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## Agent-based support for behavior change

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# 13

## Discussion & Conclusion

This chapter reflects on how Chapters 2–12 contribute to answering the research questions posed in Chapter 1. The main results and conclusions from the chapters are discussed and summarized in Section 13.1. Section 13.2 discusses the limitations of this dissertation. In Section 13.3 it is examined how the results presented in this dissertation contribute to theory and practice of support systems for behavior change and how future work can build on these contributions.

### 13.1 Revisiting the Research Questions

This dissertation aims to answer the question of *how agent-based systems can effectively support behavior change using computational models*. Two different approaches to answer this question were taken. The first was to create computational models of prominent theories in the field of decision making and behavior change. Ambient agents can use these models to simulate and reason about human behavior. The second approach was to apply these computational models, testing whether they can be used (i) to create agent-based simulations of real-world behavioral processes and (ii) to develop agent-based systems that perform interventions to promote and establish behavior change. In the following subsections the research questions defined in Chapter 1 are recalled and it is discussed how the chapters in this dissertation provide an answer to them. Table 13.1 shows which chapter addresses which research question and Table 13.2 provides a short overview of the subject of each chapter.

**Table 13.1:** Which research question is addressed in which chapter?

		Chapter										
		2	3	4	5	6	7	8	9	10	11	12
RQ	1	x	x	x	x	x	x	-	-	-	x	-
	2	x	x	x	x	-	-	x	-	-	x	-
	3	-	-	-	-	x	x	x	x	-	-	-
	4	-	-	-	-	-	-	-	-	-	x	-
	5	-	-	-	-	-	-	-	x	x	-	-
	6	-	-	-	-	-	-	-	-	x	-	x

**Table 13.2:** Chapters and their subjects

Chapter	Subject
2	behavior change for chronic patients
3	individual habit formation and learning
4	collective decision making
5	habits in social context
6	learning in social context
7	lifestyle change using social media
8	behavior change interventions for chronic patients
9	interventions to promote taking the stairs
10	human-computer interactions in e-coaching
11	crowd emergency behavior
12	human-computer team formation

### 13.1.1 Translating Theory to Computational Models

The first research question was *how can insights into processes of learning, habit learning, mirroring, social contagion and behavior change be translated into computational models?* In order to capture complex processes of behavior and adaptivity a dynamic hybrid approach was chosen: one that combines quantitative, numerical methods with qualitative, logical methods. This approach consists of the development of computational models that are characterized by states and the dynamics of these states over time.

When modeling domains in which biological plausibility or insight into the role of unconscious processes is important, physiological models are good candidates. This is especially the case when physiological causes are important factors in the processes being modeled, for example when modeling contagion between different agents. Quantitative, numerical methods that show dynamics over time are a suitable approach to model such processes. The computational models presented in Chapters 4 and 11 aim to be biologically plausible in order to adequately represent human behavior and adaptivity. As such, they incorporate neurological mechanisms such as *Hebbian learning* to update connections between states, *mirror neurons* to account for transference between states and *somatic markers* to represent how emotions affect decision making. The chosen hybrid approach has the distinct advantage that it can handle both emergent processes in large groups and logical analysis of relationships between different determinants of individual behavior that are captured by the model. For instance, the models from Chapter 4 and 11 are used to study complex processes that involve individual beliefs, emotions and intentions, as well as interaction with others. By using neurological theories on the role of emotions, reflection and social contagion in behavior and learning, computational analyses were performed to examine how different learning styles are influenced by such low-level factors.

For systems that are designed to support individual users with effective interventions, models described at a cognitive level are a better match. Though physiological models can use biophysical data as input, it is less pervasive, and often easier and cheaper to obtain psychological data (for instance from surveys) as input for a cognitive model. Because the models are used for finding targets for interventions, the cognitive constructs can be used in creating intuitive feedback describing problem areas or solutions to the user. For example, the COMBI model introduced in Chapter 2 (which is also used in Chapter 8, 9 and 10) is described at a cognitive level. Several prominent psychological theories have been integrated and formalized to construct an integrated model of behavior change, which takes advantage of the overlapping elements of those theories. When creating interventions, models based on qualitative or logical languages with causal rules

are often effective as they can be used for forward and backward reasoning about the effects of behavior change and interventions (as was done in Chapter 8). In addition, causal rules are well suited to capture expert knowledge as they are close to the natural language. The benefit of using a hybrid approach for such domains is the possibility to capture state dynamics over time. For example, using the model presented in Chapter 3, an ambient agent can reason about behavior change over time.

Hybrid models can also express interactions between the different levels of description. The models from Chapters 5, 6 and 7 are described at a cognitive level, while still reflecting underlying neurological concepts and principles. In Chapter 5 the effect of direct contagion of behavior on a physiological level is combined with the effect it has on internal states such as goals, attitudes and intentions.

