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PREDICTING PROBLEM SOLVING PERFORMANCE IN CAD USERS USING EYE TRACKING AND PERSONALITY TRAITS

ANIL KUMAR SINGH[1], DR.RAJESH SEHGAL[2],
DR. SUNAINA SARDANA,
[1]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
e-mail:ku.anilkumarsingh@kalingauniversity.ac.in,0009-0002-8764-0571
[2]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
e-mail: ku.rajeshsehgal@kalingauniversity.ac.in ORCID: 0009-0002-0344-403X
[3]PROFESSOR, NEW DELHI INSTITUTE OF MANAGEMENT, NEW DELHI, INDIA.,
e-mail: sunaina.sardana@ndimdelhi.org, https://orcid.org/0009-0002-1373-0187

Abstract
This study analyses the ability of eye-tracking data and personality traits to predict problem-solving performance in Computer-Aided Design (CAD) users. CAD tasks require a high level of spatial reasoning, attentional control, and strategic planning; thus, it is important to have an understanding of the cognitive and affective constructs driving user performance. This exploratory research focuses on the potential of a predictive model of user performance using real-time visual behaviour analysis and stable personality characteristics.Participants with varied levels of CAD experience were observed completing structured design tasks in a controlled field experiment. While completing the tasks, eye-tracking technology collected behavioural metrics associated with visual attention; fixation duration, saccadic patterns, and gaze heatmaps. Additionally, validated personality inventories were used to gather individual personality trait data in relation to the five personality descriptors; openness, conscientiousness, and neuroticism. Finally, outcomes of task performance were measured in terms of result accuracy, time, and errors.The study yielded meaningful correlations between gaze patterns and overall performance, all of which were moderated by personality profile. For example, conscientious participants with focused gaze trajectories were more efficient complete tasks overall, whereas participants with dispersed visual attention and lower openness performed less efficiently.These results provide exploratory research to indicate that individual psychological profile and real-time behavioural data have potential for a predictive model. Ultimately, the research aims to contribute to the continued development of adaptive CAD systems, that can look to personalize user experience through interfaces thatprovide pivotal information through implications.
Keywords: Eye Tracking, CAD Problem Solving, Personality Traits, Visual Attention, Cognitive Load, Design Behaviour, Engineering Psychology, Human-Computer Interaction, Predictive Modelling, Adaptive CAD Systems

I. INTRODUCTION

Computer-Aided Design (CAD) has gone from being an aid to drafting into a complex cognitive environment in which various forms of spatial reasoning, planning, and problem-solving occur. CAD technology has improved, and its functionality and usability have become sophisticated, yet the human factors that affect design outcomes are worthy of more study. Specifically, cognitive processes - attention and memory load, for exampleaffect how effectively users navigate and solve CAD-related tasks [5].
CAD performance has classically been assessed based on task completion metrics (accuracy, timing, error rate, etc.) without attention to how different cognition and behaviour impact the differences between users. Consequently, we have limited insight into the reasons why some users have greater aptitude in solving problems, and others demonstrate challenges when using the same tools and assignment instructions [2].
In this study, we show how a focus on two psychological dimensionsindividual differences in personality characteristics, and real-time eye movement datacan provide a potentially enlightening means to unpack individual problem-solving methodologies [1]. Personality determines how individuals engage a problem. Eye

tracking, on the other hand, presents real-time visual attention and cognitive load, affording a window into immediate cognition.
This study aims to examine how metrics from eye-tracking and users' personality traits can predict CAD performance [6]. Through collaboration with participants in an undergraduate CAD course, we collected CAD project data in addition to eye-tracking behaviours and personality surveys. In the following sections, we present our method and results [13].

