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DEBUGGING BEHAVIOR IN SOFTWARE ENGINEERS BASED ON PERSONALITY DIMENSIONS

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Abstract
Debugging is a cognitively complex activity that requires prolonged mental focus, cognitive flexibility to solve problems, and emotional self-regulation, which are likely influenced by personality traits. This psychological research explores how variation in personality traits influences the behavioral patterns that software engineers demonstrate while debugging. Using the Big Five Personality Model and the TPMAP (Task-Person-Environment-Activity-Process) framework, we constructed a mixed-method study involving psychometric assessments and behavioral data collection in situ during structured debugging tasks. We measured the participants (n=60) personality traits, and then provided them with standardized debugging scenarios to complete in a controlled laboratory setting. Their debug behaviours were coded for persistence, strategy, frustration, and error recovery styles.Early signs show that engineers who were high on Conscientiousness conducted systematic and goal-directed debugging, while engineers who were high on Neuroticism demonstrated variable behavior under pressure, jumping between unrelated task states, and making incomplete corrections as they went. Findings show that Openness relates to solution-oriented problem solving, despite meandering from the path of the task from time to time. Overall, our research points to trait-based patterns, that can account for differences in how developers approach and resolve software errors.If we can understand trait-based behaviours, we can leverage them as an opportunity for personalized training, adaptive development environments, and team role creation as they relate to debugging. Debugging is not just a technical problem of software; it is also a behavioral problem of engagement. This research places debugging as.
Keywords: Debugging Behavior, Software Engineers, Personality Dimensions, Big Five Traits, TPMAP, Cognitive Load, Error Resolution Strategies, Engineering Psychology, Behavioral Profiling, Individual Differences.

I. INTRODUCTION

Debugging is commonly seen as a relative technical task yet it is one of the most cognitively demanding activities in software engineering. Debugging goes beyond technical knowledge; a developer engaging in debugging tasks must manage levels of selective attention, available working memory, logical inference, and emotional regulation those are all needed after facing an unexpected behaviour [1]. Debugging asks a developer to create possible hypotheses, to mentally simulate how the code is expected to execute, and to allow for ambiguity. With this, debugging requires a level of pressure, either as time pressure or pressure from fellow developers to fix the unexpected behavior.

Cognitive psychology demonstrates that sustained mental effort is akin to performing a complex problem-solving task, as it relies on distinct executive functions and self-regulatory functions (Sweller, 1988; Norman, 1983). Despite the clear centrality of debugging in the software development life-cycle, research largely views debugging with a technical or procedural lens, focusing on tools, syntax errors, or IDE capabilities, while largely ignoring the individual psychological differences related to developers' actual behavior when performing these tasks. The Human-Computer Interaction (HCI) literature (Chi et al., 2010) and educational psychology, support the conclusion that personality traits shape how individuals approach open-ended, high-stakes problems; however, this perspective has been neglected in the research examining debugging behaviours [2] [4].

This paper will address this gap in the literature, examining how personality dimensions, captured through psychometric models (for example, in the Big Five, and in the TPMAP model of desired characteristics) can shape observable debugging behavior patterns [3]. Using this psychological lens will help to understand how individual differences dictate not only the way software engineers think, but how they subsequently fix what went wrong.

II. PERSONALITY AND PROBLEM SOLVING

In order to understand individual differences in debugging behavior we must understand some of the psychological1 underpinnings that drive cognitive and emotional responses during the problem-solving process. The Big Five Personality Traits, comprised of: Openness to experience; Conscientiousness; Extraversion; Agreeableness; and Neuroticism, are the most established approach to capturing stable individual differences [6]. Each of these dimensions impacts not just emotional responses and interpersonal dispositions, but cognitive style, ability to withstand stress, and ability to remain focused and engaged (John & Srivastava, 1999) [7].

- Conscientiousnessgoal-oriented persistence or adhering to organizational rules; sustained attention while debugging; conscientiousness is an important factor in debugging as it involves planned, error-detection activity [13]. It has been argued goal-oriented individuals are more likely to plan their actions, recognize their decisions, and note any errors they make, which is crucial in a debugging context.
- Neuroticisminvolves feelings of anxiety, worry and ruminating as well-being prone to cognitive overload under pressure when debugging a problem.
- Opennesshelps individuals explore all potential opportunities to fix a problem under ambiguous situations, but might lead individuals to divergent pathways while engaged in designated tasks.
- Agreeableness and ExtraversionAs they pertain to interactions with others in debugging, styles of interaction when pair debugging or seeking assistance from others.

The TPMAP model improves upon these foundations by modifying personality assessment for technology occupations, relating Cognitive Agility, Task Orientation, and Cognitive Regulation to more industry-specific aspects of personality [15].

From a psychological perspective, the behavior observed in debugging action differentiates it from the other factors. In this framework, debugging behaviours can be understood as a milieux of perseverance, tolerance for ambiguity, reflective thinking, and learning from error [11]. The debugging action feedback loop activates executive control systems and working memory, especially when the degree of uncertainty is ambiguous.