### 13.1.2 Simulating Human Behavior

Translating theory to computational models is a first step towards creating systems that have knowledge of a user's state and environment, and that can reason about this. The follow-up question that needs to be answered is *can these agent-based computational models adequately reproduce and simulate human behavior?* In this dissertation, computational models are successfully used to simulate human behavior in very diverse domains. Simulations, property specifications and mathematical analysis are used to demonstrate how the models perform compared to real (patterns of) behavior. Although each model has its limitations (see also 13.2), in general the models were able to adequately reproduce and simulate human behavior.

Chapters 3 and 4 contain several simulation experiments that show how the models are able to capture distinctive patterns that are described in the literature. These results are further strengthened by the formulation and testing of logical properties that describe emergent patterns which are, according to the literature, characteristic to the domain. In Chapter 3, four simulations and several property specifications show how the model is able to capture essential habit dynamics: (i) habit formation, (ii) the influence of long-term goals on behavior, and (iii) the influence of changing goals. The model proposed in Chapter 4 incorporates interactions between intentions and emotions, and between beliefs and emotions in groups. Several scenarios have been simulated to investigate emerging patterns and to explore leadership among agents. The results show patterns as identified in the literature, for example that leaders greatly affect the spread of emotions and intentions in a group, and that the majority of a population dominates the spread of the emotions and intentions when there is no authority. Formal verification of the simulation traces were used to check that leaders and subgroups could be clearly distinguished and identified. Additionally, mathematical analysis showed how emotions and intentions converge in groups. Stable equilibria were found when analyzing several combinations of parameter values for amplification/absorption and bias for emotions and intentions. For example, if an agent is negatively biased towards an emotion/intention and its emotion/intention state has a value of 0, then this state value is stable. Similarly, a high emotional state and a positive bias for an emotion also results in a stable state. In these stable states the agent is not further influenced by the emotions of others, which could identify him as a leader. Also, if an agent A (i) has the highest or lowest emotion in the group, (ii) amplifies that emotion, and (iii) has a neutral bias, the group members' emotion levels for this option will converge to A's emotion value. This suggests that such characteristics are useful for a leader who wants to the emotions in a group to mirror his/her own level. These results show how the model can be used to identify emerging patterns in groups and how emotions/intentions are influenced by group dynamics and personality characteristics. The found patterns can inspire further research to establish whether they are

indeed characteristic for human behavior and how they can be used to enhance decision making in groups.

In Chapter 5 the emphasis is on simulations that provide initial validation for the accuracy of the model. Different types of social networks (random, small world and manual groups) and different group sizes (from 2 to 1000) were explored to simulate realistic scenarios. The simulations show how contagion of behavior can persist individually and how strong hubs in a network can influence others.

Although Chapter 2 also contains some simulations of behavior change, the main method of validation for the model was introduced in Chapter 8. The model was internally validated by two empirical studies, which demonstrated that most of the trends and significant correlations that were found in the model corresponded to reality. However, the studies also identified some relations in the model that were missing or were not corroborated by significant correlations in the study. These insights can help to improve the model such that it is able to more accurately reproduce human behavior.

The ASCRIBE model described in Chapter 11 was used to simulate a panic outbreak that occurred in Amsterdam in May 2010. Data containing people's location and their direction of flight was obtained and tested against the model output. Statistical analysis showed that ASCRIBE was able to simulate the movement of people accurately. Interestingly, ASCRIBE performed especially well in the first few seconds of the scenario. Due to the complex interaction of contagion processes and the interplay of internal states, the model was to be able to deal with the fact that some agents only started moving after a few seconds (as their movement was restricted by fences and their distance to the source of disturbance was greater).

### 13.1.3 Exploring Effective Interventions

In Section 13.1.2 it was established that agent-based computational models can successfully be used to describe and simulate characteristics of human behavior and behavior change. Formalizing and simulating these characteristics are first steps towards achieving this, but deploying the models for intervention requires interactions between the system and the user. In this dissertation, the merits of such models for designing interventions for behavior change are explored, in order to answer the question *how agent-based simulations based on computational models can be used to explore effective interventions*.