II. COGNITIVE AND PERSONALITY FRAMEWORK

Design problem-solving involves substantial cognitive processes, which include analytic and intuitive processes. Dual-process theory suggests problem-solving involves two processes: System 1 is fast, intuitive, and automatic while System 2 is slow, rule-based, deliberate and analytic [11]. In CAD environments, expert users may go back and forth between systems; moving intuitively between arrangement of objects and dimensions based on internally held design criteria while managing cognitive load. Cognitive load theory states when task complexity exceeds working memory capacity, performance will decline. Therefore, maintaining concentration and managing visual information is important to success on CAD tasks.
Further, personality traits influence users' ways of processing information and interacting with design environments. For example, the Big Five model ingress of personality includes five elements - openness, conscientiousness, extraversion, agreeableness and neuroticism - and has been used widely to help predict behaviour in problems solving tasks [8]. Generally speaking, high openness is positively related to performance in visual-spatial reasoning tasks and conscientiousness is positively associated with persistence in task and reduced errors [3]. These traits may determine how users plan steps, allocate attention, or respond to uncertainty in design.
Eye-tracking studies have identified robust relationships between gaze behaviour and cognitive function. Indicators like duration of fixation, gazes path efficiency, and progression of gaze transitions detail the strategies used for complex tasks. Prior research has shown that while expert users of certain tools use gazes in a more rigid and focused way, novice users do not do the same and therefore, have a more scattered exploratory gaze behaviour [4]. When considered in conjunction, eye movements and personality characteristics provide an in-depth framework to examine individual variation in performance using CAD.

III. TASK MAPPING AND DATA COLLECTION

In this study, a controlled experimental design was employed to examine the predictive relationship between fourteen gaze variables, personality variables, and performance of problem-solving using CAD [10].

3.1. Participants

A total of 40 participants were recruited for the study, which included university students studying engineering and early-career professionals. Participants were categorized into novice (less than one year of CAD experience) and intermediate-to-advanced level users (more than 2 years of CAD experience). The majority of participants were between the age range of 19-28 years. Gender distribution was comprised of 24 males and 16 females. All the participants reported normal or normal with corrective lenses vision.

3.2. Experimental Setup

Each participant engaged in a common standardized CAD modelling task aimed at constructing a moderate complexity mechanical part (see Appendix A) using AutoCAD software. Participants were limited to a 25-minute task, in consideration of timed design conditions. Eye movement data was collected using the Tobii Pro Fusion Eye Tracker (sampling rate: 120 Hz), and each participant was calibrated before completing the CAD task.

3.3. Assessment Tools

Participants completed the NEO-PI-R (NEO Personality Inventory-Revised) to complete a Big Five personality vaccine [12]. The CAD task was recorded using screen-recording software and assessment information was collected using Tobii Pro Lab for eye-tracking analytics and with custom scripts for screen capture behavioural logging [9].

3.4. System of Evaluation

The domains of individual performance on the task were three dimensional in their evaluation:

- Success rates (completion and overall correctness of their design)
- Time on task (minutes and seconds)
- Error count (misaligned components, incorrect dimensions, failed commands)

The combined dimensions of evaluation allowed for both quantitative performance measurement and cognitive behaviourally based dimension of analysis for predictive modelling in subsequent sections [7].

IV. ANALYSIS OF VISUAL BEHAVIOURS AND COGNITIVE LOAD

Eye tracking offers a powerful and immediate window into cognitive processing when we capture users visually interacting with CAD tasks. This section concentrates on the visual behaviour pattern we observed through the performance of the task and [14].

4.1. Eye-Tracking Data Types

We analysed the following basic eye-tracking metrics:

- Fixations: Points where the eye remained still, which implies attention and cognitive effort. Reported as duration and count.
- Saccades: Rapid eye movements between fixations. Reflects the participants search strategy and scanning behaviour.
- Heatmaps: Visual overlays that highlight areas where the gaze is concentrated, implicating areas of interest and thinking.
- Scan paths: A sequential trail of fixations and saccades, indicates the user navigation round the CAD interface.

4.2. Usage of Gaze Behaviours

- The gaze behaviour of a focused user results in longer fixations on relevant toolbars and important parts of the geometry showing that they were engaging cognitively and had planned their action [15].
- The gaze behaviour of a user exploring the interface includes shorter fixations that result in a lot of saccades to areas they returned to several times, suggesting thatthey were uncertain or did not have a strategy to complete tasks in CAD.

