An Adaptive, Structural and Content Gamification Concept for Regulated Daily Routines

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Abstract: In this work, we introduce our concept for regulating daily routines in assisted living environments by the use of gamification elements. Nowadays mobile devices and sensors are ubiquitous, so they are suitable for assisting users on reaching their personal goals. One of the most pressing challenges in this regard is the preservation of long-term user motivation. In this paper we propose a gamification concept for a mobile application that support the achievement of regulated daily routines. With our assistive knowledge- and model-based approach SeMiWa, the system detects irregularities and their potential cause. These obtained insights are used to adapt the content of the application in a gamified way. A prototypical implementation substantiates our approach and introduces our forthcoming user study.

1 INTRODUCTION

Regular daily routines not only increase the overall well-being, but also affect peoples' health and the perceived stress level (Minors and Waterhouse, 2013). Large discrepancies in these rhythms may result in sleep disorder up to chronic depressions (Spork, 2011). Nowadays, daily routines can only be manually supervised by experts in order to avoid these negative consequences. The intention of our system is to offer automated and preventive assistance for this complex process. As one solution, Ambient Assisted Living (AAL) systems have been proposed (Kleinberger et al., 2007). These systems aim to assist users in their domestic environment to improve overall life quality.

One type of such systems - coming of the domain of elderly care - features domestic living environments with activity recognition. These systems monitor surrounding environments and user activities in order to ensure elderly are living safely in their own homes while staying independent in their life style. By utilising activity recognition algorithms such systems are able to detect a range of activities, e.g., walking, sleeping, and eating (Chernbumroong et al., 2013; Fleury et al., 2010). For this purpose, supervised machine learning algorithms are used to build training sets. However, beside the classification of uncorrelated activities, it becomes more and more necessary to combine these activities to daily routines. Since a permanent interruption of routines could lead to diseases, ranging from sleeping troubles up to chronical depression. Studies have shown that people, who live in regular daily rhythms, are less affected by these diseases (Spork, 2011).

We developed a concept that detects deviations in daily routines and tries to fix potential provenances with the help of gamification.

Moreover, in the initial – and sometimes during runtime – the application depends on manual user input, we motivate the user preliminarily also with the use of gamification elements.

In the following sections we detect common used game elements of mobile applications for self-improvement in terms of their motivational effect. Section 3 presents an overview of our model-based approach SeMiWa that analyses sensor events as well as performs the recognition of activities and daily routines. Section 4 outlines our gamification concept developed for reaching personal goals and the first prototypical application. Section 5 concludes this paper with a discussion and shows directions for future work.

2 RELATED WORK

We identified approaches related to our work that can be classified into research of chronobiology as well

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as approaches for gamification. As we discussed profoundly the state of the art in assisted living environments (Franke et al., 2013b; Franke et al., 2014b; Franke et al., 2014d), we omit these field in this work.

2.1 Regulated Daily Routines

Daily routines not only depend on personal matters, but also on exogenous and endogenous factors. In general cases, these routines evolve on natural rhythms of one person. For instance, measures from light exposure sensors are showing evidence in the sleep-awake rhythm.

Also the change of temperature that affect the overall activity of people. Changes in the atmospheric pressure can lead to headaches in some people and rainy conditions can reduce motivation to go outside. In contrast, spring time can lead to an extreme raise of activities until night time (Hildebrandt et al., 2013).

The field of chronobiology (Hildebrandt et al., 2013; Zulley and Knab, 2013) examines these impacts to our biological clock, such as typical sleeping cycle or times of high physical fitness. A distinction is made between *circadian*, *ultradianen*, and *infradian* rhythms.

The *circadian rhythms* last for nearly one day with exactly one peak and one low in this duration. Typical examples are the sleep-waking rhythm, overall physical and mental capacities or the hormone production. The *ultradian rhythms* remains for a few hours. Characteristic examples are eating and drinking or the raise and lower of blood pressure. The *infradian rhythms* continues beyond the day limit. These rhythms can be as long as the seasonal affective disorder (SAD) that lasts for several months or the women's menstruation cycle with a peak once a month.

All these rhythms have in common that they directly effect humans' behaviour. For instance, in the SAD it is likely to eat more food or being less attracted to go outside. We formalised rules out of these facts, firstly for the activity recogniser and secondly for giving *healthy* advices, such as eight hours of sleep or performing a "good" amount of sport activities.

