Reassessing the value of creative activity traces for understanding and supporting creative work

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In this paper, we discuss the different types of information captured in creative activity traces and describe their intended uses. We argue that research should move beyond momentary assessments of creativity or creativity tools and instead conceptualize creativity as a dynamic, longitudinal process that unfolds across a professional career.

CCS Concepts: • **Human-centered computing → HCI theory, concepts and models**; *Interactive systems and tools.*

Additional Key Words and Phrases: creativity, creativity support tools, creative activity traces, generative AI

1 Introduction

Generative AI is transforming the practice of creative work. Image and video generation tools support early-stage ideation, conversational agents help users reason through strategic decisions, and coding assistants amplify software engineering productivity. The widespread use of these kinds of tools has raised many questions for creative industries, including their efficacy [2], the quality of associated work [21], and how it impacts users' cognitive abilities and wellbeing [5, 25].

Fortunately, these tools also create opportunities for new ways to understand creativity. These opportunities arise from both human interactions with creativity support tools (CSTs) and the shifting creative ecosystem enabled by their rapid growth. Users of digital CSTs are quickly adopting new tools that demand changes in both workflow and their relationship to their creative process [1, 17]. As with commercial products, academic CSTs are increasingly capable of logging detailed information about users' interactions, generating rich traces of creative activity that open new opportunities for deep user understanding. Creative activity traces can be rich, multifaceted signals about the user, their process, and their creative artifacts, reflecting creativity at multiple levels of analysis and timescales.

Here, we argue that research on creative activity traces must consider not only these diverse information types, but also how they will be used to understand and support creativity. We provide examples from our own and others' research to illustrate the value of these complex, layered representations of creative processes. We conclude by discussing how research on digital creative activity traces can be designed to better support creative professionals throughout their careers.

2 Types of Information in Creative Activity Traces

We organize our synthesis around the kinds of data represented by creative activity traces and their temporal resolution. Temporal resolution reflects the frequency of data collection (e.g., continuous v. event-based), the duration (e.g., single-session v. project-based), and the unit of analysis (e.g., seconds v. hours). The temporal profile of the creative activity can provide insight into how the experience will be represented in the worker's mind and how it may impact learning and memory [8].Given that people experience creativity differently [11], it is also important to understand creative activity traces in the context of the person (e.g., personality, demographics) and their

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environment (e.g., work, leisure). In the remainder of this section, we discuss different types of information that can be stored throughout the trace.

2.1 Artifact Changes

The most common type of data collected, **artifact changes**, concerns the evolution of artifacts during a design task. The *artifact* is the product of the design task and exists separately from the user. Depending on the task, the artifacts may be images, videos, presentations, software, UX mock-ups, or 3D models [3, 16]. The creative activity trace consists of temporally ordered sets of intermediate or candidate artifacts, along with a selection of artifacts highlighted by the user.

To illustrate, consider our research on how abstract semantic prompts influence design decision making. Participants created chairs that met a specific design goal (e.g., "Design a chair that is *cheerful*") in a custom Unity environment where they could modify a variety of discrete and continuous parameters to achieve their vision. The full state of the chair was recorded with each parametric modification, producing a creative activity trace dataset reflecting the evolution of a design artifact over time [19].

2.2 Design Information Gathering

Creative tasks involve many tasks beyond artifact creation. In early-stage design, **design information gathering** is an essential task. Therefore, creative activity traces can extend beyond the design artifact providing important information that can illuminate the designer's underlying creative process.

Our Personagram system, which supports persona-interactions for reference product-guided 2D conceptual design, offers an illustrative example [13]. Using this CST, participants created new concepts for different product types (e.g., chairs and helmets). In design information gathering, they interacted with synthetic personas to identify reference products and design features to create new 2D concepts. In addition to capturing design artifacts, the system also logs interactions with personas and reference product features.

2.3 Physiological Sensing

In addition to personal traits, an individual's creative process is influenced by their psychological and physiological state. Creative activity traces can include *in situ* information about the creative workers themselves through **physiological sensing**. Researchers have augmented behavioral and self-reported measures of creativity with physiological responses, such as electroencephalography, heart rate variability, pupillary responses, and galvanic skin responses (e.g., [4, 10, 20, 24]. Physiological sensing can improve researchers' ability to understand creative processes and infer the mechanisms through which CSTs impact creativity [6].

For example, we have studied which AI-generated images evoke surprise and delight designers [28]. After demonstrating canonical pupil responses associated with arousal, we show that the physiological responses complement the standard self-reported measures across generated images in a bike design task. We demonstrate how this can be used to identify the less than 1% of images that were rated as highly desirable across relevant design dimensions.