A user is confused when their scan path is chaotic in nature, if they are fixating on unrelated areas for a longer time than they possibly should, and if they are looking at a toolbar or component frequently while selecting or re-selecting a tool.

4.3. Indicators of User State

- Confusion: fast gaze shifts between unrelated elements of the UI and hesitations that occur prior to giving a command.
- Exploration: Scanning or exploring of the design space or other UI menus for actions they were contemplating prior to any confirmation actions.
- Cognitive focus: fixating densely on dimensional constraints or edges of geometry during precise editing.

4.4. Example Visual Outputs

- Heatmap traces from high performers were very focused on the command tools and key geometric points, including minimal peripheral focus.
- Scan paths of low performers were not organized as simply random movement. These patterns would suggest a trial- and-error behaviour or that the action was cognitively taxing.
- The visual patterns act as behavioral markers for performance and were subsequently cross analysed with personality profiles as to the trait-linked cognitive strategies of performance.

V. TRAIT-BASED PERFORMANCE PREDICTION

This section reported on the links between personality, activity, performance and task outcomes, as distinguishing the influences of psychological traits on CAD problem-solving performance is paramount to completing this research, a model using a combination of personality, and the eye-tracking data was developed as a predictive measure of performance level.

1. Multiple Linear Regression Model
   A belief of predictive performance (e.g. time, accuracy) from:
   Personality traits (Big Five) and Eye-tracking data (fixation counts, saccadic lengths, etc.)
   Example:
   $$\text{Performance Score} = \beta_0 + \beta_1(\text{Consccientousness}) + \beta_2(\text{Saccadic Variability}) + \cdots \epsilon$$
2. Logistic Regression or decision tree classifier
   Classification of users in higher/mid/lower performers based on trait + eye data.
3. Cluster analysis (e.g. K-Means)
   Modelling behavioral personas using multivariate profiles (traits + eye gaze behaviours) and adds quantitative structure to the persona section.

5.1. Personality Traits and Visual Strategies

Analysis identified different patterns between the two distinct types of Big Five traits and visual behaviour:

- Openness to Experience: Participants that obtained high scores on the openness trait showed broad but efficient visual exploration. Their scan paths were systematic as well as they adapted to new tasks quickly suggesting that they were able to create a strategy to traverse the new - primarily visual- system.
- Conscientiousness: was strongly correlated with focused gaze patterns, the least amount of switching of tools and the least number of errors. This user was able to complete all the tasks successfully and in a timely manner with only because their conscientiousness to the task was high.
- Neuroticism: higher neuroticism scores were associated with gaze regressions, hesitation to use commands and erratic scan paths suggesting they were behaving anxiously which often could lead to less effective performance of tasks.
- Extraversion and Agreeableness: were less helpful in a predictive sense but indicated minor trends for example engaging in puffing tool activity when participants scored high in extraversion.

5.2. Correlation with Task Outcomes

- Conscientiousness had a strong positive correlation with task accuracy ($r= 0.68$, $p < 0.01$),
- Openness had a positive correlation with the speed of design completion ($r= 0.51$, $p < 0.05$),
- Neuroticism had a negative correlation with accuracy and gaze focus ($r= -0.56$ $P < 0.05$).

5.3. Predictive Models

Two different models were produced:

- A multiple linear regression model to predict continuous outcomes such as time and accuracy from their trait scores, and fixation metrics. The model accounted for 64% of the variability in performance (Adjusted $R^2 = 0.64$).
- Classification Models (Decision Trees): Users were classified either as high, moderate, or low performers using attributes based on personality-nested clusters. Tree-based models revealed that the combination of conscientiousness + mean fixation duration offered the most predictive possibility.

The results indicate support for the hypothesis that personality traits combined with real-time visual behaviours may provide meaningful predictions of problem-solving performance when users are working within CAD environments.