2.2 Gamification

The field of Gamification describes the application of game design elements in non-game contexts (Deterding et al., 2011). The success of existing learning and self-tracking apps (e.g. the language trainer Duolingo[1], the running app Nike+[2] or Withings[3] App) confirms that gamification can be an effective tool to motivate user activity and long-term use. Gamified apps can support users to consistently pursue personal projects and goals. User motivation is generated by various game elements used in self-improvement apps. These elements can be defined as specific characteristics of games that can be applied in gamification (Deterding et al., 2011; Werbach and Hunter, 2012). In the literature, game elements are often introduced on different levels of abstraction. The game component points for example is a numerical representation of the games progression and can therefore be considered as a more- specific form of the element progression (Werbach and Hunter, 2012).

Kapp et al. (Kapp, 2013) distinguish between two general types of gamification: structural and content gamification. Structural gamification on the one hand means that the structure around the content becomes game-like to motivate users to go through the content. Exemplary elements of structural gamification can be points, badges or leaderboards. On the other hand content gamification alters the content, e.g. by means of avatars and challenges, to make it more game-like. According to Kapp et al. (Kapp, 2013) the combination of both, structural and content gamification, is the most effective way to increase the users motivation. In a literature review Hamari et al. (Hamari et al., 2014) gathered different game elements as motivational affordances tested in empirical studies, identifying points, leaderboards and badges as the most commonly found elements. However, the question rises, which elements have a particularly motivating effect on users.

There are already a few approaches to gamify assisted living systems (Burmeister et al., 2013), but to the best of our knowledge, a usage of a combination in structural and content gamification is not used within such systems so far.

3 SeMiWa - SEMANTIC MIDDLEWARE

To unify and process heterogeneous sensors in assisted living environments, we use our approach called Semantic Middleware (SeMiWa) (Franke et al., 2013a). This model-based, event-driven middleware acts as an intelligent discovery and routing service for events. The middleware is parted into a semantic stor-

[1] http://www.duolingo.com
[2] http://nikeplus.nike.com
[3] http://www.withings.com

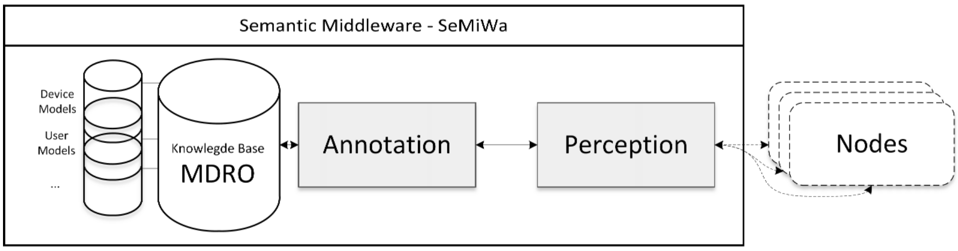

Figure 1: SeMiWa Overview (Franke et al., 2014a).

age (MDRO), a semantic processing unit (Annotation Component) and a network transparent interface for data transmission (Perception), illustrated in Figure reffig:semiwa.

3.1 Architecture Overview

The SeMiWa's Knowledge Base provides a central semantic storage for all semantic data within the system, such as sensor models, activity patterns, routine models, publish-subscribe (PubSub) registration and lifecycle information about all registered *Nodes* (Franke et al., 2014b).

The *Annotation* component annotates all transferred data (i.e. register messages, sensor values and PubSub patterns) according to our models situated in the knowledge base. This detection, respectively classification, is done by using meta-information about the sensor in the register messages (Tan et al., 2012). These register messages consist of identity information (unique sensor id), the classification information (sensor type, model and unit) and a timestamp for lifecycle purposes. As we work on predefined sensor models, only one exact match is found and no machine learning approaches has to be applied for this semantic enrichment. Furthermore, all sensor values are used to enhance them to user's activities (Franke et al., 2013b; Franke et al., 2014a).

The *Perception* component opens a uniquely identified, bidirectional, network transparent channel for Node registration and events. By means of the knowledge, coming from the Knowledge Base, it routes events to subscribers (PubSub) and service calls from invoking Nodes to selected ones (RPC). RPC calls are services on the selected sensors, such as configure the location of the weather sensor or changing its frequency.

Our main concept is to handle and describe all possible elements, such as applications, sensors or actuators, uniformly as *Nodes*.

