**Article Summary — The Artistic Design of User Interaction Experience for Mobile Systems Based on Context-Awareness and Machine Learning**

Liu (2022) explores how context-awareness and machine learning can be leveraged to establish an artistic and interaction design principle for mobile systems. The study approaches interaction as a contextual act (i.e. a process that is influenced by the current states of a user’s body, emotions, and environment) instead of an isolated experience measured with usability criteria. Liu (2022) positions users as a situated audience who, when they interact with systems, perform an artistic act of perception, emotion, and embodiment. This approach aligns with our mobile computing framework’s definitions of “context-specific” and “location-aware” since Liu (2022) also posits that mobile interaction design must be cognizant of and appropriate for the user’s temporal, spatial, and social contexts.

**1. Theoretical framework and design principles**

The author first models the study on four theories: digital display theory, intangible cultural heritage education theory, embodied cognition theory, and gamification design theory. These serve as an analytical lens for looking at user-system interactions as digital and symbolic practices in which multi-sensory information is used to inspire knowledge and experience. The research then generates three main design principles, which are discussed below:

the heritage education principle, which advocates for encouraging user participation in knowledge generation and preservation;

the somatic interaction design principle, which centers around somatic (gesture- and body-based) communication; and

the content design principle, which emphasizes empathy and aesthetics.

Together, these principles rely on a context model that supports situationalization through machine learning to form a design model that personalizes information based on users’ actions and environmental contexts. Liu (2022) designs an ontology-based user knowledge model using a multi-situational similarity measurement and constructs time-based tensor scores to represent the users’ evolving preferences. This method provides the user with evolving, context-aware, and data-driven artistic recommendations.

**2. Context-aware and machine learning model design**

The main machine learning methods used by Liu (2022) are Graph Neural Networks (GNNs) and Message Passing Neural Networks (MPNNs) to serve as the knowledge representations for using and modeling context and for context-driven inferences. Environmental contexts such as location and interest (e.g. interaction counts or topic name) or physiological states such as emotions are semantic factors mapped as node attributes in a graph-structured model. Liu (2022) applies GNNs and MPNNs to construct a recommendation system that can “recognize, process, and respond to” users’ situations and create a continuously and dynamically context-aware system.

In this study, context-awareness is used as the design principle’s perceptual layer. Context-awareness in the system can sense the user’s identity, their location, and their action to identify which information the system should deliver or artistically recommend and in what form. For instance, by perceiving and modeling gesture recognition or voice tones and locations as situational data, machine learning can infer real-time adaptation. Machine learning can also be used as an interpretive layer as a predictive engine—i.e., to help the system identify patterns and make inferences about users’ needs based on their prior contexts. Liu (2022) makes “mobile computing” into an ecological architectural design model where art, human cognition, and computation are triangled.

**3. Mobile interaction as embodied art**

In this section, the most compelling portion of the study was on “somatic interaction” and “embodied immersion”. Liu (2022) redefines interactivity as an expressive, sensory dialogue that blends with a user’s meaning-making. The author classifies immersion into three levels: perceptual immersion, narrative immersion, and embodied immersion. Perceptual immersion can be defined as the user’s degree of engagement and their level of interactivity with the mobile system. It is the initial and basic form of immersion that arises when a user can apply real-world, physical actions they are familiar with (e.g. pushing, clicking, and swiping) to virtual input devices, resulting in a seamless, intuitive feedback loop. Narrative immersion is the second level and it is achieved when the user develops a degree of emotional involvement with the information. This happens when the system’s informational content is curated so that users can be engaged on an emotional level. Embodied immersion, the third and final form of immersion, happens when users achieve an increased level of immersion and a physical awareness of a content domain such that they feel an intuitive presence in the digital environment. The model proposed by Liu (2022) uses her design principles to propose that contextually aware mobile systems must sense the user’s context and adapt to this in an artistic form to ensure that a system can have “a direct connection between behaviour and meaning generation” (Liu, 2022, p. 6725).

**4. Experimental evaluation and results**

The author, Liu (2022), validates the framework through some applied experiments that explore the potential of using context-aware mobile systems in augmented reality, interactive education, and adaptive recommendation systems. The author splits the data into a training set, which is 75%, and a test set, which is 25%. The model is able to show that deep learning methods that are based on context, especially those that use autoencoders with GNNs, perform much better in terms of predicted values compared to more traditional machine learning algorithms such as the collaborative filtering (CF) technique. Models that used only interaction information or models that did not use context-aware deep learning had a Pearson correlation coefficient of 0.567 for predicting interaction results, but a context-aware and behaviour-driven model performed significantly better, achieving a Pearson correlation coefficient of 0.998 for predicting interaction results (Liu, 2022, p. 6727).

In addition to statistical accuracy, Liu (2022) also conducted a qualitative evaluation using a field study of students and teachers in the classroom. This shows that students can report better levels of engagement with the subject content when they use AR tools that are context-aware for learning about cultural heritage. The students also reported better and higher levels of emotional engagement with their learning. Teachers, on the other hand, reported that the system was easier to use as it offered them clarity and reduced their cognitive load. The study shows that this is, in part, because context-aware systems are more satisfactory and improve users’ trust in the system.

**5. Relevance to the TripRace project**

TripRace and Liu (2022)’s insights have numerous ways in which they intersect. Liu (2022)’s perspective on interaction as a transient, adaptive, and embodied process can be extended to the TripRace prototype’s situation since TripRace is also bounded by mobile and changing contexts. These include a changing travel context (location), temporal context (time), and social context (friends). Liu’s (2022) idea of “context-aware artistic dialogue” can also be borrowed and used by TripRace to make the usually unexciting process of group decision-making among friends an expressive and creative experience.

Machine learning for context modelling is a feature that Liu (2022) applied to form personalized context models and this can be extended by TripRace for evolving its group recommendation to meet the users’ needs. For example, TripRace can also use the algorithmic awareness and sensitivity Liu (2022) used for tailoring context-aware recommendations to augment the application’s voting system. Such an adaptation could involve reweighting outcomes in real-time based on additional data inputs from the current location or group sentiment. Therefore, TripRace can be conceptualized as an applied extension of Liu’s (2022) interaction design theory for mobile systems since it has practical use cases in an area of mobile systems (i.e. interaction design) that involves machine perception, context awareness, and emotion.

**6. Conclusion**

To conclude, Liu (2022) reimagines mobile systems as contextually intelligent, artistic machines. By using deep learning and embodied interaction design, Liu (2022) shows how systems can be enabled to become more perceptive of their users’ current contexts and generate meaningfully immersive and human-centric experiences. The author transcends traditional conceptions of usability by introducing design elements that are cultural, emotional, and environmental. The paper is relevant to TripRace because it captures many fundamental components of TripRace as a prototype situated in the context of mobility, information diversity, and social presence. As such, the design of TripRace should be done to ensure every interaction between the users and the application is not only functional but also contextually sensitive.

**Reference**

Liu, L. (2022). The artistic design of user interaction experience for mobile systems based on context-awareness and machine learning. *Neural Computing and Applications, 34 (11),* 6721–6731. <https://doi.org/10.1007/s00521-021-06160-x>