scorer in openness to experience may adapt to decisions being made by the AI system, while a highly neurotic person may entertainingly contemplate the consequences of a decision or mitigate their uncertainty by never relying on the decisions/inputs of the AI system.

Because of these differences, we see individual variance represented as trait-based trust thresholds, individual characteristics that setspecifications for how much trust an individual is willing to place in automation in the context of its actual performance. Calibration, knowing, and having a record of these thresholds will generate information that will support the introduction of humans to work within human-AI teams. Psyche metrics include the Big Five Inventory (BFI), NASA-TLX (cognitive load), and trust in automation scales to highlight these tendencies.

If we understand trait dimensions, both HR and the designer of the AI system can help to align humans with roles they can perform based on their psychological profiles. We can improve role fit, increase performance levels,and further enhance common knowledge and trust under stress and pressure, while allowing us to better recognize the risks of burnout when agents begin to distance themselves from the AI system and their trust diminishes. These measurements and awareness in regard to human-AI interactions will contribute to the development of satisfactory evidence-based workforce planning roots.

**TPMAP-Inspired Model: Mapping Trust, Personality, and Role Alignment**

The TPMAP Framework, or Trust, Personality, Mission Alignment, and Performance, provides a basic tactical framework for incorporating psychological variables into the design of the human-AI team. In a surveillance context, where decision-making speed and accuracy are paramount, the individual must have trust that is actively managed based on personal personality traits and the individual's mission alignment with the expectation of the task to be completed [9]. The TPMAP model emphasizes that trust is not simply an interpersonal or technical problem; trust is dependent upon the psychological fit in the team and task environment [10].

While personality traits differ among people on teams, the traits may affect the people's ability to interpret, accept, or reject the AI decision. For instance, a very conscientious person might systematically verify the system's outputs, whereas a person who is high in agreeableness may quickly adopt the AI-suggested action to avoid any potential discord. In addition to personality traits, personal values and how they relate to tasks affect trust. Passion is the personal value that impacts mission alignment and will moderate trust consistency, especially when under pressure.

To apply this to the practical sphere of the human-AI trust domain, we introduce the Trust–Personality Fit Matrix that matches psychological profiles with appropriate surveillance roles, along with trust calibration strategies. The Trust-Personality Fit Matrix can influence decisions made by HR in hiring, assigning tasks, and organizing teams. The TPFM, which includes psychometric analysis, provides a basis for evidence-based action and proactive input. Organizations can build more resilient, well-balanced teams, prevent trust breakdowns, and support ethically sound role allocation in AI-augmented surveillance operations [4].

**Table 1: Trust–Personality Fit Matrix**

| Personality Trait | Trust Disposition | Recommended Surveillance Role |
|---|---|---|
| High Openness | Adaptive Trust | Dynamic decision-making, pattern recognition |
| High Neuroticism | Distrustful Vigilance | Anomaly detection, alert escalation |
| High Conscientiousness | Calibrated Trust | System verification, compliance monitoring |

| | | |
|---|---|---|
| High Agreeableness | Over-trusting Risk | Human interfacing requires AI oversight |

Table 1 connects major personality traits (from psychometric evaluations) to related trust dispositions and suggested role types in AI-augmented surveillance teams [12]. It will assist HR professionals and team leads with making appropriately informed decisions about role assignment, training requirements, and trust calibration plans. The matrix reveals how operators' psychological profiles determine how they, as individuals, present themselves working with AI systems, from over-trusting tendencies to skeptical ones. The matrix informs the inherent relationships that pair traits with trust behaviour and optimal operational role [1]. Consequently, the matrix supports adaptive team design, reduces risk, and develops long-term performance sustainability [13]. It also informs HR on operational requirements, such as whether the operator will require additional system validation prompts or stress-management techniques to safely and effectively work with AI.

Through rigorous analysis, this matrix enables HR and team leads to make more evidence-based decisions when assigning people to tasks that not only fit their capabilities but also fit into their trust profiles, based on the psychological trust data. Psychometrics may also suggest rotational policies, signal potential mismatches in trust, and anticipate where adaptive training interventions or trust recalibration will be necessary.

By incorporating personality and mission into operational planning, the TPMAP-embedded model increases human-system integration and organizational resilience to the degree that trust could no longer be a coincidence, but calibrated on who the team members are, what the mission requires, and actualized within the real-time socialized AI settings.

**3.1 Conceptual Trust Calibration Model**

To connect psychological profiling to operational trust management, we have formulated a Conceptual Trust Calibration Model,a logic-based guide that synthesizes psychometric characteristics to estimate a person's baseline trust disposition. This model is not a statistical algorithm, but rather a method to inform strategic selection and HR consistency for surveillance teams.

In the spirit of a model, the TCI (Trust Calibration Index) integrates weighted personality values into an outcome index to estimate a likely pattern of contact with AI systems:

$$\mathrm{TCI} = (\omega_1 \cdot \mathrm{Openness}) + (\omega_2 \cdot \mathrm{Conscientiousness}) - (\omega_3 \cdot \mathrm{Neuroticism}) + (\omega_4 \cdot \mathrm{Emotional\ Stability})$$

Where:

- $\omega_n$ = adjustable weights based on role demands
- Trait scores are normalized (e.g., on a 0–1 or 0–100 scale)
- Higher TCI suggests greater adaptive trust; lower TCI indicates cautious or unstable trust patterns

The TCI can be used to:

- Identify high-risk trust profiles (e.g., extreme over-trust or skepticism)
- Identify task-type matching using TPMAP aligned role profiles
- Provide system interface customization (e.g., additional transparency for low TCI users)

The model is best used when supplemented by real-time behavioural feedback and qualitative information from supervisors as a hybrid human-machine trust management tool [7].