3.2 Modular Daily Routine Ontology

The base of our activity recognition approach is a formalised *Modular Daily Routine Ontology (MDRO)* (Fig. 2) (Franke et al., 2014b). It provides a RDF-S/OWL vocabulary for annotating data sources, such as sensor values, factual knowledge from Chronobiology, recognised activities and routines. The four MDRO modules (sensor, activity, routine and user) represent different facets of the activity recognition domain. They refer to each other and to other existing ontologies as needed. In the following sections, we describe the essential parts of the ontology, which are used for recognising current activities and determining daily routines.

3.2.1 Sensor Module

The sensor module provides a semantic description for all sensors, provided by an ontology derived from the StarFL sensor ontology (Malewski et al., 2012), extended by a combination with QUDT[4] and OWL-S[5]. Therefore, it is possible to semantically unify sensor values and data types within the overall system. Instead of broadcasting raw integer or double values, all transmitted sensor data is annotated with semantic information, such as "*Temperature* data in *degC*" or "*Humidity* in *%*" thus providing knowledge for the system how the raw sensor values can be interpreted.

A full list of properties can be found in (Franke et al., 2014b). The most important feature regarding this work is the *healthyInterval*. These intervals are formalised from the field of chronobiology. For instance, we abstracted a light exposure interval, a step count interval of more than 10000 steps or a body mass index between 18.5 and 25. These properties are used later for the adaptive content gamification (cf. Sect. 4).

[4] http://www.qudt.org
[5] http://www.w3.org/Submission/OWL-S/

3.2.2 Activity Module

The activity module holds information about recognisable *Activities of daily living* (ADL). As initial, but extendable set, we used the caring descriptions, also mentioned as basic ADLs (Fleury et al., 2010) and transferred them in a hierarchical semantic model.

Furthermore, this module stores the semantic training set. Every classified activity is linked to one or more sensors from the sensor module and with the corresponding sensor values. This is necessary to justify the classified activity to the user, since we do not use all sensors at anytime for classification (Franke et al., 2014b).

Regarding this work, we extend the classifiable activities by the properties *healthyDuration*, *tooLowDuration* and *tooHighDuration*. These durations are stored in generic classes, such as *SportsActivity*, to sum up all derived sub classes (*Walking*, *Hiking*, *Swimming*), in case no different duration is given. Some examples of these durations are *Sleep* (per day) between $6.5h$ & $9.5h$ and an optimum at $8h$ and *Sport* (per week) between $2h$ & $7h$ and an optimum at $5h$.

3.2.3 Routine Module

The routine module saves a directed chain of ADLs with corresponding transition probabilities. Every part of a routine is a unique instance of the activity module, combined with the daytime. The probabilities are calculated during the user's history. For example, four days with transitions from *Sleep* to *Breakfast* and one with a transition to *Work* will result in transitions of 80% and 20%.

As a common vocabulary we utilised the Personal Information Model Ontology (PIMO) (Sauermann et al., 2007), as it is the quasi standard for semantically describing daytime sequences. With this ontology, we can describe duration, start and end of one activity (*hasActivity*). This combination keeps a chain through our activity module and works in conjunction with other calendar-based applications due to the usage of the PIMO standard.

Based on these semantically saved routines, we can perform the deviation and cause detection, as our ontology keeps the chain to our activity module and moreover to the sensor module (cf. Sect. 3.5).

3.3 Activity Recognition Algorithm

The activity recognition algorithm creates an ordered list of possible detected activities for the current sensor snapshot. The algorithm ranks the possibility of one activity according to the current time. This sorting is assigned by factual knowledge; classified sen-

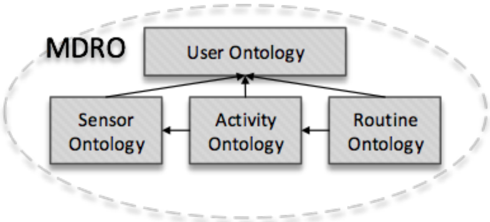

Figure 2: Modular Daily Routine Ontology (Franke et al., 2014b).

