User Acceptance of Cognition-Aware E-Learning: An Online Survey

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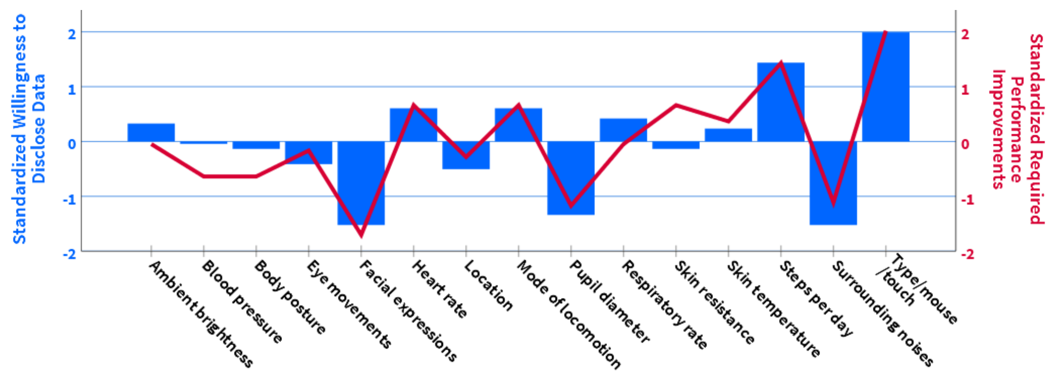

Figure 1: User acceptance regarding different sensors. Both analyses (A) and (B) are transformed to the same scale in the range $[-2, +2]$**, where positive values indicate high willingness/low required improvements to disclose data.**

ABSTRACT

The idea to enhance the learning experience of e-learning platforms by incorporating measures about the user's cognitive state, e.g. the cognitive load, boredom, or attention, has been proposed several times and shows promising results. However, the works have mostly dealt with conceptual implications and technical possibilities to detect the state, without considering the user acceptance. This paper therefore investigates whether users would actually be willing to provide access to sensor data such as heart or skin measurements for the sake of making e-learning systems cognition-aware. The results of an online survey with 50 participants show that people would provide access to behavioral data like keyboard input without major concerns; however, other sensors are considered more sensitive and would require strong learning experience improvements to make disclosure worthwhile. Participants also appear less concerned about sensors that are integrated into consumer devices than about less widespread ones. Furthermore, we report the general opinions regarding cognition-aware e-learning and discuss ideas on how best to adapt to the cognitive state.

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CCS CONCEPTS

• **Human-centered computing → User studies**; **Empirical studies in HCI**.

KEYWORDS

cognition-awareness, e-learning, privacy, sensor data

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1 INTRODUCTION

The e-learning industry is continuously growing, with a predicted compound annual growth rate of 7% until 2025 [17]. Modern e-learning systems offer a variety of customization possibilities, including the possibility to work through the content in a self-chosen order or speed. Recommendation engines can support this customization process; however, they often only consider the previous behavior of the current or other learners. This neglects the user's cognitive state, i.e. the cognitive load experienced, or factors like the perceived stress, tiredness, boredom, or attention, which we argue can strongly influence the content or speed that is appropriate for his/her current state (see e.g. [34]). Those factors are also given appropriate consideration by human teachers in traditional learning, as they react to their students' needs and moods. Taking this to the e-learning domain, an application-oriented video showing a learned technique in practice might be well suited when a user feels overloaded, while a complex technical article could be overwhelming and therefore not effective in this situation. In contrast, the same video might feel boring in another cognitive state, where the article could be more appropriate. Furthermore, informing the instructor about the learners' cognitive states could help improve the learning content and tailor it to individual needs.