VI. DESIGN PERSONAS AND BEHAVIORAL INSIGHTS

In order to extract and translate psychological and behavioural data into actionable insights, participants were grouped into design personas based on the relationship (interaction) between eye-tracking behaviours and personality traits. Each persona reflects a unique way of cognitively approaching CAD problem-solving in a CAD environment, and will be useful to influence training and facilitate tool customization, and support assigning roles in teams working in engineering contexts.

6.1. User Personas Derived from Gaze + Trait Profiles

1. The Visual Planner, Traits: conscientiousness (high), openness (moderate). Gaze behaviour: longer fixations on critical geometry, least tool-switching afforded. Performance: high accuracy, low error rate, stable completion time and Implications: good for roles requiring precision and reliability; enjoy the limited
2. 1. The Strategic Explorer, Characteristics: high openness and moderate conscientiousness in personality type. Gaze Location Strategy: wide but intentional scan paths; structured but exploratory. Performance: highly creative; moderate speed; few serious errors and Implications: strong fit for conceptual design, early-stage prototyping phase; allows for flexible interface formats; allows for testing tools, not just layout
3. The Trial-and-Error Explorer, Characteristics: low level of conscientiousness and low emotional stability, i.e. high level of neuroticism, in personality type.Gaze Location Strategy: frequent shifts in gaze; attempts different tools multiple times; indecision.Performance: greater time to completion and more errors at completion and Implications: would benefit from guided CAD environments with error-reducing prompts, and training in confidence building strategies
4. The Intuitive Executor, Characteristics: high extraversion and moderate openness in personality type.Gaze Location Strategy: quick scan paths; quick decisions; minimal rechecking.Performance: rapid execution with variable accuracy andImplications: suitable for activities that are time-sensitive and errors have no severe consequences; would benefit from real-time visual feedback and tools that support undo decisions

6.2. Practical Implications

- Team Composition: Mixed persona teams can reduce speed accuracy trade-offs and enhance creative ideation. For example, when Visual Planner is teamed with Strategic Explorer, it provides a balance of stability with a desire for innovation.
- CAD Training Programs: Custom training can be designed on persona. Trial-and-Error Explorers likely need cognitive scaffolding, while Intuitive Executors appreciate feedback loops established within structured environments.
- Adaptive UI Design: The next generation of CAD tools may leverage behavioral recognition to modify or adjust tool groups to allow or disallow their visibility altogether or simplify interface elements or adapt workflows to user persona.

6.3. Human-Centered Design Suggestion

A cognitive companion is different from a passive environment. A CAD tool can evolve from being a passive task environment to being someone or something designed to understand the individual. This will be achieved with psychological profiles conducting the logic behind the user interface to adapt to the strategies that suit users (+-) as it promotes cognitive skills and may lower cognitive weaknesses to improve the overall design experience.

VII. CONCLUSION AND FORWARD DIRECTIONS

This research shows that eye-tracking data and personality traits act as strong predictive analytics for problem-solving performance for end-users of CAD. We recognize and accountability the intrinsic relationship between real-time visual attention and stable psychological attributes to develop models showing distinct cognitive strategies related to design task performance. Focused gaze behaviours are associated with having traits like conscientiousness and openness, while visual disorganization and performance degradation are related to traits like neuroticism. These results are meaningful; they demonstrate the possibility of creating psychological profiles to depict the place between behaviour and design performance, adding to a growing understanding of variability in behavioural and cognitive design, related to design performance outcomes. This multi-dimensionality exceeds traditional metrics we consider for 'performance', and provides grounded behaviours that describe how user connect overall behaviours in a digital design environment.Future research in this stream can lead to adaptive CAD user interfaces that respond to an end-user's user state (in real-time) by reducing the number of CAD features available, ways users can be supported by academic or commercial software through intelligent prompts for knowledge and questions, or the use of user-tracking for scope out an individual's visual-cognitive profile. Affective data (e.g., emotional arousal, indicators of stress) might be incorporated as well to predict user support needs or better support user problem solving or design process.Beyond research, the findings from the current study can be leveraged to improve and understand the individual experience for: the evaluation of programs of design education (personalized paths); the development of CAD software (Intelligent Interface Learning); and in the selection of talent that match the identified constituent traits from this study.

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