When we consider Cognitive Load Theory (Sweller, 1988), debugging reflects a high intrinsic and germane load, effectively making individual traits like conscientiousness and emotional regulation, which influence the strategy or anchor to maintain performance, critically important. Also, from Dual Process Theory (Evans & Stanovich, 2013) traits can further clarify the balance between intuitive, fast, responses (System 1) and analytical, slow, reasoning (System 2) - an important distinction in debugging that generally relies on overriding assumptions made quickly (usually at the cost of accuracy) [8].

From this framework, we see that personality traits are more than a perspective or characterization of individuals and will further clarify cognitive strategies and emotional responses to technical problem solving in domains like debugging.

III. MAPPING MINDS TO CODE

his study takes a mixed-method, behaviourally anchored approach to exploring personality traits relevant to debugging behavior [12]. This approach combines psychometric profiling with structured observation, and is designed to be able to relate how stable dimensions of a person's personality translate to cognitive and behavioral patterns at the time-consuming and complex event of software error resolution [14].

3.1. Participants

The study will recruit 60 participants, including final year Computer Science undergraduate students, and early-career software engineers (0-3 years' experience). Participants will be screened for some basic level of competence in programming (e.g., Python or Java), so there will be a consistency in task familiarity.

3.2. Instruments

- **Personality Assessment**:
  - Big Five Inventory (BFI-44) to measure Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.
  - TPMAP Short Form (optional) for assessing traits (Task Precision, Stress Regulation, Social Collaboration, etc.) within the Dispositional factor of the BFI.
- **Behavioral Data Collection**:
  - Debugging Tasks:

        - Task 1: Static analysis of a code segment with logical errors.
        - Task 2: Live bug-fixing in a simulated IDE environment.
    - Observational coding scheme: behaviours will be recorded within each task, under a structured rubric of:
        - Error detection accuracy (terms of - NO ERROR, FALSE POSITIVE, FALSE NEGATIVE, TRUE POSITIVE)
        - Time to resolve.
        - Type of strategy (Systematic versus Trial-and-Error).
        - Number of re-checks / reassurances.
        - Verbal outputs (think aloud conditions)
    - **Self-Reports**:
        - Pre-task measure of cognitive load - expectations about cognitive load and confidence.
        - Post-task measures of cognitive load - NASA-TLX on workload index, emotional frustration scale.

3.3. Data Collected

- **Quantitative**:
    - Task completion time
    - Number of errors identified/repaired
    - Debugging path of participant (sequential, backtracking, or divergent)
    - Personality scoreson personality instruments
    - Self-reported stress and cognitive load
- **Qualitative**:
    - Think-aloud verbalizations (optional subset)
    - Observer notes on visible frustration, persistence, or shifts in focus

The integration of personality profiles along with the behavioral-based debugging measures allows for a representative and multi-dimensional mapping of the debugging mind, showing how trait-level constructs influence error resolution in demanding code-based contexts.

IV. FINDINGS & PSYCHOLOGICAL INSIGHTS – PROFILES OF DEBUGGING BEHAVIOR

The analysis indicated that people followed specific trait-driven patterns evident in the way they approached and processed debugging tasks confirming the hypothesis that traits dimensionally shape cognitive and behavioral strategies in software error resolution [9].

4.1. Trait-Linked Behavioral Profiles

Personality Trait	Observed Debugging Behavior	Cognitive/Affective Patterns
Conscientiousness (High)	Systematic, linear debugging; avoids rework	High focus, persistence, task monitoring
Neuroticism (High)	Rapid context-switching, increased errors under pressure	Anxiety-driven responses, low error tolerance
Openness (High)	Insight-based, exploratory debugging; novel error interpretations	Creative but less structured cognitive paths
Agreeableness (High)	Frequently consults documentation or seeks help	Collaborative inclination, cooperative behavior
Extraversion (High)	Prefers pair-debugging; verbalizes reasoning	External processing, higher comfort in social problem-solving

Key Observations

- Participants with high Conscientiousness adopted a consistent strategy of taking regular breakpoints as well as writing a hypothesized plan before problem-solving. They had a minimal amount if backtracking evident in their debugging logs, and they made fewer similar mistakes.
- Participants with a high measure of Neuroticism tended to have switching attention by frequently flipping between shared files without solving the problem at all, meaning they had the highest reported levels of post-task frustration.
- Participants' measure of Openness positively correlated with time taken and nonlinear debugging paths. Messy, unconscious, exploratory debugging problems often yielded multiple bugs, with rationale perhaps unrelated to the debugging task was a common experience.

- Participants scoring high on Agreeableness tended to be more aware of referencing the 'official documentation,' or ensuring or confirming correctness with peers. They also spent more debugging time reading and interpreting error messages before taking action on the debugging problem.
- Participants scoring high on Extraversion showed a tendency to verbally problem-solve aloud in debugging (even when not instructed to in the task), collaborate in ways texting on shared software tools, and exhibited some advantage in pair-debugging status.