These and other adaptations would be possible if e-learning systems had the ability to estimate the cognitive state of a user. Plenty of approaches to measure cognitive load, stress, etc. have been proposed in the literature and allow some form of cognition awareness [2, 26, 30]. Many of the sensors used in these works are nowadays even integrated into consumer devices like smart watches/smartphones/laptops, making the concepts feasible in practice. The presented work is the first to explore which of these numerous approaches to capture the cognitive state during e-learning would be accepted well by users. Would they be willing to provide their physiological data for the sake of an improved learning experience? Do they have different privacy concerns depending on the kind of sensor that is used? To answer these questions, we present the results of an online survey with 50 participants. Our results guide practitioners developing cognition-aware systems to achieve broader user acceptance and show researchers which measuring methods are perceived as intrusive.

2 RELATED WORK

Several forms of adaptive e-learning have been proposed in the literature: Kuo et al. [12] propose the idea of a context-aware learning system that considers factors like facial expressions, human voice, or body temperature. Recommendations of learning content based on ontologies about the learner and the content, as well as behavioral, positional, temporal, and technological data, have also been proposed [23, 37]. Furthermore, dynamic user interface adaptations [10] and adaptive visualizations [6], driven by physiological parameters, were suggested to support learning. The concept of affective e-learning, which uses emotion feedback to improve the learning experience, was proposed in [29]. The work showed in a feasibility study that biosensors can be utilized for this purpose. A review of affective computing in education can be found in [36], which highlights the essential role that positive emotion has on comprehension performance. Bahreini et al. [2] investigate emotion recognition using webcams and microphones to better respond to the affective states of students, as human teachers would in traditional learning. Ishimaru et al. [11] link eye tracking data, including fixations and pupil diameter as well as thermography, to surveys about the cognitive states of high school students while studying a digital physics book. Leony et al. [15] showed that such adaptations can affect cognitive processes like memorization and decision making. Sensor data was also linked to a subjective measure of flow [13], stress detection [26], and motivation [3] for the case of adaptive e-learning.

These works focused on the concept of cognition-aware e-learning and potential measuring methods, but did not investigate user acceptance. In contrast, privacy concerns regarding sensors, albeit without the context adaptive e-learning, were also investigated:

Fensli et al. [8] analyzed how well patients accept wearable sensors in the medical context. While medical information and the healthcare context are perceived as particularly sensitive, many health apps capturing similar data show poor information privacy practices [28]. Perez and Zeadally [22] split privacy issues and solutions for consumer wearables into three areas: context privacy, bystander privacy, and external data-sharing privacy. Relevant for our use case are context privacy and external data-sharing privacy, which include users' fears, location disclosure, etc. Privacy concerns when wearing a sensor suit were seen as most critical in the context of conversation and commuting; collecting stress information, temporal and spatial data, as well as sharing the data with the general public, increases these concerns further [25]. Lehto et al. [14] find that participants do not perceive the numerical information collected by wearables as sensitive; however, health records including written information are considered very private. Motti and Caine [21] show that users have different concerns based on the type of data collected, the sensor used, and the purpose of the wearable: Microphones and cameras pose the most privacy concerns followed by GPS, while heart rate monitors or activity trackers are seen as less problematic. According to [33, 38], most fitness tracker users only express minimal privacy concerns and show only an average level of concern if their data were compromised. Users also tend to underestimate or ignore potential risks, e.g. the lack of a keyboard makes users assume the collected data cannot be sensitive [18]. In a study with college students [31], users assumed that the producer of the wearable would take appropriate measures against privacy issues and therefore felt safe. The willingness to share personal data is also linked with the trust in the security [1] and the storage location [16] of fitness tracker data. A developed taxonomy on privacy risks for consumer health wearables [4] reveals that these risks refer to the perceived data sensitivity, data variety, and tracking activity. In general, however, users often share private information even when they claim they are concerned about privacy [35], which can be seen as an attitude-behavior gap.

Extensions to technology acceptance models [32] for the case of e-learning have also been proposed [24, 27], some investigating users' privacy concerns [5, 19, 20]; however, these works focus on general e-learning and not on cognition-aware e-learning.