Although not yet empirically tested, the work in Chapters 6 and 7 describe how interventions should not just be targeted at specific individual characteristics, but also on the social interactions people have, using information of social network structures. Chapter 6 focuses on the effects of social contagion of emotions on learning processes of different types of learners. The models are able to show how emotions flow between several (co)learners and their tutor and how emotions can stimulate the learning process. Technology-enhanced learning environments can use these models to predict which groups of students are most likely to perform well together or whether emotion spirals will negatively influence the learning process. Several suggestions for creating optimal learning environments have been made, of which enabling and monitoring emotion contagion are the two most important ones. In particular, the emotions related to valuations of behavior options, as well as valuations of performed behavior, goals, and attitude should be able to spread through groups. Emotion recognition and knowledge of the social network structure of the learners is needed to accurately identify this spread. Successful interventions should focus on making the learners aware of the emotions they experience. Chapter 7 also stresses the importance of the social network structure to create successful interventions. Several scenarios in which the presented models demonstrate successful interventions for behavior change

were explored. In the scenarios, an ambient agent monitors and analyses social interactions between people in a social network. Based on these analyses, it acts out one of several intervention techniques, taking into account both the network structure and individual attributes. These techniques can be, for example, to identify opinion leaders and support them in changing behavior (which in turn will stimulate behavior spread through the network), or to target the strength of social links in a network. As an example of the last technique, incoming or outgoing contagion strengths can be manipulated by interventions that change the expressiveness, openness, or channel strength between network members. Several simulations have shown how these interventions can be successful.

In Chapter 2 a model for behavior change is proposed that was implemented in a system designed to provide tailored interventions to both patients and non-patient individuals. eMate uses a mobile phone app and a website to target individual characteristics that play a role in behavior change, in order to help people through different stages of behavior change. eMate uses the COMBI model of behavioral determinants to reason about a person's bottlenecks that obstruct his/her behavioral change. Once the bottlenecks are identified, eMate sends tailored messages that aim to resolve them. In Chapter 8 several observations were made about the reasoning process based on two pilot experiments, one with chronic patients, and one with non-patient individuals. First, the bottlenecks identified by eMate are indeed often evaluated by the person as the most problematic determinants that prohibit behavior change. Second, in some cases the identified bottleneck did not correspond to the construct with the lowest value in the model. This indicates that eMate does not always identify the construct with low values at the end of the causal paths (top level). Both the second and the third observation can be attributed to the fact that the reasoning mechanism prunes the model graph to target those constructs that have the highest probability of improving the person's stage of change.

Chapter 9 describes a monthlong validation study in which the eMate system was deployed to coach students to use the stairs more often. It was found that eMate accurately identifies and targets the problematic constructs in the model. Also, the results on calculation and prediction of the construct values, though preliminary, were encouraging.

#### 13.1.4 Performance of Complex Models

Behavior change is a multifaceted challenge that includes both individual and social determinants and interactions between those determinants. When modeling such complex processes, one can easily get lost in the complexity of the models themselves. There is a delicate balance between complexity and understanding: models need to be complex enough to accurately capture the modeled processes, but also transparent and simple enough to show how the model constructs influence each other. This perspective gave rise to the question of *how complex models of behavior that integrate individual and social processes perform compared to simpler models*.

Chapter 11 provides an answer to this question for a model of collective decision making that was applied to an evacuation scenario. The presented ASCRIBE model includes complex interactions and contagion of emotions, beliefs and intentions. Its performance is compared to a baseline model (in which agents do not move), a variant of the ASCRIBE model (in which no contagion takes place), and — what was referred to as — the Helbing model (which is a variant of a social force model designed for simulating dynamical features of escape panic). The original ASCRIBE model proved to have a lower average error rate per time step. Statistical analysis showed a significant difference between performance of all models, and that ASCRIBE more accurately simulated human movement patterns than the other tested models except for

the Helbing model (although further analysis indicated that ASCRIBE was able to outperform Helbing as well).

The chapter also describes a related study in which ASCRIBE was compared to an epidemiological model (Durupinar) and another model of contagion in which the agents inherit the highest fear level of neighbouring agents (ESCAPES). ASCRIBE was able to produce more realistic dynamics than the Durupinar model and was shown to outperform the Durupinar and ESCAPES models on most measures. However, the version of the ASCRIBE model used for this validation was a somewhat simplified version as it did not include dynamics between emotions, intentions and beliefs, but focused only on the spread of emotions.

In short, although the inclusion of the additional factors in the ASCRIBE model comes with the price of added complexity and computational costs, the improved performance of the model makes it worth it to pay that price. The results from Chapter 11 also show that the contagion of mental states is an essential element in models of behavior of crowds in panic situations. Considering the advantages and disadvantages of increasing model complexity, it seems better to start off with a model that captures human behavior as well as possible — even when it comes at a computational cost — instead of compromising in an early stage. Once the model is scaled to accommodate large groups of agents, it will be harder to adjust the internal structure of a simpler model to incorporate more complex processes than to simplify a more complex structure. Abstraction techniques can for example be used to achieve the latter (see also Section 13.2).

