Affective Assistants: A Matter of States and Traits

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ABSTRACT

This work presents a model for the development of affective assistants based on the pillars of user states and traits. Traits are defined as long-term qualities like personality, personal experiences, preferences, and demographics, while the user state comprises cognitive load, emotional states, and physiological parameters. We discuss useful input values and the necessary developments for an advancement of affective assistants with the example of an affective in-car voice assistant. With our work we help to shape the vision of our community regarding affective interfaces, not just in the automotive domain but also for other application areas.

CCS CONCEPTS

• **Human-centered computing** → **User models**; **HCI theory, concepts and models**; **Interaction design theory, concepts and paradigms**.

KEYWORDS

Affective Computing, User Model, Virtual Assistants, Natural User Interfaces, Automotive User Interfaces, User-Aware Interfaces

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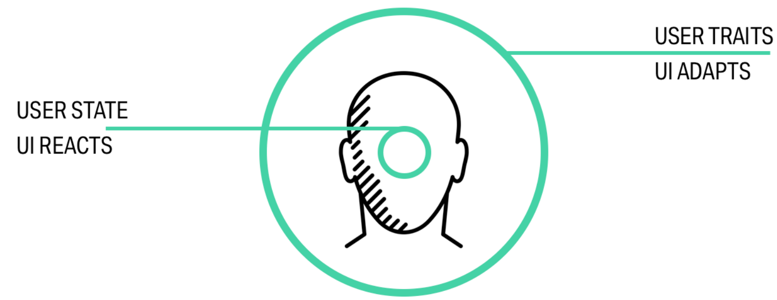

Figure 1: We propose a user model for affective assistants, based on stable user traits and a fluctuating user state. A system should be aware of the traits and adapt its general conduct accordingly. The momentary user state should be used to trigger short-term reactions.

INTRODUCTION

As virtual assistants we understand digital agents which can handle tasks on behalf of the user. Modern assistants can be interacted with via natural text (chatbots), voice (Siri, Alexa, ...), or images (Bixby, Google Lens). They can interpret input and answer through speech synthesis or by enhancing the given input. While the usability of virtual assistants depends on their functionality, user experience and trust towards the system can be improved, e.g., by adapting to the user's affective states [8], personality [1], or the surrounding situation [18].

We propose a model of user states and traits based on a thorough review of psychological literature and previous work, and show a concept of an affective in-car voice assistant. Cars provide an ideal environment for affective assistants, as the available interaction space is enclosed and can comfortably be equipped with sensors to monitor the driver and passengers. Users also generally interact with in-car systems over long periods of time, which allows for continuous data analysis.

Contribution

Our user model is based on the definitions of interindividual and intraindividual differences used in psychological assessment to describe stability and change in human behavior [19]. By taking into consideration both permanent traits and temporary states, assistants can make sense of human behavior and thus cover the blind spots each approach creates when used separately [23]. The model can be of help for researchers and practitioners who work on human-centered information systems, especially for designers of virtual assistants, e.g. in the automotive industry. We hope to inspire a holistic approach to user-aware interfaces with this fundamental concept of user modelling.

USER TRAITS

Interindividual differences, or user traits, are expressed by permanent behavioral patterns each person acts upon during their daily life. These traits are seen as stable in adult humans and only change through personal development over long time spans [4]. Steyer et al. define traits as components that are free of situational and/or interactional effects [19]. Digital systems can learn traits by observing users regularly over a longer period of time and adapt their behavior accordingly [11].

Demographics & Culture

Demographics are statistical characteristics of populations which can be used to describe big structures within user groups and connect them to behaviors or needs. Examples for demographic user properties are age, gender, education, income, or location. The demographics as well as the concomitant cultural conventions of a location or social class influence how users expect a virtual assistant to behave [3] and also have an impact on functional requirements, for example for in-car systems [10].

Personal Experiences & Preferences

To further understand the long-term behavior of users, prior experiences and resulting preferences can be used. Experienced users often show proficiency gained through learning and only need information on new features, while new users need to be introduced to general operating principles. The necessary data can be acquired through usage statistics [16] and preferences can be queried during setup and avoid misconceptions, e.g. wrong personalization, which can dramatically debase UX [1].

Personality

Various psychological paradigms have been drawn up to assess human personality, for example Cattell's 16-Factor Model, Eysenck's Big Three, or the Big Five Model [6]. The latter is the most used approach in personality research today, and consists of the dimensions Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (OCEAN), describing general tendencies of behavior [13]. An individual's personality traits affect social behaviors like collaboration, group dynamics, and social relationships, and influence their preferences of, e.g., assistant characteristics [1, 11]. Assessing personalities comes with a potential self-report bias. However approaches for data-driven personality detection by analyzing online conversations or workplace behavior, exist [11].