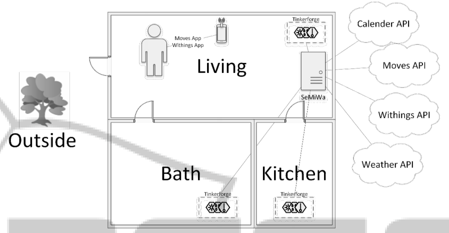

Figure 3: Sensor selection (Franke et al., 2014a).

sor values; and user generated knowledge (Franke et al., 2013b; Franke et al., 2014a; Franke et al., 2014d). The Equation 1 illustrates its fundamentals:

$$P = \frac{1}{n := \{2,3\}} * r_f + r_c(+r_u)) \qquad (1)$$

1) Factual Activity Knowledge. The factual activity (r_f) knowledge is defined by a set of rules from *Chronobiology*, e.g., verified statements such as "infradian sleep cycles". These rules consist of a condition, e.g., time of day, and a probability (Franke et al., 2014b).

2) Classified Sensor Values. The classification probability (r_c) is calculated by our classifier according the current sensor information. The activity recognition, respectively the routine recognition, reuses approaches based on *Support Vector Machines* (Fleury et al., 2010; Chernbumroong et al., 2013).

3) User-shared Knowledge. The factor r_u is associated with our concept of employing the user-generated knowledge through using collaborative filtering (Franke et al., 2014d). It is either the previous activity, done at the same time or the algorithm tries to foresee a possible rating based on similar users.

The meaning factor n is assigned with $n = 2$ if neither a previous activity at same time can be found, nor a prediction can be calculated. In all other cases it is assigned with $n = 3$ to keep the equivalently rating of all factors.

Finally, the complete list of activities is ordered based on combined probabilities P for each mapping. This ranking is used to assign the most probable activity to the user's daily routine.

3.4 Sensor Selection

For our purposes, we use a selection of sensors and devices to stay mostly comparable to nowadays activity recogniser systems (see Figure 3) (Franke et al., 2013b; Franke et al., 2014a; Franke et al., 2014c):

Physical Sensors. We abstract physical, climatic and surrounding sensors out of the NetAtmo[6] sensor station. Each station consists of a temperature, a humidity and a CO2 sensor. Additionally, we can use one barometer and sound sensor in the main room. All sensors are assigned to a specific location that is described by spatial coordinates in the domestic environment. This information is later used to reduce the dataset according to the classification and cause detection (Franke et al., 2014c).

Location Sensor. With the aid of the Moves[7] app and API, we built a location sensor, which records basic activities (walking, cycling, transportation and running) and the user's locations (Franke et al., 2013b).

Body Sensors. Besides the Moves app, we use two Withings[8] devices for health tracking. First of all, the Withings Pulse for measuring covered distances, sleep cycles and pulse measures, and second, the Withings Smart Scale for measuring weight and body fat mass.

Weather Sensor. We wrapped the WeatherUnderground[9] service, which provides information about temperature, humidity, air pressure, luminance, and in general the weather on the users location.

Calendar Sensor. As 'hint generator' for the classifier, we abstracted an online calendar, which publishes calendar events predefined by the user.

3.5 Deviation Detection

To acquire an active assistance for the user, the proposed system detects causes of anomalies proactively, and reactively. The reactive anomaly detection recognises anomalies in one chosen feature at a particular time interval, e.g., influencing factors of sleep duration last week and the proactive anomaly detection recognises anomalies in the daily routines during runtime, based on different time slots (e.g., week, month, quarter). These anomalies were directly presented to the user in our previous work with the help of an assistive mobile application. For the relevant technical details on deviation detection consider our previous work (Franke et al., 2014c).

[6]http://www.netatmo.org
[7]http://moves-app.com
[8]http://withings.com
[9]http://wunderground.com

4 GAMIFICATION CONCEPT FOR REGULATED DAILY ROUTINES

First of all, in order to compare commonly used game elements with regard to their motivational effect to the user, we designed an online survey as preliminary study. After analysing different existing gamified apps for self-improvement, we identified frequently recurring game elements that had to be assessed with respect to their motivational effect on the participants. Thereby, commonly used elements of both, structural and content gamification, were considered (cf. Figure 4).

By integrating screenshots of selected examples of gamified apps for self-improvement into the survey, we evaluate the central question: "Which game elements in this app motivate you to achieve your goal?" At the time of writing, a total of more than 40 participants completed the survey. The age of the participants varies from 13 to 55+ years, 63% female and 37% male. The majority of the participants (91%) are registered at one or more social networks and 84% of them are using Facebook. This aspect is relevant, since more and more gamified apps are integrating social networks for social sharing or competing against friends.