### 13.1.5 Producing Behavior Change

Creating accurate models of behavior and behavior change is necessary in order to execute precisely those interventions that have a high probability of producing the desired behavior change. In order to evaluate models and the systems that deploy them, it should be examined whether the designed *agent-based behavior change support systems produce behavior change*.

Both Chapter 9 and 10 answer this question for the BCSS eMate. In order to examine the system's performance and broad applicability, it was used to stimulate students to take the stairs more often, which is a domain in which behavior change can occur in a relatively short period of time. Results showed that when eMate sent messages that targeted problematic constructs for non-adherence, this positively influenced those constructs. There were two model constructs that had decreased after the intervention: commitment and social support. However, there were no indications that the diminished constructs could be attributed to adverse effects of the coaching. In fact, it was found that targeting by eMate generally improves construct values and promotes progression through stages of behavior change. The eMate system can therefore be successfully used to target causes of non-adherence. However, though overall the participants improved with respect to the number of stairs they took, these differences were not significant. Also a consistent, but non-significant increase in the mean of the self-reports for taking the stairs (of approx. 0.2 points) was found. These results were obtained by considering all participants. Future work has to determine whether the reported number of stairs did increase significantly for those that were in a position to improve their stage of change.

In conclusion, the first results with respect to the effectiveness of eMate are fairly positive. Empirical research has shown that eMate functions properly and often successfully with respect to coaching users towards behavior change in their daily lives. The results from Chapters 9 and 10 are an indication that the promise of computerized behavior change support systems to establish effective and desired behavior or attitude changes can indeed be fulfilled. In particular, it demonstrates that autonomous (agent) systems can give relevant and helpful feedback to patients without adding to the workload of human practitioners. Moreover, it has been shown that

Behavior Change Support Systems can benefit from a general and dynamic setup, which allows them to be used in different domains and for different target populations.

### 13.1.6 Human-Computer Interactions

When agent-based support systems are deployed to support human decision making and behavior change, they have to interact with their users. Using sensory information about user activity, asking questions to deduce cognitive or emotional states, and providing tailored feedback all require some form of interaction, though some more than others. In order to design systems that can act effectively as a coach or decision support system, it is important to identify *which social factors play a role when humans interact with agents and how these factors affect the interactions*.

In Chapter 10 an empirical study on computer-mediated coaching is described that involves a deception about the type of coaching that participants received. This experiment tested whether people have different coaching experiences when they are coached by a computer rather than by a human coach. Chapter 10 focuses on three outcome measures: the effectiveness of the coaching, the perceived influence of the coaching, and the trust that coachees developed in their coaches. From the results it was concluded that the belief that coachees had about the identity of their coach had no effect on the effectiveness of the coaching. This is an indication that e-coaching can be successful without the (known) involvement of a human coach. Secondly, analysis showed that people do have a bias towards human coaching with respect to judging how much positive influence coaching had on their behavior. Lastly, people showed no difference in trust towards human coaches or computational agent coaches. Both coaches were judged as being averagely trustworthy, which is an important finding, considering that trust is the key ingredient of successful coach-coachee relationships. Moreover, this judgement is further evidence that people do treat computers as social actors.

Chapter 12 is an empirical study of the interaction between humans and agents in a more general team setting. Whereas Chapter 10 is concerned with the social factors that influence the relation between e-coach and coachee, Chapter 12 presents a behavioral study of fairness and trust in a collaborative setting where people can choose teammates from both computer agents and human participants. It investigates people's choice of teammates and their commitment to their teams in a dynamic environment that was characterized by a high degree of uncertainty and changing information. It was found that people preferred to create teams with others with whom they had positive interactions (humans and agents alike), rather than with those who offered them large rewards. Furthermore, it was found that when negotiating to create teams, people offer less reward to agents than they do to people, but that people are as loyal to agent-led teams as they are to human-led teams.

In sum, several social factors were examined for their influence in human-agent relationships. It was found that beliefs of human involvement affect *fairness* and *perceived effectiveness*. People display fairer behavior towards (what they believe to be) human teammates than towards (what they believe to be) agent teammates. Also, people judge the positive effects of coaching higher when coached by (what they believe to be) human coaches. The following social factors were not significantly influenced by the interaction with either (perceived) humans or (perceived) agents: previous successful interactions (*reputation*), team defection (*commitment*), and *trust*.

## 13.2 Limitations

**Modeling choices** In this dissertation, computational models are used to describe and predict human behavior and adaptivity. Several advantages of using computational models for this task



are pointed out in this section and in Chapter 1. State dynamics have been described using differential equations (e.g., Chapter 4, 11) and causal rules (e.g., Chapter 2). Although these computational models have proven very suitable for the task at hand, it is not the only valid modeling approach to create models and support systems for behavior change. Several alternatives can be considered, such as bayesian models or state transition models. Also, the model-based reasoning approach can be substituted by methods of case-based reasoning, probabilistic reasoning or inference reasoning.