There exist only a few publications on privacy concerns regarding data of wearable sensors in the learning domain: Fessl et al. [9] investigate physiological sensors in the workplace, with the goal to learn by reflecting on data like the stress level in different situations. They found that a clear benefit must be provided for users to use such sensors, and asked under which circumstances users would wear activity trackers. Engen et al. [7] qualitatively evaluate opportunities and privacy pitfalls of using wearable technologies in the classroom. Their particularly young participants (14-year-olds) were not overly concerned with privacy issues and saw no issues in sharing data like GPS locations. They further could not understand the privacy enhancing measures performed by the researchers.

To summarize, adaptive e-learning has been proposed several times, and promising results in terms of detecting the user's cognitive state based on a variety of sensors, including ones that are widespread nowadays, were achieved. However, the works mostly dealt with conceptual implications and technical possibilities to detect the state, without considering the user acceptance. While privacy perceptions were analyzed for both wearables and e-learning individually, no systematic evaluation of the users' privacy concerns regarding cognition-aware e-learning exists; that is what this paper contributes. Our online survey finds that people would provide access to behavioral data like keyboard input without major concerns; however, other sensors are considered much more sensitive. Participants also appear less concerned about sensors that are integrated into consumer devices than about less widespread ones. Furthermore, we report the general opinions regarding cognition-aware e-learning and discuss ideas on how best to adapt to the cognitive state.

3 INVESTIGATING THE USER PERSPECTIVE

The literature suggests that extracting the user's cognitive state during e-learning should be feasible and that adaptive e-learning systems have the potential to enhance the learning process. To gather feedback on the user acceptance of such systems, we conduct an online survey with a variety of potential e-learning users. The evaluation has been approved by the university's ethical review board as well as the data protection officer.

3.1 Method

The survey consists of the following blocks:

3.1.1 Demographics & background: The survey starts by asking about the participants' demographics and their usage of e-learning.

3.1.2 Willingness to disclose sensor data (A):. Then, we ask about their willingness to share sensor data with an unspecified application, without providing the context of e-learning. The 4-point scale asks whether they could imagine sharing the data, ranging from "not at all", to "would rather not", "probably would" and "completely". This question always appeared before B, to receive replies that are not biased by the context of e-learning.

3.1.3 Required performance improvements (B):. After explaining that such data could be used to detect the cognitive state for adaptive e-learning, we let them judge how big of an improvement (in terms of faster learning or making fewer mistakes) would be necessary for them to disclose the individual sensor data, ranging from "none" to "small", "moderate", "strong" and "immense" improvements. This can be seen as a similar approach to [1], which investigated the amount of money necessary to share otherwise private data in retailing. Note that the decision to formulate both questions positively (without artificially negating one), leads to the right-most value of B being related to the left-most value of A.

3.1.4 Sensors: We use the following list of sensors, which covers a wide (yet incomplete) set of approaches for context awareness and cognitive load detection: heart rate, skin resistance, skin temperature, respiratory rate, body posture, blood pressure, typing/mouse/touch behavior, eye movements and blinks, pupil diameter, facial expressions, steps per day, mode of locomotion (e.g. in a vehicle), surrounding noises, ambient brightness, and location.

3.1.5 Adaptation ideas & general feedback: Last, we ask participants for ideas on how e-learning tools could adapt to the users' states and what their general attitude towards this idea is. These open-ended answers are clustered based on manual coding conducted by the authors.

3.2 Results

On average, participants needed 9:09 minutes to complete the survey (sd=5:02). The following sections present the results for the different blocks of the study.

3.2.1 Demographics. Overall, 50 participants, aged 19–48 (mean=28.7, sd=6.32, 19 female), were recruited using Academic Prolific, where we paid more than the minimum wage. The only screening criterion we had was that their first language was German, since (a), the questionnaire was in German and (b), cultural differences might occur in such a privacy analysis. The participants had a rather high level of education, with only 7 participants not having general qualification for university entrance, 20 having this qualification but without a university degree, 15 having a bachelor's degree, and 8 having a master's degree or diploma. Furthermore, they had strong experience with technical products (mean=3.9 out of 4, sd=0.46). All of them used a computer and smartphone, half of them a tablet, and 22% a smart watch or fitness tracker. 10 reported having no experience with e-learning systems, while the remaining 40 reported an average experience of 2.75 (sd=0.71), which tends towards "rather high" on a 4-point scale. On average they learn electronically for 3.25 (min=0, max=20, sd=5.13) hours per month and mainly use a PC or laptop for this (29/40). As e-learning platforms, participants mostly use Duolingo, Babbel, Moodle, Udemy, Codecademy, and Coursera. These platforms also make sense if one considers the main goals reported by the participants: learning of languages, learning programming, or using them in the university.