As an introduction to each section of the questionnaire, the relevant app was presented. The main questions are related to the personal evaluation of the motivational affordances using assessment tables (from "totally motivating", "rather motivating", "rather not motivating", "not motivating at all" or "I dont know"). The participants answers to the questions are presented in Fig. 4. Of particular interest is that only 2% of all respondents agree that sharing achievements through social networks (cf. Social Sharing in Fig. 4) is motivating, although most of the participants are registered at a social network. However, over 80% are convinced that challenging and varied tasks are motivating. Furthermore, the game components content unlocking with a score of 79%, progress indication and levelling up with 77% approval achieved similar good results.

From these preliminary results it can be concluded, that progress indication and levelling up are particularly motivating game elements of structural

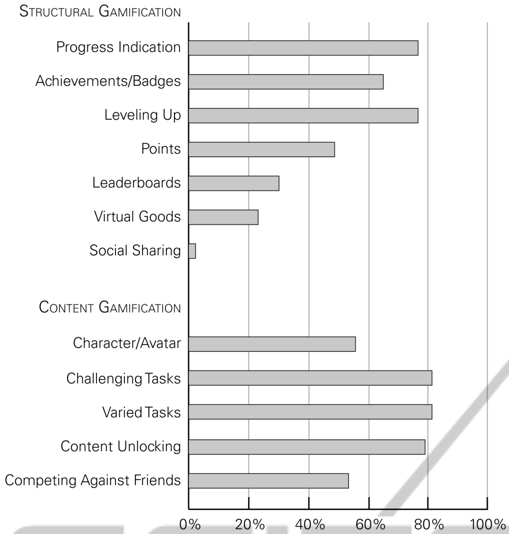

Figure 4: Long-term motivation comparison of varying gamification elements.

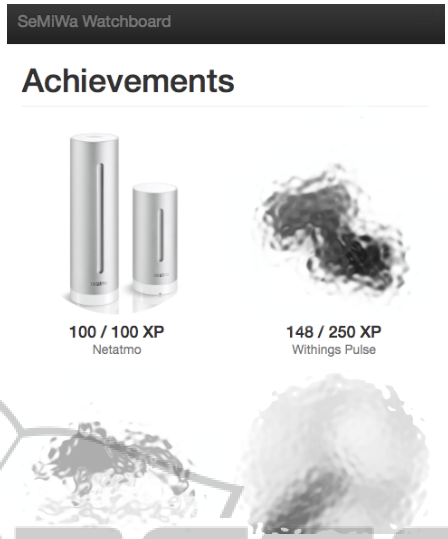

Figure 5: Structural Gamification Concept.

gamification. Similarly, challenging and varied tasks as well as content unlocking have a motivational effect for the majority of the respondents. Consequently, the higher-level elements challenge and curiosity (Kapp, 2013) can be identified as important motivational affordances in the field of content gamification. It should be noted that the presented questionnaire results were averaged over various apps. When regarded individually, it is evident that the same game elements (e.g. leaderboards) were assessed differently for particular apps. This indicates that the motivating effect of game elements is also influenced by other factors. Consequently, subsequent studies need to consider additional aspects, e.g. demographic user data, the visual design of game elements and other contextual criteria. However, one usable trend is already evident: not all game elements have the same motivating effect.

In order to apply gamification concepts, we are developing a mobile advisory application in the field of regulated daily routines. In Figure 5, a screenshot of the prototypical mobile application "SeMiWa Watchboard" is illustrated. With interactive gamified activities around adaptive, weekly changing subjects (e.g. sleep and sport durations) the user can adapt, monitor and evaluate his own lifestyle habits. By mastering a weekly challenge the user is confronted with a balanced work-life, sleep-wake, or sport amount in a playful way.

4.1 Structural Gamification

At the first stage of our application, we make use of structural gamification. As it is necessary, to train the classifier (cf. Section 3.3) for activity and routine recognition, manual inserts or corrections of activities has been done for nearly two weeks. Furthermore, a suitable amount of different sensors has also to be present (especially Moves and Withings data).

The manual entering of these data and usage of additional sensors has - at this point - no benefit for the user, as neither good classification, nor *healthy* routine detection can be done. For that reason, we decide to motivate the user with elements of structural gamification, as our preliminary study shows a strong evidence between the raise of motivation and the elements of *"progress indication"* and *"levelling up"*. We introduce the elements experience points (XP) and levels to our application, as these prove good results for a short term motivation and also gives us a chance not to overburden the user.