When translating theory to models, it is often necessary to make assumptions that are not explicitly represented in the theory. The formal specification of computational models requires detailed specifications of interactions between model constructs that are often not obvious from the literature. For example, the use of threshold values to determine the activation of states in Chapter 6, and the way in which different intentions affect each other in the model of Chapter 3, are both assumptions. A modeler also has to decide which factors to abstract from and which to include. This is often a trade-off between complexity and understanding. On the one hand the processes that are the subject of the models are often complex, and as a consequence the models that aim to gain insight into the different interactions between the determinants are also complex. For example, the model for group decision making and social diffusion in Chapter 11 contains many dynamics — it includes biases, leadership, and influence of information and emotions — which results in a very rich model that can capture many behavioral phenomena, but at the same time is harder to understand than a simpler model. On the other hand, deciding not to include certain factors found in the literature can help to keep the model controllable and clear, yet may affect its accuracy. For instance, in the COMBI model in Chapter 2, social influences are aggregated in the concept *social norms*, but this is a very simplified and non-complete representation of the social processes that influence behavior.

The basis of the COMBI model, which is used in the studies addressed in Chapters 2, 8, 9, and 10, is the Transtheoretical Model (TTM) of behavior change. The TTM models behavior change as a process that involves progress through a series of stages (Prochaska and Velicer, 1997). The notion of behavior change as dynamic process is intuitive and has been applied to a wide range of health-related behaviours. Combined with the ability of the model to account for changes in stages and determinants over time, these properties make the TMM very suitable to function as the core of an agent-based reasoning system. As TTM also provides an easy way to tailor interventions to individual behavior dynamics by means of their stage (Kim, 2008; Prochaska and Velicer, 1997), the model was used as the core component of COMBI. However, it should be noted that there are also many criticisms of the TTM and concerns about its use (Adams and White, 2005; Brug, Conner, Harre, Kremers, McKellar, and Whitelaw, 2005). Several reviews have concluded that there is limited or no evidence for the effectiveness of stage-based interventions (Bridle, Riemsma, Pattenden, Sowden, Mather, Watt, and Walker, 2005; Horowitz, 2003; Salmela, Poskiparta, Kasila, Vähsärja, and Vanhala, 2009). In particular, studies that used longitudinal study data instead of cross-sectional data have reported only partial support for the internal validation of the model (Plotnikoff, Hotz, Birkett, and Courneya, 2001), and did not find that stage-matched information contributes to the promotion of behavior change (de Vet, de Nooijer, de Vries, and Brug, 2007). Notably, some studies have showed that stage transitions are common even without interventions, and that these transitions can occur in short time intervals (de Nooijer, van Assema, de Vet, and Brug, 2005). Another point of criticism is that the algorithms and questionnaires that have been used to determine someone's stage of change, have not been standardized or validated (Adams and White, 2005; Sutton, 2001). The issues raised indicate that although the TTM shows promise as a model for behavior change, it should be used

with caution. When interpreting the results from Chapters 2, 8, 9, and 10, these limitations should be taken into account.

**Validations** Several of the models that were presented in this dissertation have not yet been thoroughly validated by empirical data, among which are the models from Chapters 5, 6, and 7. Although simulations based on the models are promising, their merit for describing and predicting behavior and behavior change needs to be evaluated in future work.

Furthermore, the degree to which the relations and abstractions in the model correctly represent reality (related to the previous paragraph) needs to be established, for example by comparing different model variants or by establishing correlations between the model constructs. The latter can be done with self-assessment surveys (as was done in Chapter 8), but for models at the physiological level this is more challenging. It is expected that in the future the use of sensors for biophysical measurements can help to provide the data necessary for this type of validation.

For those chapters that do describe empirical validations, it should be noted that there are several limitations to the empirical setup and statistical analyses. First, the conclusions and implications drawn from the data are valid only for a relatively small sample set and a specific domain. For example, Chapter 8 describes two pilot studies for validation of the COMBI model with 17 chronic patients and 40 non-patients respectively. Considering similar successful results obtained by the eMate validations for taking the stairs in Chapters 9 and 10 ( $n=82$ ), there is reason to be optimistic about the effectiveness of the eMate system in different domains of lifestyle change and with different target groups. The results of the ASCRIBE model (Chapter 11,  $n=35$ ) needs to be confirmed in different scenarios and domains in order to demonstrate that it consistently performs well. Second, no multivariate statistics were performed and there was no control for confounding variables. In the presented analyses, causal relations were often inferred from found correlations, for example between the constructs of the COMBI model (see Section 8.1), or between the interventions and the values of the targeted COMBI constructs (see Section 9.5.3). Explanations that included a third (confounding) variable that influenced both the independent and the dependent variable (e.g., a very cold winter, which could affect both someone's *emotions* and *attitude* to exercise more often) were not investigated. Third, the experiments discussed in the empirical chapters were not set up as randomized controlled trials (RCT), in which participants were randomly allocated to receive either interventions or not. Consequently, no baseline was obtained of behavior of people that did not receive interventions. Although a longitudinal randomized controlled trial is currently being done to study the effects of the use of eMate on chronic patients, these results were not in at the time this thesis was written.