USER STATE

Users also show intraindividual differences, which we call the user state. Steyer et al. define a state as a situational and/or interactional component which changes rapidly and may come with a measurement error as it is depending on a lot of environment factors [19]. A system that takes into account the user state needs to monitor the user in a live loop, so it can react to momentary fluctuations.

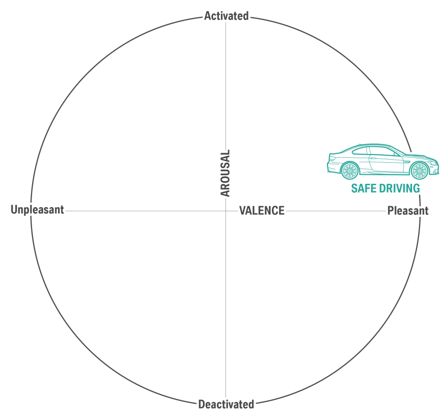

Figure 2: Emotional driver taxonomy based on Russel's circumplex arousal-valence model [17] and the Yerkes-Dodson law [22]. Positive valence and medium arousal values have shown to least affect driving performance in a negative way.

Physiological State

Physiological sensors allow digital systems to react to bodily responses [7]. Measures like heart rate, blood pressure, body temperature, breathing rate, galvanic skin response, or EEG can provide the input for classification algorithms to quantify fatigue, engagement, or medical conditions [9].

Cognitive Load

Cognitive Load Theory assumes a competition for limited resources between perception, cognition, and response activities [21]. Increasing visual, haptic, auditory, and/or vocal utilization rates through interaction with a digital assistant can decrease the amount of environmental information a user can perceive [14]. Hence, interaction with a digital assistant can lead to unsafe behavior, which is especially apparent in multi-task situations. An assistant may estimate free cognitive resources, e.g. by monitoring limb and pupil movements, and so find the least distracting moment and modality [12, 14, 15].

Emotional State

Digital systems can deduce human emotions from various signals, such as facial expressions or from physiological measures. Emotional signals can show the user's satisfaction with a system, or influence the way they react to stimuli. Davidson and Ekman define emotions as short affective states which bias user actions and last for a short time, usually several seconds [5]. Moods in contrast are defined as conditions lasting longer periods of time, affecting an individual's cognition [5]. Emotions can be classified within categories of basic emotions [5] or on continuous scales like arousal and valence [17].

BUILDING AN AFFECTIVE IN-CAR ASSISTANT

This model can be applied to any user-aware system. We explain an exemplary in-car assistant, as the focus of our work lies in the automotive domain. Previous research shows that car owners actively wish for situation-aware assistance, more personalization, and less distraction [2]. We conceive a system which derives user traits from demographic questionnaires, a Big Five self-assessment, and a preference panel for general settings. The driver state is monitored with a camera system (facial emotion detection, cognitive load from pupil dilation [15]), heart rate and respiration are estimated with wearable sensors, and galvanic skin response and skin temperature are calipered off the steering wheel. An additional stream of information comes from the OBD-II interface which provides vehicle information like throttle position to infer driving behavior [20].

The voice assistant incorporates the model presented above (see Figure 1) in two modules: user traits influence the assistant's display of personality which we found to be beneficial for trust and system likability [1], and they influence its behavior, as novice drivers, for example, expect more assistance than experienced drivers [2].

The second module manages the conversation and security functionalities based on the current user state. It can cater to live inputs, e.g. offer a simplified interface when the user is frustrated, or trigger interventions when an unsafe driver state (angry driving) is detected. The emotional driver state is classified using the dimensions valence and arousal (see Figure 2), other possible triggers are medical emergencies, or increased cognitive load.

OUTLOOK

This work sets an outline for user-aware assistants in general and proposes the development of an affective in-car voice assistant. The presented protoype is curerentl being tested and first findings suggest added value through an adaption to user traits [1]. Based on this we aim to find out which user states are meaningful triggers for live interactions and how such systems should be designed. We see the importance of driver-aware assistance which can adapt and intervene to make driving more safe in the future. The discussion at CHI should be used to debate meaningful input variables and the ethical questions we have to expect. This way, we can shape the vision of our community regarding affective interfaces, not just in the automotive domain but also for other application areas.

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