In the first levels, the user has to earn XP by registering new sensors one after another. As we need a base of different sensors for a good training set results, in the first week, the user earns XP by gathering sensor values for the *Annotation* component. This XP are used to put it in certain levels that achieves the next sensor and so on (*"levelling up"*).

In the process, we also show the current and needed experience points to the user (*"progress indication"*, cf. Figure 5). In that way, we can avoid to confront the user with the internals of the classifier or a fixed duration of training. By the use of the error rate in activity recognition algorithm (cf. Sect. 3.3), the system is able to unlock the *Master Sensors* and the *Advice Mode* of the application (*"content unlocking"*).

The structural gamification stays always active, even after all sensors are unlocked. Beside the experience points to unlock new sensors the user also earns usable points with every achievements (*"points"*). These points are used as a virtual currency to ensure the system has always enough data to perform in a stable way. If the usable point score falls under a given threshold, the application becomes locked and has to be reactivated by earning new points (i.e., by re-activating sensors or training the classifier).

4.2 Content Gamification

At the second stage, the application uses elements of content gamification to establish a long-term motivation for the user. Based on the deviation detection, an adaptive content gamification can be applied.

The mentioned (cf. Section 3.5) proactive deviation detection recognises anomalies in the daily routines, based on different time slots (e.g. week, month, quarter). The system detects, if the routine differs from previous ones and calculates on which basis this difference was determined. For instance, if a daily routine shows too short to *Sleep* cycles or unusual intermediate activities. The differing transition is used for finding all causes in the sensor values.

These findings are used to build the dynamic gamification elements. The system chooses the desired feature (resp. sensor), e.g., mood or sleep duration, and calculate the main factors influencing the chosen feature (Franke et al., 2014c). For instance, features, that affect the sleep duration could result in room temperature, noise and sports duration. Beside the influencing factors, we implemented rules that handle whether this change is a positive or negative one. The foundation of these assessments is derived from chronobiology and formalised in our sensor module, as previously stated (cf. Section 3.2).

The varied tasks are built due to this causes and trends. If the sleep duration decreased significantly influenced by the sport duration, the next task will be performing more sport, instead of confronting the user with the *real* problem. This method avoids the annoyance of the users, as they often recognise the problems (no good sleep duration) themselves and get frustrated if an application also shows the same facts to him. Our study, e.g., shows that the Withings App showing such annoying messages: *"You've never done so few steps on a Wednesday. I'm sure you can do more tomorrow :)"*.

With this procedure, we cover the two significant content game elements *"content unlocking"* and *"varied challenges"*, as the challenges change weekly adapted to the current habits.

5 CONCLUSION

In this paper we presented a general gamification concept for daily routine deviations and gave an overview of common used game elements in gamified apps for self-improvement. In addition, we introduced our previous work SeMiWa in order to demonstrate and evaluate the suggested concept.

The purpose of our preliminary user study was to identify game elements that have a particularly positive impact on the user's motivation. We analysed various gamified apps for self-improvement and carved out common used game elements that were used for the online survey. Although the preliminary results only consider a small number of participants, the outcome shows, which game elements are already of importance: progression, levels, challenge and curiosity.

Our future plans include completing the gamification concept and using it as a design framework for gamified apps for self-improvement. A major requirement for our general concept is modularity. Game elements and their visual representations are considered as two separate components. This is particularly relevant regarding adaptivity, as it should be possible to vary game elements and visual representation depending on the target group in the future. As a result, functionalities and the graphical user interface will be adaptable according to user context (such as age, gender, experience). In this regard, we will include a novel component into our concept to cover the user context.

In order to be able to make a quantitative statement on the motivational effect of the identified common used game elements, we will conduct an extended user study. The involvement of user context aspects in our survey will allow for a more user-centric gamification concept. Identifying important game elements in terms of various user context aspects, enables different rules for the Game Element component as well as the Visual Game Element module. This is necessary for reaching different target groups.

Our study is also limited by its method, which only provides an introduction of different apps for self-improvement, not including the use of the apps in real world context. The lack of interaction with the gamified apps only enables replies to questions from the user's experience. For this reason we plan to further develop our prototype, so that a qualitative user study can be carried out in a real world context. Furthermore, a long-term study with end users will allow us to investigate the game elements with regard to their long-term motivation.

We believe our approach can offer added value for giving awareness of regulated daily routines by providing a general gamification concept as well as an overview of significant structural and content game elements.