**Scalability** The discussed models are all based on individual agents and are tested in limited settings of group interactions ranging from 2-100 agents. However, if the models were to be deployed to describe, predict or influence behavior in large socio-technical systems, their scalability might become an obstacle. Complex models that have many states, calculations over time might become computationally costly. Also, the agents might have to deal with uncertainty and incomplete information. Although the local determinants of agent behavior can be captured relatively easily, global patterns that emerge from interaction between the agents in large-scale social-technical systems are far from trivial, and are difficult to infer directly from the local dynamic properties of individual agents. For instance, although the models from Chapters 4, 5, 6, and 11 perform well for individual agents or small groups, large-scale simulations and validations need to be performed to examine whether they are able to accurately model these processes when the

agents interact in large social networks and when the agents can have multiple goals, intentions, or feelings.<sup>1</sup>

### 13.3 Implications and Future Work

In this section several implications of the findings discussed in this dissertation will be reviewed. First, it is outlined how the findings can affect future work on modeling human behavior and behavior change.

**Models that enable tailored support in various domains** At present there are few models that address behavior change in different domains. Many models are limited to one domain, which is not surprising given that the needs and preferences of a user can depend heavily on the domain and the specifics of the context for which the behavior change is desirable. However, this also implies that the results of such models in one domain are not transferrable to other domains. Developing more general frameworks for behavior change has several advantages over such domain specific models, both for developers and for users. It allows developers to rely on one general model structure and to ‘plug in’ modules with domain-specific information. Methods for reasoning or for sending tailored feedback can be reused across the domains. Users will benefit for example by only having to use one app or website to access their various support systems. They will not be confronted by a multitude of different support approaches. The COMBI model and eMate system are a first attempt to create such a framework for a variety of health-related domains. However, both COMBI and eMate need thorough testing in different domains, and much progress has to be made with respect to creating effective reasoning strategies and intervention methods that are adaptive to different users and domains. In short, future work faces the challenge of developing models that are general enough to be applied to different domains, but at the same time specific enough to enable tailored feedback in specific contexts. This can be done for example by developing frameworks for behavior change support that offer low-level configurability for domain-specific plugins.

**Model-based reasoning to identify and predict effective interventions** In order to create behavior change support systems that are more than just tools for self-monitoring, they have to incorporate some techniques that can persuade users to change. It is not hard to find smart-phone apps that enable people to keep track of their calorie intake, exercise patterns, sleep patterns, or energy consumption, yet these apps do not actively stimulate behavior change. Instead, such apps exploit the knowledge that enhancement of motivation and self-reflective responses are among the consequences of self-observation (cf., Bandura and Cervone (1986); Kanfer and Karoly (1972)), but they generally do not include any models of behavior change. The demand for such models in apps is growing rapidly though, and reasoning systems that use models can create many opportunities to explore and initiate effective interventions. In their 2008 article, Michie, Johnston, Francis, Hardeman, and Eccles stated that: “Ideally, researchers designing interventions would choose a small number of the theoretical frameworks based on empirical evidence of their predictive and intervention value, i.e., there should be evidence that the theory can predict the behavior and that interventions which change these determinants achieve change in behavior.”(Michie et al., 2008) Theory-based and model-based interventions hold great promise for effectively changing behavior, yet they are hardly used in BCSSs.

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<sup>1</sup>One possible solution to this challenge is to use abstraction methods that allow for the substitution of a large number of interacting agents by single group entities, see e.g., Sharpanskykh and Treur (2011).

Some of the models presented in this dissertation can be used to create interventions. However, they can be improved by optimizing the parameters that are part of their formal specification. For example, parameter tuning can result in a set of parameters that are optimal in general for all agents, or a different set of optimal parameters can be used for each individual agent. As of yet, parameter tuning has only been done for the ASCRIBE model; the parameters for the other models in this dissertation are assigned values on the basis of literature, expert knowledge, educated guesses, trial and error, and a combination of the aforementioned methods. Also, support systems could use user profiles to establish (for example using a nearest neighbour algorithm) the parameter set most likely to be successful for a new user. Lastly, support systems should be able to learn from the effect of their interventions, and be able to change their persuasive strategies depending on the outcome of these evaluations.

