ShatterModel: Leveraging Proxemics to Design Human-AI Interactions in Adverse Environments

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Jacob Yank[1], S. Park[2], Brandi Simpson[3], Justin Ginsberg[4], and Cesar Torres[5]

[1]Jacob Yank; Dept. of Computer Science, UMD - College Park; e-mail: jyank@terpmail.umd.edu
[2]Seongjoo Park; Dept. of Computer Science, UTA; e-mail: seongjoo.park@uta.edu
[3]Brandi Simpson; Dept. of Art and Art History, UTA; e-mail: brandi.simpson@mavs.uta.edu
[4]Justin Ginsberg; Dept. of Art and Art History, UTA; e-mail: ginsberg@uta.edu
[5]Cesar Torres; Dept. of Computer Science and Eng., UTA; e-mail: cearto@uta.edu

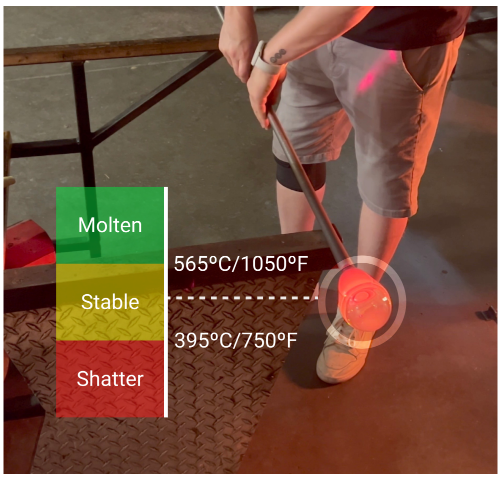

Figure 1: Through practice and patience, a glassblower develops an intuition of the temperature of glass on the rod. While shapeable in its molten state (above 1050 ℉), the glass can quickly cool and can shatter if it falls below 750 °F. We explore how an AI model can support glassblowers in predicting the temperature state of the glass.

Introduction

Integrating sensor-driven AI interactions within makerspaces is a challenge, especially since spaces are continuously evolving, requiring AI models to be resilient against model degradation, data shifts [2], target shifts, and changes in environmental conditions. Within creative spaces, embedding AI models through conventional user interfaces (desktop, GUI) can introduce a tether that limits the fluidity of motion and actions inherent in physical practices [1]. In order to work towards the concept of a smart makerspace, we need to understand how human-AI interactions can be embedded into creative physical environments [3]. In this work, we foreground how spatial analyses can be used to design for natural, intuitive, and collaborative spatial interactions. In the context of glassblowing, we describe our proxemics-based approach where we first study a glassblower's motions and activity in space to delineate regions of interaction. We demonstrate how an AI model that predicts the temperature state of glass, the ShatterModel, can be designed to integrate within the natural glassblowing process. In conducting our work within a hot glass shop, we show how proxemic analysis is effective in designing intuitive human-AI interactions that are able to be integrated within technology-adverse environments.

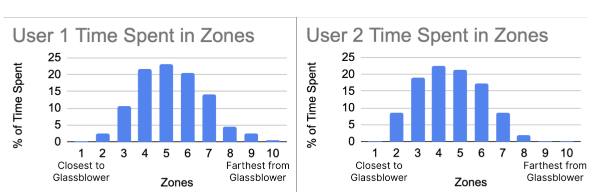

Figure 2: The rail can be divided into 10 zones, each 2.4 inches in length. Zone 1 is the closest zone on the bench, while zone 10 is the furthest.

Figure 3: To capture the data necessary to train our ShatterModel, we used a setup of two cameras and two pyromaters each capturing different angles of the glass. The glass shop forms a adverse environment for technology: (1) the furnace operates in temperatures well outside technology operating ranges; (2) the tools and workbench change their position daily; (3) every space is critical to glassblowing – with just a few cameras and pyrometers set up, much of the usable space is taken up.