3.2.2 General Feedback. At the end of the survey, after having introduced the concept of cognition-aware e-learning, we asked participants about their opinions on this idea. Here, the answers were rather inconclusive, at 2.62/4 (sd=1.01), where 3 means "somewhat positive". Analyzing if there is a correlation between e-learning experience and the participant's opinion on the idea of cognition-aware e-learning, we find that numerically it exists, but the link is not significant, with p=0.101 for two-sided correlation, or respectively p=0.0505 if we assume a positive correlation in the first place.

When asked whether the participants have misgivings regarding the concept of cognition-aware e-learning, 22 participants reported that this was the case. The reasons stated by the participants are all of the form "data protection/surveillance/data theft". In contrast, 20 participants either had no misgivings, finding it "flexible/performance oriented", or saw no issues under the assumption that the data used would be communicated transparently, not sold, utilized only for this purpose, and that the user could self-define the individual sensors from which data is being used. Further comments were of the form "would be absolutely great/intriguing". 2 simply stated that they know their current state and which content is suitable for their situation themselves. Lastly, 6 participants provided no opinion on this question.

3.2.3 Adaptation Ideas. Interesting ideas on how to adapt e-learning tools towards the current situation and cognitive state of the user were provided. We clustered the participants' various proposals: 29 proposals were of the form *adapt content*, either by recommending the content itself, or by adapting duration, difficulty, speed, level of detail, or intensity. Furthermore, 17 participants suggest *varying* *the duration*, e.g. by proposing breaks in between, by changing the duration of learning intervals or by splitting learning content into parts of different length. 3 suggestions were to *recommend times for learning* where one could learn most efficiently. Another 3 proposals suggested *adapting the interface* to reduce strain through optical changes. 2 suggested relaxation exercises, e.g. some form of meditation, when high loads are detected. Among the other infrequent proposals was the idea to detect when the user only scans through text, to adapt the time limits, vibrate on attention loss, provide individual learning goals, simply use it for a quantified self-style motivation, provide individual feedback, or use the data to improve the learning content for the future.

3.2.4 Willingness to Disclose Sensor Data (A). When asking participants on a 4-point scale (1–4) about their willingness to disclose data from different sensors, by simply assuming that *an application* would require this information, we get very indifferent results: the averages per sensor are in the range [2.16, 2.92], where 2 is “somewhat disagree” and 3 is “somewhat agree”; standard deviations are within [0.966, 1.216].

We test the results for each individual sensor with two-tailed t-tests for significance against 2.5, which is the mean of our four points, to get a clear understanding of the overall tendencies. The results can be seen in Table 1. This shows positive significant differences, meaning that there is a clear tendency to disclose the data, for typing, mouse and keyboard behavior (with p<0.05). Furthermore, we find negative significant differences, meaning that they would rather not disclose it, for facial expressions, ambient noises, and pupil diameter (p<0.05). For all other sensors, we do not find significant differences; however, we report the tendencies that we saw in the data: movement (number of steps), mode of motion, heart rate, breathing rate, surrounding brightness, and skin temperature showed a positive tendency (towards disclosure), while location, eye movement, skin resistance, body posture, and blood pressure showed a negative tendency (against disclosure).

3.2.5 Required Performance Improvements to Disclose Sensor Data (B). After having introduced the general idea of an e-learning system that can adapt to the user’s current cognitive state based on sensor data, we ask participants how big the improvement gained would have to be, e.g. in terms of faster learning, or making fewer mistakes. We also told them to assume that the data is used only for this purpose. Here, we got different mean values and a greater spread than for A: the averages are in the range [1.74, 3.00], and the standard deviations within [1.258, 1.443], where our 5-point scale was from 0 (“no improvement at all required”) to 4 (“immense improvement required”).