**Models for persuasive interventions that combine social and individual processes** Several models presented throughout the chapters combine social and individual aspects of decision making and behavior. This approach has shown great promise in accurately capturing behavior change (see e.g., Chapter 11), and combining these aspects can result in innovative ways of creating tailored interventions. For example, the persuasive approach or message content will need to be different for those who occupy different locations in social networks (e.g., taking into account whether someone is an influencer or someone being influenced) (Steiny, 2008). The same holds for message content. In addition, the characteristics and effects of persuasion in groups are likely to differ from those concerned with individual human-agent relations. Future work can contribute to understanding how persuasive techniques can be deployed for groups and how the structure of and position in social networks influence the effects of such techniques.

The work in this thesis also has implications for developing support systems. In the paragraphs below several implications are mentioned and it is discussed how future work can build on them.

**Choice Architecture** In Section 1.1 it was observed that creating interventions is essentially a manipulation of choice. Supporting behavior change then is the art of presenting choices such that the likelihood of someone making a desirable change increases, for example by presenting choices that the user did not think of before, or by convincing the user that the presented choice is the one with the best outcome. *Choice architecture* is about creating the most persuasive context that can attain that effect of behavior change. The challenge is to create one's surroundings thus that it helps one to make better decisions towards one's goals (Sunstein and Thaler, 2008). Creating effective choice architectures is not trivial however. There are a number of questions relevant for designing choice architectures, such as:

1. How can we know that persuasive aspects in the choice architecture will have the desired effects?
2. How can we distinguish between what is a persuasive context for one person and for another?
3. How can we nudge groups of people in high-risk contexts?
4. Can we personalize choice architectures?

The eMate system presented in this dissertation uses several persuasive techniques to create a persuasive context, among which giving positive feedback, relating the user's behavior to his/her goal, and providing personalized information. Showing the user status icons (the green/red/orange thumbs displayed on the website and on the smartphone, as displayed in Figure 8.2d and 8.3a)

can be considered a small *nudge*: a type of intervention that entails the use of positive reinforcement and indirect suggestions to achieve uncoerced compliance (Sunstein and Thaler, 2008). Nudges are subtle factors that can significantly alter human behavior, and which are used in trying to influence the motives, incentives and decision making of groups and individuals. Nudges play an important part in choice architectures. Due to relatively low costs and potentially big impacts, nudges appeal to policy makers. For example, stickers of flies in urinals is an example of a nudge that results in cleaner bathroom areas, brightly painted footsteps on the stairs nudge people towards taking the stairs more often, and putting a collecting box next to the counter is a nudge to give more to charity.

Models as proposed in this dissertation can help to simulate and predict the effects of nudges, sensors can capture the individual context (including mood, attention or location), and reasoning techniques can help to tailor persuasive content. Also, persuasive technology can be used to create nudges, for example by giving people insight into their current behavior (creating awareness) or by showing how other people are doing (facilitating social comparison). An interesting direction for future research is to incorporate these intelligent (technical) solutions into the notion of choice architecture and to examine how they can be used to increase people's health, wealth and safety.

**Bridging the gap between health practitioner and patient** Thanks to the invention of smartphones and apps, e-coaches and decision support systems have the potential to reach many people. Because of this, the development of support systems has taken a flight recently. A simple search for 'health coach' results in several dozen hits in the Apple iTunes Store, and monitoring devices have become smaller and less invasive. These apps and devices collect a wealth of information about users' habits and lifestyle patterns, including information about diet, exercise and addictions. As such, they have huge potential for facilitating the transfer of information between health practitioners and their patients. For example, stored information about the patient's lifestyle can help the practitioner to tailor therapies to the patient's needs, and in turn the app could include specifics of the therapy that was recommended.

However, in the course of this dissertation research, three things were found with respect to the design and deployment of support apps:

1. With respect to existing apps, it is often unclear whether the apps are based on relevant theories about health behavior and behavior change and whether they have been validated with regard to their use and effects.
2. Those apps that are known to be based on research and have been validated, are often still in a conceptual phase or exist only as prototypes.
3. Enlisting the help of health care practitioners in testing and deploying support apps is essential, but doing so requires better integration of the apps into the practitioners' workflow.

The first two findings seriously limit the usefulness of these support apps to health care practitioners. For instance, without transparency about whether an app is evidence-based, it is difficult for health practitioners or domain experts to recommend the use of such apps. Designers of support systems should therefore distinguish themselves by focusing more on (i) explanation, (ii) validation, and (iii) the shared interests of patient and care giver.

