Predicting technology acceptance using CAMs as an additional measurement tool to enrich questionnaire data

By means of attitude measurements using questionnaires, actual usage behavior of a technology can be predicted according to the technology acceptance model (Venkatesh & Bala 2008). However, questionnaires only allow previously known influencing variables to be queried and often require at least a prototype of the technology to be measured (Davis & Venkatesh 2004). In order to identify further influential factors on technology acceptance so called **"Cognitive Affective Maps" (CAMs)** can be applied (Livanec et al. 2020). CAMs are a quantitative and qualitative research tool to identify, visually represent and analyze existing belief structures (or in general any semantic knowledge).

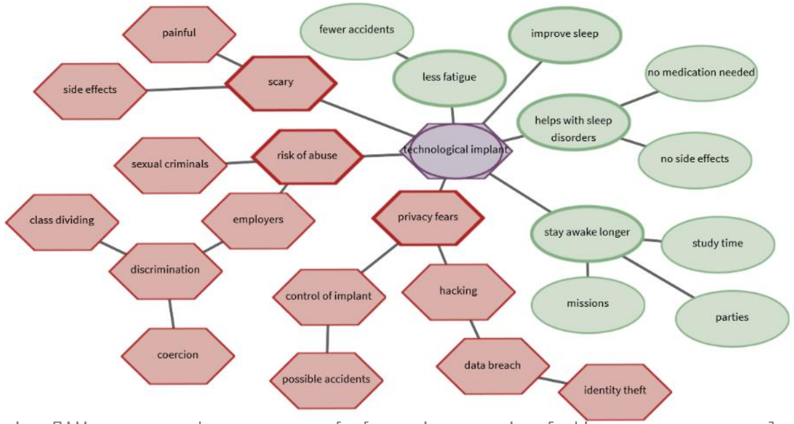

Figure 1. example a CAM concerning the acceptance of a fictional nano implant [publication in preparation]

Only recently have CAMs been increasingly researched quantitatively (e.g. Reuter et al. 2021), but up to date there is no software that can quantitatively evaluate the CAM data sets. Therefore I have written an **R package**, which is currently under development, to quantitatively analyze this kinds of networks (aggregating CAMs, computing complex network indicators, .. is already possible for example).

Pilot study

Subjects (N=90) were presented with a scenario text about a technological implant for sleep-wake regulation and subsequently answered questionnaire scales and created a CAM related to the technological implant. In a repeated measurement, the participants were presented a CAM with the opposite affective connotation to their previously CAM as a treatment. Subsequently, the participants answered the same questionnaires again and drew a second CAM. In addition, there was a control group that received no treatments. The study design allows for two central hypotheses to be explored, which will result in two publications:

1. Can CAM data provide additional information and thus increase the prediction of an outcome variable?
2. Does the treatment, the engagement with a CAM with the opposite affective connotation, have a measurable impact beyond the (possible) temporal instability of CAMs?

Preliminary data analysis

Regarding central hypothesis 1. In simplified terms, this acceptance process regarding an outcome variable could be structurally presented as a context-process-input-output model and theoretically we could apply arbitrarily complex **structural equation models**. To account for the non-normal distribution of the questionnaire items and the small sample, the DWLS estimator was used and the X^2 statistic was mean and variance adjusted (e.g. Hancock & Mueller 2013).

Table 1. Predicting behavioral intention to use the nano implant

predictors	est (std.)	se	pvalue
PANAS scale negative	-.218	.054	< .01
PANAS scale positive	.543	.064	< .01
Perceived usefulness of the nano implant	.217	.059	< .01
mean valence of drawn CAM	**.455**	.082	< .01

Taking into account different questionnaire scales, there is a significant influence of the mean valence of the drawn CAM on the intention to use the fictional nano implant.

Regarding central hypothesis 2. The study design is a mixed design with 2 (within) x 3 (between) levels. This allows the use of **multivariate multilevel models** (Lischetzke et al. 2015) to measure the effect of the treatment:

Table 2. Predicting mean valence of drawn CAM

predictors	est (se)	predictors	est (se)
Constant	-0.120 (0.079)	factor scores PANAS neg.	-0.122 (0.059)**
post	0.149 (0.091)	post x neg. CAM presented	-0.757 (0.162)***
neg. CAM presented	0.515 (0.142)***	post x pos. CAM presented	0.564 (0.169)***
pos. CAM presented	-0.464 (0.145)***	post x factor scores PANAS neg.	-0.131 (0.072)*

There is a stronger predicted change in the individuals' pre-/post difference if a negative CAM was presented compared to the control group.

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Exploring cognitive affective maps as a new mode of data collection – a future complementary survey research method?

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