Adverse Environments

Studying human-AI interactions in adverse environments is useful for designing technology that is resilient and robust. Our work in an academic hot glass shop typifies an adverse environment (Fig. 3) and can serve to emulate the situations encountered in other adverse makerspaces. Some notable conditions include: 1) **Shifts –** Glassblowing is a creative and expressive practice; the variety of shapes and material-tool combinations make it difficult for models to maintain their performance. New glassblowing tools, layouts, and materials are introduced frequently; 2) **[Extreme Conditions] –** The hands and body of a glassblower are subjected to extreme heat from molten glass 1150 ℃ (2100 ℉), limiting the placement of worn or environmental sensors; 3) **[Purposeful Spaces] –** The space in the glass shop is very limited; every space has a specific purpose, such as how glassblowers stand and move around the bench, which is critical to spatial cognition; 4) [**Cultural Misalignment**] – Digital technology, historically, is not part of the glassblowing tradition. As a manual skilled practice, glassblowing often requires 2-3 people to coordinate actions using non-verbal cues.

Interaction Design Method

To meet the challenges of integrating AI within the hot glass shop, we first experienced the glass shop through participant observation. We later leveraged sensor ethnography methods to analyze spatial movements; during this process, we collected data to train our ShatterModel. The resulting model was then deployed on a IoT sensor network and feedback interactions were iteratively developed leveraging the proxemics of a glassblower's bench.

Spatial Analysis

In order to design an unobtrusive spatial interaction, we first conducted a spatial analysis for understanding how glassblowers move and act when blowing glass on a bench. We recorded two experienced glassworkers forming a glass cylinder; from this video, we segmented the rail on the bench (Fig. 4) and divided the rail into 10 zones. We then computed the frequency of rail-rod interactions that fell within these respective zones. Using proxemic theory, we assigned Zone 1 (closest to the glassblower), which was used exclusively by the glassblower's body, as the *intimate zone*. Zones 2-7 had the most rod-rail interactions (Fig. 2),

Figure 4: The glassblower uses the rail to support their blowpipe while rotating their piece. The rail can be split into two areas of spatial interaction, a making zone and a social zone. The making zone houses the majority of rotations, while the social zone is often used to communicate with the assistant.

designating the *making zone*. Zones 8-10 were used to coordinate actions with assistants and for entering and exiting the bench, which we assign as the *social zone.*

Shatter Model

Creating the ShatterModel consisted of three steps, (1) data gathering, (2) model training, and (3) model deployment. To label the images, we used a pyrometer pointed at the molten glass as it cooled (Fig. 3). Since the temperature read by the pyrometer was displayed on a screen, we also trained a YOLOv5 model on a dataset of 2000 7-segment digit images to automate the labeling of individual frames. We trained a convolutional neural network using 564 images, exactly like what is seen in the white circle of Fig. 1, and split them 80/20 for the training set and the validation set. The F1 score of the model we trained was 96%. Finally, we deployed our model on a server connected to a camera. Then the camera will look at the live glass to make its predictions.

Hot Spot Interaction

We are in the process of integrating the AI model with our benchmarking proxemics. Our "hot spot" interaction facilitates the glassblower prompting the AI model for feedback by moving the glass rod past the making zone and into the social zone. We argue that this interaction makes use of a pre-existing communication system embedded within the glassblowing process. The furthest part of the rail of the bench as seen in Fig. 4, is often used as silent communication between the gaffer (the person actively working on the glass) and their assistant.

Evaluation

We have designed a user study with 2-5 glassblowers to understand how placing the human-AI interaction within different proxemic spaces affects a glassblower's perception of privacy and trust with the AI model. The study aims to probe AI agent interaction in the intimate, making, and social zone to validate the use of proxemics to design natural interactions. We will collect self-report of comfort, effectiveness, and qualitative feedback on their relationship with the AI agent. Initial pilot studies indicate that the hot spot interaction is well received.

Conclusion

We showcased how proxemics could be utilized to inspire the design of a spatial human-AI interaction. Preliminary findings suggest that this approach holds promise in prompting AI intervention. However, we envision even greater potential by delving into layered, deeper interactions through the development of a comprehensive language of spatial interactions, enabling practitioners to engage in sustained conversations with AI agents. Although our focus was on the glass shop domain, the principles of proxemics we explored can be generalized to other makerspaces confronting similar challenges in adverse environments. Our approach serves as a valuable template for implementing AI solutions in diverse makerspace settings, paving the way for enhanced human-AI collaboration and problem-solving.

Acknowledgements

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