The third finding demonstrates the need for a better connection between health care researchers and practitioners. The expert knowledge that practitioners have can contribute to the design of successful support systems that are readily adopted by patients. Ideally, a support app is recommended to the patients by a trusted authority, such as the treating physician. There is a growing number of health care practitioners that acknowledges the usefulness of e-coaching

systems. However, they often have difficulty integrating these systems into their workflow. As such, an effort should be made to involve practitioners in state of the art research and to integrate newly designed DCSSs with the systems already in use in health care practices. This will significantly increase the ease of deployment for the practitioners, and will allow them to monitor the use of the support system. This integration will contribute to the practitioner's motivation for testing the system with patients.

### 13.4 A bright future for e-coaching

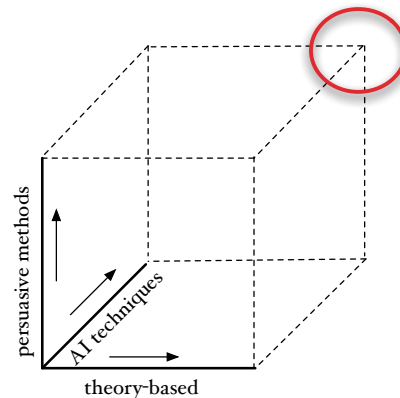
Building on the findings mentioned above and the work done in this dissertation, existing approaches to e-coaching can be categorized using three characteristics: the complexity of persuasive techniques, the use of artificial intelligence techniques, and whether they utilize user models that have a solid theoretical foundation. These characteristics can be viewed as axes in a 3-dimensional space in which e-coaching system can be positioned, as depicted in Figure 13.1. The circle in the framework symbolizes e-coaching systems that use complex artificial intelligence techniques for autonomous and intelligent coaching, that incorporate multiple persuasive methods, and that are based on validated theories and user models. Very few e-coaching systems currently occupy this 'sweet spot' of e-coaching approaches.

With respect to using persuasive methods, "the majority of persuasive technologies leverage merely one or two persuasive tricks" (Kaptein, Markopoulos, de Ruyter, and Aarts, 2010). While effective persuasive techniques consist of a combination of many moderating factors, in current practice usually one or two are singled out (e.g., authority or number of arguments). Kaptein et al. argue that this is undesirable, because although such tricks might be effective, it has been shown that straightforward tricks can sometimes have counterintuitive effects (see also Petty and Cacioppo (1986)). Furthermore, persuasive methods have different effects in different situations on different people. As such, in many cases the persuasive tricks will not be sufficient, and more complex persuasive methods need to be incorporated in e-coaching systems in order to effectively change attitudes and behaviors.

With respect to using theory as a basis for the coaching and interventions, the existing e-coaching approaches fall short. For behavior coaching and interventions in the health domain — which is currently the most prominent domain for e-coaching — it was found that "[t]o date, only a subset of mobile health behavior interventions have been theory-based" (Riley, Rivera, Atienza, Nilsen, Allison, and Mermelstein, 2011, pp. 68). Nevertheless, the authors continue that "a theory-driven iterative model of mobile intervention development holds promise for improving not only our mobile health behavior interventions but also our theoretical and empirical understanding of health behavior change."

With respect to the use of techniques from artificial intelligence, the majority of e-coaching systems can greatly improve their degree of intelligence and autonomy. Although there are numerous apps that provide tools for self-monitoring, the number of apps that implement techniques from artificial intelligence to provide tailored support is still small. Additionally, many apps do not operate autonomously but mediate the feedback or interventions of human coaches (cf. Kleiboer, Sorbi, Mérelle, and van Doornen (2009); Moskowitz, Melton, and Owczarzak (2009); Philips (2011)). The use of intelligent techniques (e.g., pattern recognition, reasoning, learning) can greatly contribute to the development of e-coaching systems that are personalized, cost-effective, and versatile.

Relating this dissertation to the three axes of the 3D e-coaching space, it is clear that Part II of this dissertation is focused on the horizontal dimension, elaborating on computational models for

**Figure 13.1:** Three dimensions of e-coaching approaches

different domains of change. Although the chapters in this part address only the ‘theory-based’ dimension, these proposed models were designed with their future application in support systems in mind. It was shown that the presented models enable agents to deal with context and timing, to be adaptive and act proactively, and to personalize and tailor information. In Part III of the dissertation the three axes of e-coaching approaches are integrated. Several studies of eMate, a BCSS that incorporates elements from the three different dimensions, are described. With eMate, a first attempt has been made to create a BCSS that could claim a position within the sweet spot of the e-coaching space. The initial results of eMate are encouraging, and demonstrate how the promise of successful e-coaching can be fulfilled by systems that incorporate elements from the three dimensions. Designing for that sweet spot should be the next frontier in support systems research because it is the key to a bright future for e-coaching.

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