Significance testing is conducted similarly to A, but against 2 (“moderate improvement required”), due to the different scale. Compared to A, we also have an inverted scale polarity: high values indicate greater skepticism. The results can be found in Table 2. We find positively significant differences, meaning strong improvements would be necessary, for facial expressions, ambient noises, pupil diameters, body posture, blood pressure (≤0.001), location, eye movements/blinking, breathing rate, and ambient brightness (<0.05). No significant differences were found for the remaining sensors; however, we report the tendencies here: they were positive, (meaning strong improvements are likely required) for skin temperature, skin resistance, heart rate, and mode of movement, and negative (meaning small improvements are possibly required) for typing/mouse/touch behavior and movement (steps).

Table 1: Tendencies to disclose data depending on sensor (A).

	Sensor	p-val	mean	sd
Positively significant (tendency to disclose)	Typing/mouse/ touch behavior	0.003	2.92	0.97
Negatively significant (tendency not to disclose)	Facial expressions	0.033	2.16	1.10
	Surrounding noises	0.042	2.16	1.15
	Pupil diameter	0.049	2.20	1.05
Positively insignificant (tendency to disclose)	Steps per day	0.061	2.80	1.11
	Mode of locomotion	0.438	2.62	1.09
	Heart rate	0.474	2.62	1.18
	Respiration rate	0.623	2.58	1.14
	Ambient brightness	0.699	2.56	1.09
	Skin temperature	0.797	2.54	1.09
Negatively insignificant (tendency not to disclose)	Location	0.394	2.38	0.99
	Eye movements and blinks	0.487	2.40	1.01
	Skin resistance	0.803	2.46	1.13
	Body posture	0.803	2.46	1.13
	Blood pressure	0.908	2.48	1.22

3.2.6 Link between A and B. We hypothesize that negative correlations exist between A and B, since a high willingness to disclose the data (A) should reduce the required improvement threshold (B), and a low willingness to disclose the data (A) should result in a high threshold for improvement (B).

Pearson correlation analyses show that this is the case, as all correlations for the sensor data are negative, strong (all $r < -0.5$), and significant (all $p < 0.01$). This can also be seen in Figure 1, where A and B are plotted against each other on a scale with equal polarity and ranges for both questions. For this, we linearly scaled the answers from A in the range [1,4] to the range [-2,+2], and mapped the answers from B such that 0 (“no improvement”) corresponds to the highest value +2 and 4 (“immense improvement required”) to the lowest value -2.

3.2.7 Participant and Sensor Group Differences. We further test for group differences based on interesting sub-groups of our participants, which we defined according to their demographic data.

Analyzing the differences between *“smart watch/fitness tracker users” vs. “everyone else”* using a t-test per sensor shows that for A, a significant difference ($p < 0.05$) for the steps per day and an almost significant difference for mode of locomotion ($p = 0.051$) exist, with the “smart watch” group being more likely to disclose data.

Separating the participants into *“techies” vs. “non-techies”* (e.g. software developer vs. nurse) and *“teachers” vs. “non-teachers”* based on their job descriptions and using a t-test, as well as separating the

Table 2: Tendencies for performance improvements necessary to disclose data (B).

	Sensor	p-val	mean	sd
Positively significant (strong improvements required)	Facial expressions	<0.001	3.00	1.28
	Surrounding noise	<0.001	2.80	1.28
	Pupil diameter	<0.001	2.82	1.32
	Body posture	<0.001	2.64	1.26
	Blood pressure	0.001	2.64	1.34
	Location	0.012	2.52	1.40
	Eye movements and blinks	0.019	2.48	1.40
	Respiratory rate	0.023	2.44	1.33
	Ambient brightness	0.028	2.44	1.37
Negatively insignificant (small improvements required)	Typing/mouse/ touch behavior	0.175	1.74	1.34
	Steps per day	0.764	1.94	1.41
Positively insignificant (strong improvements required)	Skin temperature	0.137	2.30	1.40
	Skin resistance	0.302	2.20	1.36
	Heart rate	0.317	2.20	1.40
	Mode of locomotion	0.332	2.20	1.44

education levels *"no high school graduation" vs. "high school graduation" vs. "college degree"* together with a multivariate ANOVA, does not lead to any significant differences, neither for A nor B.