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REFERENCES

Burmeister, D., Schrader, A., and Carlson, D. (2013). A modular framework for ambient health monitoring. In *PervasiveHealth*, pages 401–404. IEEE.

Chernbumroong, S., Cang, S., Atkins, A., and Yu, H. (2013). Elderly activities recognition and classification for applications in assisted living. *Expert Systems with Applications*, 40(5).

Deterding, S., Dixon, D., Khaled, R., and Nacke, L. (2011). From game design elements to gamefulness: Defining "gamification". In *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, MindTrek '11, pages 9–15, New York, NY, USA. ACM.

Fleury, A., Vacher, M., and Noury, N. (2010). Svm-based multimodal classification of activities of daily living in health smart homes: sensors, algorithms, and first experimental results. *Information Technology in Biomedicine, IEEE Transactions on*, 14(2).

Franke, M., Keller, I., and Schlegel, T. (2014b). Mdro - a modular daily routine ontology for assisted living. In *Workshop on Wearable Technology and Human - Wearable Robot Interaction, (IEEE RO-MAN 2014).*

Franke, M., Keller, I., and Schlegel, T. (forthcoming 2014a). Enabling cloud-based and personalized sensors in assisted living environments. *International Journal on Collective Intelligence*, 4(4).

Franke, M., Keller, I., and Schlegel, T. (forthcoming 2014c). Monitoring daily routine anomalies in assisted living environments. In *Workshop on Attention for Social Intelligence, (ICSR 2014).*

Franke, M., Lehmann, H., and Schlegel, T. (2014d). Capturing and reusing empirical knowledge for activity recognition in assisted living environments. In *New frontiers of service robotics for the elderly, (IEEE RO-MAN 2014).*

Franke, M., Seidl, C., and Schlegel, T. (2013a). A seamless integration, semantic middleware for cyber-physical systems. In *Networking, Sensing and Control (ICNSC), 2013 10th IEEE International Conference on*, pages 627–632. IEEE.

Franke, M., Wuttig, A., and Schlegel, T. (2013b). Enabling virtual, cloud-based sensors in assisted living environments. In *2013 IEEE 5th International Conference on Cloud Computing Technology and Science (CloudCom)*, volume 1.

Hamari, J., Koivisto, J., and Sarsa, H. (2014). Does gamification work?–a literature review of empirical studies on gamification. In *System Sciences (HICSS), 2014 47th Hawaii International Conference on*, pages 3025–3034. IEEE.

Hildebrandt, G., Moser, M., and Lehofer, M. (2013). *Chronobiologie und Chronomedizin Biologische Rhythmen Medizinische Konsequenzen*. Human Research.

Kapp, K. M. (2013). *The Gamification of Learning and Instruction Fieldbook: Ideas Into Practice*. John Wiley & Sons.

Kleinberger, T., Becker, M., Ras, E., Holzinger, A., and Mller, P. (2007). Ambient intelligence in assisted living: Enable elderly people to handle future interfaces. In Stephanidis, C., editor, *Universal Access in Human-Computer Interaction. Ambient Interaction*, number 4555 in Lecture Notes in Computer Science, pages 103–112. Springer Berlin Heidelberg.

Malewski, C., Simonis, I., Terhorst, A., and Bröring, A. (2012). Starfl–a modularised metadata language for sensor descriptions. *International Journal of Digital Earth*, (ahead-of-print):1–20.

Minors, D. S. and Waterhouse, J. M. (2013). *Circadian rhythms and the human*. Butterworth-Heinemann.

Sauermann, L., Van Elst, L., and Dengel, A. (2007). Pimo-a framework for representing personal information models. *Proceedings of I-Semantics*, 7:270–277.

Spork, P. (2011). *Das Uhrwerk der Natur: Chronobiologie-Leben mit der Zeit*. Rowohlt Verlag GmbH.

Tan, R., Gu, J., Zhong, Z., and Chen, P. (2012). Socom: Multi-sensor oriented context model based on ontologies. In *Intelligent Environments (IE), 2012 8th International Conference on*, pages 236–242. IEEE.

Werbach, K. and Hunter, D. (2012). *For the win: How game thinking can revolutionize your business*. Wharton Digital Press.

Zulley, J. and Knab, B. (2013). *Unsere innere Uhr: natürliche Rhythmen nutzen und der Non-Stop-Belastung entgehen*. Mabuse-Verl.