2.4 Longitudinal Monitoring

One tension in studying creative work is that, in practice, it extends both temporally and spatially across multiple sessions. Consequently, creative activity traces that include **longitudinal monitoring** better align with professional experience. Consider our recent five-week, just-in-time intervention study of creative well-being with professionals [22]. Because of intellectual property considerations associated with observing in-the-wild creative work, logging artifact changes was impossible. Instead, we leveraged *passive sensing*, sampling browser behavior and keyboard/mouse interactions; to infer the associated cognitive states and deliver effective interventions.

3 Uses of Creativity Activity Traces

Broadly, creative activity traces function as a means to understand and support creativity. When considering which information to include in creative activity traces, it is necessary not only to consider the creative task, but also the role of the creative activity traces in the scientific process. In this section, we discuss three main uses of creative activity traces.

3.1 Understanding the Creative Process

One benefit of creative activity traces is the relative ease with which creativity can be assessed across large, diverse populations, yielding new insights into the creative process. In a digital context, creative activity traces can be resolved with high precision at millisecond timescales, supporting the development of computational models of behavior that are better aligned with creative processes (e.g., [18]). Moreover, design theory has traditionally relied on ethnographic studies to validate theories and surface new hypotheses. Administration of such studies has historically been extremely time-consuming (e.g., researchers observing and coding team behavior for qualitative analysis). Today, creative activity traces can be combined with AI tools, resulting in new approaches to studying human behavior at scale. Consider Fuzzy Linkography, which demonstrated the utility of AI for accelerating the analysis of over 1000 creative activity traces to understand design moves [26].

3.2 Evaluating the Claims of CSTs

Creative activity traces also offer observable metrics that complement experiential self-report measures commonly used to evaluate the efficacy of CSTs. A CST designed to support divergent thinking is enriched by high-resolution creative activity traces that provide behavioral evidence of the users' exploration of the creative task space. These traces can be analyzed using computational frameworks like reinforcement learning that make clear, testable predictions about the creative decision making process [7]. Consider our Personagram system which claims that transforming personas from static abstractions to an interactive part of the design space will facilitate creative work [13]. An analysis of the creative activity traces can assess the degree to which the CST impacts designer interaction with personas.

3.3 Training Humans in Creativity Tasks

Exposing creative activity traces directly to users can have further benefits, such as strengthening metacognitive control (as [15]). By externalizing indicators such as time spent on subproblems or idea screening effectiveness (e.g., frequency with which low-novelty ideas are generated and discarded), CSTs can help individuals calibrate their attentional focus or refine their screening strategies, leading to more adaptive creative behavior at design time.

3.4 Training AI Systems in Creativity Tasks

Creative activity traces can also increase the capabilities of AI systems. Instead of relying solely on finished creative artifacts with subjective labels, creative activity traces can encode every interaction and intermediate result, providing information that can be used to guide generative processes. For example, the VideoCAD dataset, a synthetic dataset for 3D CAD design, has been used to create a benchmark for important AI systems, including goal inference and 3D spatial reasoning [16]. Human understanding gleaned through creative activity trace data can also be used to design and control generative AI processes. Our group demonstrated this in the context of intervention design, using computational models of creative decision making to guide the creation of novel generative AI interventions to support creativity [9].

4 Opportunity: Supporting Creative Wellbeing

Reflecting on the recent growth of CSTs, the primary goal of new CST development has been supporting the creation of creative content, with improved fundamental understanding being a secondary outcome. We argue that the explosive growth and diversity of new CSTs, present an opportunity for researchers to reconsider fundamental assumptions about creative processes and creativity support. New theories should take the breadth of new creative activity trace data from these tools into account as well as the analysis of AI systems performing creative tasks. We should note that this recommendation should not displace or devalue human creativity. Instead, new research should be human-centered, prioritizing human agency, autonomy, and wellbeing. Thus, although training AI systems in creative tasks may become an important focus of new CST development, we expect humans to remain central to creative process, with meaningful, sustainable human-AI co-creativity taking a more prominent role.

Viewed in light of the rapidly shifting context of creative work, the need for a deeper understanding of human creativity is clear. Creative activity traces, especially when acquired *in situ* as individuals interact with CSTs, provide an opportunity to rapidly test theories to improve understanding. This approach can also serve to mitigate the potential harms of the changing creative ecosystem, where creative professionals are increasingly expected to adopt new technologies and prioritize immediate productivity gains over long-term creative output [14, 27]. Because creativity is strongly linked to meaning-making and identity [12, 23]—phenomena that develop over longer timescales—it is paramount to helping individuals sustain their creative practice *while also protecting the creative self and its wellbeing* at work. Creative activity traces enable multifaceted understanding creative processes at different timescales. Then key insights can guide the design of new, more effective CSTs that promote creative wellbeing both in the moment and over a lifetime.

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accepted 6 March 2026