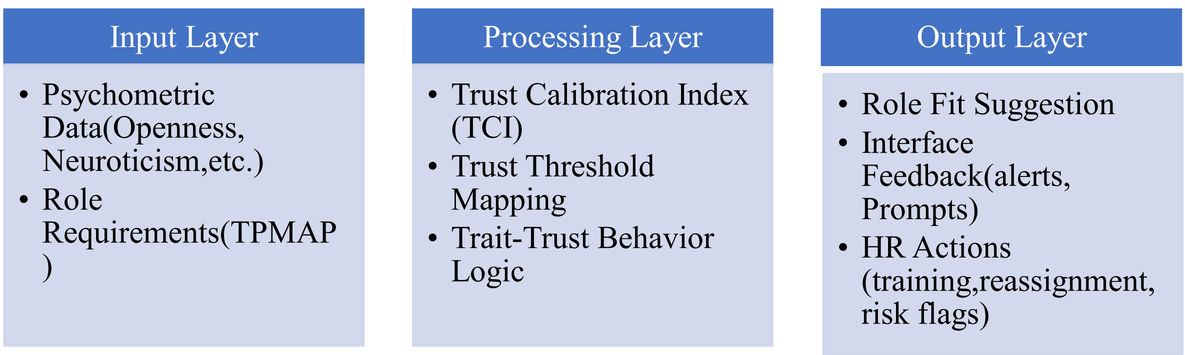


**Figure 1: Psychometric Trust Calibration Flow Model**

Figure 1 builds upon the psychometric profile and the TPMAP framework. The process begins with the input of individual psychological data collected by validated psychometric measures, some examples of which include individual's personality traits such as openness and neuroticism and individual's cognitive load and emotional stability data, the psychological data is transformed to create the Trust Calibration Index (TCI) to capture an individual's only natural trust disposition towards AI systems. The TCI is then incorporated into the Trust-

Personality Fit Matrix, which allows user profiles to be assigned to the best possible task role for surveillance operations. The TCI would then inform human resource actions the model might recommend for a person (e.g., hiring, rotation, or training change) as well as system-level recommendations (e.g., user interface, prompts for feedback, or trust alerts). Our output will be to dynamically calibrate trust at the person level for trust based upon the individual improving human AI collaboration, team performance, and ethical responsiveness indecision-making systems.

This model brings together the understanding of the psychology behind trust with practical, real-time operational support by ensuring that employees and stakeholders understand that we are not over-trusting or under-trusting when working with surveillance. Our model is designed to ensure that trust in surveillance, alongside the resources supporting it, is as safe and resilient as possible.

**Calibration Logic and Ethical Boundaries in Human-AI Trust Profiling**

Trust is not a static entity; it is something that needs to be calibrated dynamically as the enterprise processes through surveillance. The model proposed in this chapter will establish the baseline trust profile using various psychometric inputs, and then calibrate it dynamically based on system and individual performance. Some people may inherently under-trust or over-trust AI, possibly due to certain cognitive or affective traits or predispositions. For instance, someone with agreeable predispositions may be more likely to rely too heavily on AI when deciding what course of action to take; in contrast, someone high in neuroticism may unreasonably distrust all systems, even the highest quality systems. With this understanding, adaptive interfaces can apply corrective and contextualized visual indicators, warnings, or feedback loops to stimulate the user's reflection or verification, or even to confirm, amend,or update what they do.

There are significant ethical issues when implementing this model. The psychometric assessment must guarantee respect for individual privacy rights, informed consent, and that full data protection is observed. One possible risk is that some organizations will create systems that effectively survey their employees under the notion of trust management, damaging autonomy and fairness. The potential for misuse also runs the risk of resulting in biased HR decisions based on psychological vulnerability as a result of their psychological predisposition, rather than their actual performance.

With a possible implementing bias, over-reliance, or ethics issues, this framework will need to be fundamentally inclusive, a trust regulation interface designed to include a number of essential safeguards; transparency, audit, and accountability trails, and human override. However, trust calibration should be designed as a supportive and non-invasive process, this way enhancing the team function without compromising psychological safety. Ethical integrity is vital in addressing multiple facets ofthe construction of both reliable and.

## CONCLUSION

This paper has illustrated the potential of psychometric trust calibration as a method for improving human/AI collaboration in surveillance environments. By assessing how cognitive and emotional traits can clarify and direct how trust develops and shifts, organizations can move from a reactive approach to a more proactive management of human/AI teams. When trust calibration is connected to psychological and human factors, organizations can do a better job of matching or realigning human tasks while being aware of misuse of the system, avoiding failure of communication, decision resolution, and the communication that develops from the cycle of human/AI. For HR, this model facilitates implications in a number of key areas. Recruitment and hiring might be aligned with trust predisposition assessments, ensuring candidate skills and psychologies are consistent with task demands. Communications regarding rotation and assignment should be developed based on cognitive load, emotional fatigue, and burnout reduction. Retention strategies are focused on sustained alignment of individualslonger-term trait habits with mission task requirements. It is possible to enhance risk forecasting by acting upon individual psychological trust thresholds to assess within operational data.Further research should explore the longitudinal stability of trust profiles, cross-cultural variations of AI trust, and the potential implications for psychometric trust processed trust calibration data in HR analytics capital-driven platforms. Psychometric trust calibration represents a psychologically focused, human-centered, ethically sound, and performance-driven approach as AI continues to influence surveillance and security roles.

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