SmartEater will be an evidence-based mobile health (mHealth) application. Findings from the ERC Starting Grant's NewEat, together with an existing technological platform (PsyDiary, the SmartEater predecessor without predictional capabilities, see this link for screenshots of PsyDiary) will be combined into the evidence-based mHealth app SmartEater. SmartEater will be the first mHealth app focusing on behavior change processes at the transition from the clinic to everyday life specifically for individuals with eating and weight disorders. It will warn about upcoming eating crises based on past stress/craving ratings, and smartphone sensor/usage data through machine-learning algorithms. Based on these predictions, individual tips will be delivered to curb such crises. It will furthermore be the first application with this focus to fulfill the requirements of a medical device (CE certification) and with a rigorous data security protection approach.

Properties and innovations of SmartEater:

A) Assessment of relevant target behaviors. Three key predictions will feed into the design of the SmartEater app:

I) Snacking behavior is important: The focus of SmartEater will be on determinants of between-meal snacking, namely craving for tasty foods. Our findings have shown that food craving time courses can predict unplanned and unhealthy snacking, dependent on stress (but relatively independent of hunger and main meals). Furthermore, individuals' cravings follow specific time courses that allow prediction of characteristic 'craving peaks' based on the past time series.

II) Stress is subjective: Stress prediction can be enhanced by including situational context data, acquired by a smartphone.

III) Consideration of age, gender, body mass index and certain personality factors increase the precision of the statistical prediction of future craving and resultant overeating.

B) Adherence and data quality. It has been shown that smartphone apps that require intense user inputs (e.g., several times a day) quickly challenge adherence: users become 'sloppy', the resulting data spotty and selective and therefore uninformative to the user or medical staff. SmartEater solves this problem through a combination of two strategies:

I) cumbersome input of meal composition or meal photos are not required, instead, the focus lies on the key determinants of between-meal snacking: food cravings and stress. Likewise, subjective stress can be estimated with only a few well-validated questions.

II) Data entry will be facilitated and data quality increased by input substitution. User data entry will be successively reduced by using statistical models to estimate these data based on the past data and several data sources that are automatically recorded by the user's smartphone. Importantly, in addition to substituting for - and reducing - necessary user input, this also allows predictions about future values, which represents one of the unique selling points of our solution. Machine-Learning algorithms (illustrated by the three gearwheels in Figure 1) recognize a similar pattern later and predict an upcoming craving/stress peak (red dashed lines). Based on these predictions, but before craving has generated force, a customized prompt/behavioral tip is launched, which attenuates/prevents this craving episode (flattened craving and stress values as result of the tip, green dashed lines). Optionally, a message can be sent to a caregiver (e.g. in a clinic).

Figure 1. Illustration of craving (top), stress (middle) and smartphone-derived digital context data (bottom) daytime timelines: early stress peak precedes craving peak during strong smartphone activity (left half). Similar situation is recognized later and situation-appropriate tip is launched (right half) leading to a reduction in craving and stress.

C) Meaningful and context-dependent feedback and tips. While advanced prediction technology can optimize feedback timing, what about the content of the tips? It has been shown that adherence to app use is reliably increased when 'real' human feedback is involved or when tips are individualized. Therefore, the SmartEater's approach to a tip system focusses on aftercare of inpatient treatment (the weeks/months that follow in-patient treatment). Specifically, the individual SmartEater tips database is jointly developed by the therapist and the patient, during the last 2 weeks of treatment with the aim of applying these tips during critical time windows in aftercare (when back in everyday life).

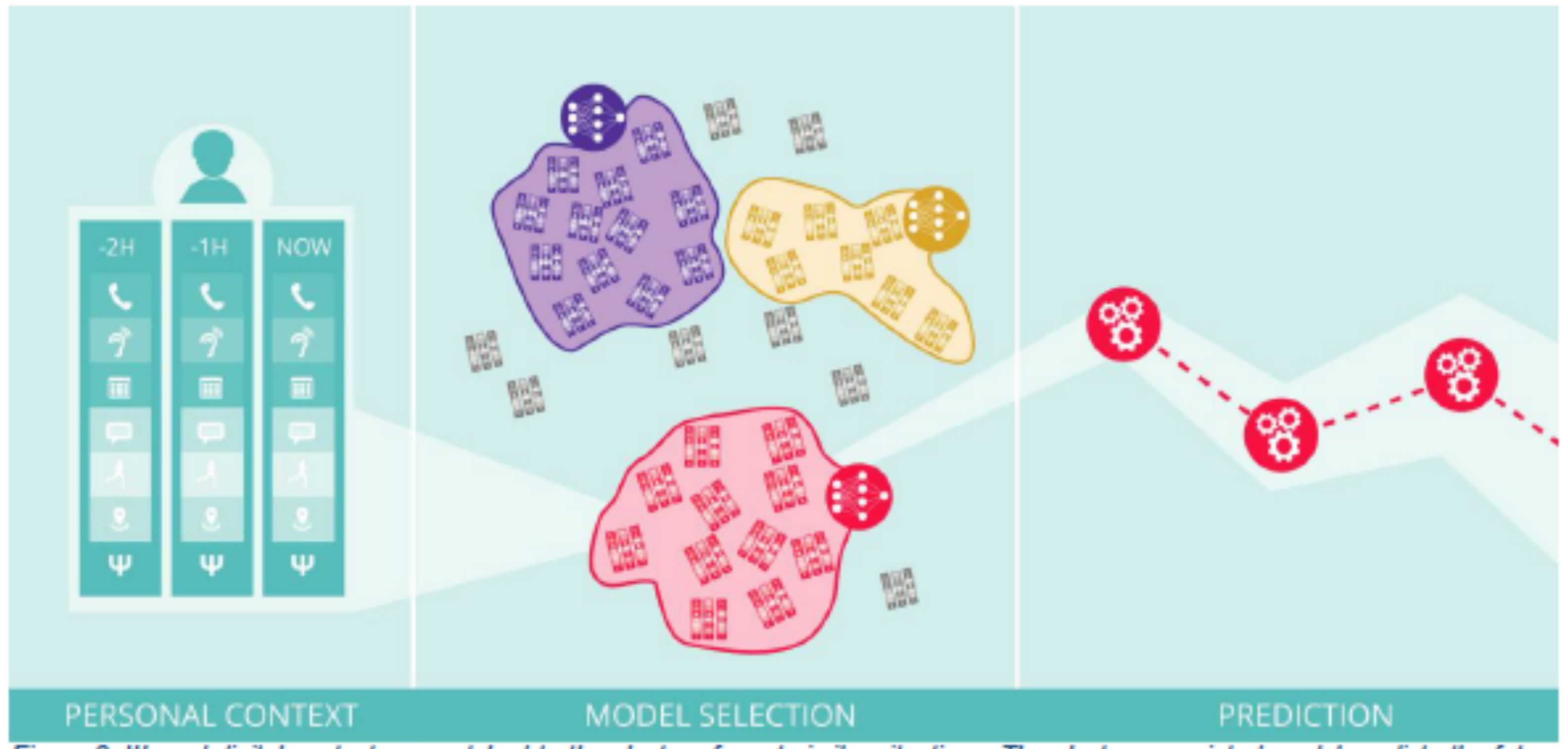

Figure 2: Ψ- and digital context are matched to the cluster of most similar situations. The cluster-associated model predicts the future development.

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