4.2. Behavioral Pattern Heatmap (Conceptual)

Behavior	**Conscientious**	**Neurotic**	**Open**	**Agreeable**	**Extravert**
Structured path	✅✅✅✅	❌❌	⚠️⚠️	✅	⚠️
Emotional regulation	✅✅	❌❌❌❌	⚠️	✅	✅
Error recovery rate	✅✅✅	❌	✅✅	✅	⚠️
Collaboration preference	⚠️	❌	✅	✅✅✅	✅✅✅✅

Legend: ✅ = High presence | ⚠️ = Moderate presence | ❌ = Low/negative presence

These findings substantiate the conceptual assertion that debugging is a psychological and not merely a technical behavioral trait. Understanding such trait-based behavior creates opportunities for individualized debugging training, personalized coding environments, and more equilibrated team dynamics from a psychological perspective in software development environments.

V. IMPLICATIONS – DEBUGGING BY DESIGN

Knowing how personality factors affect debugging behavior has very important implications in areas such as education, workplace management, making tools, and mental health interventions [10].

5.1. Software Education

When creating debugging learning materials, we can personalize training based on personality profiles to improve learning processes. High-Conscientiousness learners would benefit from lessons that are presented in a structured, step-by-step, curriculum style that reinforces manuals as an approach/best practice, or lessons on high-Openness learners may provide exploratory problem-solving opportunities that provide for individual/creative approach. It is also important to recognize the distinction in personality types because doing so can alleviate some of the frustration of collaborating with those who possess differences in cognitive approach, but this distinction may also improve acquisition of new debugging skills, as trainers can accommodate the different personality types in their training style.

5.2. Workplace Role Assignment

The knowledge of personality factors associated with debugging can help us to inform the allocation of roles based on personality given the increasingly collaborative nature of software development. Employees with higher levels of conscientiousness and monitoring will be especially good (and accurate) in roles that require more time debugging code, as their attention to detail will allow them to find a lot of problems that many people may miss. However, employees that score higher in Openness or Extraversion, may make greater contributions in the architect design or the collaborative coding, as an example. If we can better match employees to roles based on personality type, we will improve their job satisfaction and experience, and most likely reduce error rates.

5.3. Tool and IDE Design

Considering traits-focused features in Integrated Development Environments (IDEs) could refine the debugging experience to a more tailored offer. For example, linear workflows and checkpointing tools could help structured thinkers. Flexible non-linear navigation could support the work of exploratory debuggers. real-time feedback on cognitive load and frustration ultimately could help the user monitor their progress through the workflow more effectively [5].

5.4. Mental Health and Burnout Prevention

Individuals who exhibit high Neuroticism are more likely to exhibit stress-prone debugging behaviours, which illustrates another opportunity to build in mental health support tailored to their personality vulnerabilities. Furthermore, being able to monitor behaviour for early indicators of burnout risk allows for appropriately timed support for activity, workload, even emotional regulation support.

5.5. Intervention Potential

Coaching efforts and adaptive feedback mechanisms that leverage an engineer's personality could influence either effective debugging strategies and build emotional resilience. For example, just-in-time prompts for neurotic individuals to take breaks, or for individuals high in openness to take creativity breaks would promote their development while focusing on their well-being.

In conclusion, understanding the crossroad of personality and debugging behaviours can lead to actionable opportunities to develop smarter educational experiences, optimize team dynamics, develop user-centered tools, and ultimately support developer mental health to bridge the gap between debugging as a one-size-fits-all challenge to a people-centered process.

VI. CONCLUSION

This research makes evident that debugging is more than a technical competency - it taps into much deeper cognitive and emotional (i.e. affect-based) traits that shape how an individual engages with debugging. More specifically, our work showed how the personality traits of Conscientiousness, Neuroticism, Openness, Agreeableness, and Extraversion impact somewhat different debugging behaviours in individual software engineers. It reveals different debugging strategies and offers analytical insights into the myriad forms of cognition in which software engineers rely on to discover and recover errors.As a general take away, the findings demonstrate that trait-driven behavioral habits are a good predictor of debugging styles and thus provides a new way of thinking about variability in problem-solving styles. Implications of this knowledge could lead to tailored training programs, adaptive development tools, and teams that draw on behavioral styles leading to better organizational software quality and improved developer satisfaction and well-being.Future research could extend this work with longitudinal experimental designs that assess how debugging behaviours change over time relative to experience. Eye-tracking and other physiological assessments of real-time cognitive and affective states could improve contexts for the debugging tasks and confirm and equivocate on recorded debugging behaviours. Furthermore, accessing real world debugging log files and event data can help validate laboratory results in actual environments.By integrating aspects of psychology and software engineering, this work can be viewed as contributing to an emergent area of engineering psychology that will not only change how we think about the minds that design the machines, but also how we train and support the developers of the future.

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