Since we explicitly asked participants at the end of the survey whether they had misgivings regarding cognition-aware e-learning, we also clustered participants into the groups *"misgivings" and "no misgivings"*. For A we found, for all sensors except location (where both groups tend towards the middle), that the "no misgivings" group is more willing to disclose the data. Similarly for B, for all but three sensors, the "no misgivings" group requires significantly less improvement to disclose data. The exceptions are location, as well as ambient brightness and typing/mouse/touch behavior, where both groups have similar opinions.

Last, we group the sensors into *"consumer device sensors" vs. "non-consumer device sensors"*, where the "non-consumer device sensors" comprise blood pressure, body posture, eye movements and blinks, pupil diameter, and respiratory rate, which are not commonly built into smart phones, smart watches, or fitness trackers. All other considered sensors are part of the "consumer device sensors" group. The results show that there is no significant difference for the general privacy concerns (A) with $t(49)=-1.33$ and $p=0.190$, but that for the required improvements (B), there is a significant difference $t(49)=2.90$ and $p=0.006$, meaning that stronger improvements are required for sensors that are not commonly built into consumer devices than for the commonly built-in sensors.

4 DISCUSSION & CONCLUSION

In this work, we investigated the perceptions users have towards data disclosure for cognition-aware e-learning. In general, our participants would most likely disclose typing/mouse/touch behavior, while pupil diameter, facial expressions, and surrounding noises would not likely be disclosed. We see this as two dimensions of intimacy, where users feel less unique in their typing/mouse/touch interactions, while observing someone's face or surrounding noises could feel more intimate; this is in line with [21], which found that sensors like cameras and microphones pose the most privacy concerns. Regarding required performance improvements for e-learning, such information about the surroundings and physiological data would only be disclosed by our participants in exchange for strong improvements. Interestingly, we found significant differences for improvement requirements between sensors integrated into consumer devices (e.g. heart rate or skin resistance) compared to less common measures (e.g. pupil diameter). This could mean that users are more concerned about the new or unknown and that they might become less skeptical once sensors become more widespread. Interestingly within the learning domain, the level of education did not significantly influence the tendency to disclose data, nor the improvements required for disclosure.

While the averages for most sensors tend towards the middle, thereby making effects small, we still found several significant tendencies. A reason for this trend towards the middle could be that for the critical topic of privacy concerns, people do not claim to willingly disclose all personal data without any concerns, but at the same time they know from previous experience that they do share data for convenient features [35]. This, combined with a fear of the unknown, might have led to the small differences in means. The fear of losing sensitive data, paired with the potential gains in learning success that our participants envisioned, might also explain the overall inconclusive judgements regarding the idea of cognition-aware e-learning systems.

Furthermore, we see that a strong link between the data disclosure readiness (A) and the required performance improvements (B) exists, indicating that the concerns are more of a general nature than specific to the context of cognition-aware e-learning.

Misgivings about the idea of cognition-aware e-learning exist mainly with regard to data protection; however, many users reported no concerns if topics like transparency, security and opt-ins are properly addressed. This indicates that these aspects should be of the highest priority when implementing the concept in practice. We further found plenty of interesting adaptation ideas, reflecting the interest in the topic that was also expressed in the form of approval/praise. There is also a (non-significant) tendency that users with more e-learning experience have more positive feelings towards the idea of cognition-aware e-learning.

The main limitation of this work is that we only asked about data disclosure in a survey, without having tested a cognition-aware e-learning system in practice, which will be our next step. Furthermore, we only sampled German participants, so cultural differences might occur for different countries.

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