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Towards Sustainable Mobility Behavior: Research Challenges for Location-Aware Information and Communication Technology

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Abstract Private transport accounts for a large amount of total CO_2 emissions, thus significantly contributing to global warming. Tools that actively support people in engaging in a more sustainable life-style without restricting their mobility are urgently needed. How can location-aware information and communication technology (ICT) enable novel interactive and participatory approaches that help people in becoming more sustainable? In this survey paper, we discuss the different aspects of this challenge from a technological and cognitive engineering perspective, based on an overview of the main information processes that may influence mobility behavior. We review the state-of-the-art of research with respect to various ways of influencing mobility behavior (e.g., through providing real-time, user-specific, and location-based feedback) and suggest a corresponding research agenda. We conclude that future research has to focus on reflecting individual goals in providing personal feedback and recommendations that take into account different motivational stages. In addition, a long-term and large-scale empirical evaluation of such tools is necessary.

Keywords Mobility · Sustainability · Behavior · Information and Communication Technology · Location-Awareness

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1 Introduction

1.1 Motivation

Transport currently accounts for about a quarter of global CO_2 emissions [4], thus having a significant effect on global warming [41]. Given current trends, this figure is to increase by roughly 50% by the year 2030 [4]. Even if emissions were to be eliminated immediately and completely, the atmospheric concentration of CO_2 would only be reduced by 40 ppm (i.e., roughly equivalent to its 1995 levels) in the remainder of the 21st century [79]. In order to (at least) slow down this trend, it is indispensable that immediate actions are taken by legislators, industry, and private individuals alike. Studies have shown that even small changes in people's individual behavior can lead to significant reductions in carbon emissions [86]. For example, Dietz et al.[26, p.18452] estimate that the adoption of easily implementable actions on a household level (e.g., changing one's driving behavior by slower acceleration and adhering to speed limits) can "save 123 million metric tons of carbon per year", a figure that equals 7.4% of U.S. national carbon emissions.

Common approaches that aim at changing a person's behavior rely on providing generic normative information, i.e., communicating whether or not a given behavior is appropriate in a given context (e.g., "No littering!"). However, considering the fact that most mobility-related activities are shaped by an individual's spatial, temporal, and social constraints, as well as are not tightly bound by social norms, generic normative information (e.g., "Use public transport more often") is often too unspecific. For someone who has no (perceived) choice as to use privatized transport, or does not know of any alternatives to perform an activity equally effectively (but in a sustainable manner), more targeted forms of communication are needed.

In this paper, we explore how location-aware information and communication technology (ICT) can contribute to support private individuals in engaging in a more sustainable life-style without posing unrealistic restrictions on their mobility needs. ICT enables novel interactive, participatory, and collaborative approaches to support people in becoming more sustainable, because it can provide real-time, user- and location-specific feedback on current, as well as recommendations for future behavior. In two meta studies Hamari et al. [39,40] found that ICT aimed at changing a person's behavior can indeed be effective, i.e., most analyzed studies showed positive or at least partially positive results.

Although such "eco-feedback" technologies targeted at behavior change are an active research area (cf. [27]), there are still many open questions on how such systems can be designed effectively, e.g.:

- How can we avoid systems that patronize users, i.e., dictate behavior and do not allow for empowerment? (cf. [15,82])
- How can we integrate a person's "principle goals" [63] (e.g., to become more sustainable) into their daily and established routines?

– How can we account for an adequate use of “motivational affordances” [96], i.e., how can we design systems that are easy to attend to, engaging, and take individual skillsets into account? Often, user inhibitions towards a system cannot be overcome due to its complexity, or perceived lack of usefulness.
– How can feedback be designed, such that it is equally effective across all of one’s motivational stages (cf. [43])?
– How can we make sure feedback on current behavior affects long-term behavior, i.e., how sustainable is behavior change?
– How can we harvest the expertise of large numbers of socially connected people to solve issues of sustainability collectively and interactively? (cf. [58])

1.2 A Running Example

Throughout this paper we will use a running example of two individuals, each of whom has a different background and preferences with respect to mobility behavior and attitudes towards sustainability.

Our first character’s name is Bob and he is a high-school teacher who lives in the outskirts of Zürich. Bob does a daily 45 minutes commute by public transport. After work, he frequently goes to the gym for a workout, or (if time permits) runs errands, such as buying groceries. For these after-work activities he typically uses his own car. Bob is a typical LOHAS[1], i.e., he is concerned with reducing his CO_2 footprint and wants to live an active healthy life. Bob is not particularly technology-savvy, likes to play (board) games, and is mainly interested in finding an efficient way to integrate his goals towards becoming more sustainable into his daily routine.

Our second character’s name is Alice and she is a freelance designer who lives in downtown Zürich. She does a daily 10 minutes commute, for which she takes her private car. Her job involves a lot of traveling (abroad and domestic) under restrictive time constraints. In general, she has problems fitting all her commitments into her daily schedule. Environment and sustainability are not among her top priorities, because she fears that becoming more sustainable would interfere with her job. Alice is technology-savvy and mainly looking for a mobile planning app that helps her cope with her schedule (cf. [1,3,2]).

1.3 Contribution

Designing an effective and successful system that promotes sustainable mobility behavior faces all of the challenges mentioned above. For example, Alice does not want to feel patronized by the system she uses, because she has a strong sense of freedom and is looking for technology that supports (but not dictates) her activities and any associated time management. Similarly, Bob

[1] Lifestyles of Health and Sustainability

would like to use such a system, but is skeptical about its usefulness and the long time required to get familiar with it. In addition, he is afraid that the application would not be capable of taking into account all his different goals implied by his daily routines.

As we will discuss in this paper, supporting Alice in making their activities more sustainable is a major challenge, because it requires the careful embedding of an external goal (i.e., sustainability) into her internal personal activity history, as well as her schedule. The embedding of external goals is ideally done by supporting people in adding them to their own goals. This requires both supporting their future activity planning, as well as giving goal-dependent feedback about their past.

In this paper, we provide a systematic survey of research challenges, the corresponding state-of-the-art, as well as future research opportunities of location-aware ICT targeted at making people's behavior more sustainable. For this purpose, we identify the information necessary to allow for behavior change in terms of required information processes, taking into account both the analysis and planning aspects of sustainable activity alternatives. We then identify open research questions by means of a literature review on the state-of-the-art research, ranging from goal planning and activity detection, over activity scoring, to the effective communication of sustainable alternatives. As a result we suggest a research agenda that aims at tackling the identified open challenges.

1.4 Organization

In the next section, we argue why location-aware ICT can act as a supportive tool for people who want to engage in a sustainable mobility life-style. In section 3, we discuss central information requirements involved in influencing and changing mobility behavior. Section 4 is a detailed discussion of related information technology, state-of-the-art research and open research gaps for each required information component. Section 5 concludes our discussion in terms of a research agenda.

2 Location-Aware ICT: Supporting Behavior Change

2.1 Information Requirements for Behavior Change

There are several information requirements necessary to allow for some established behavior to be changed. Note, the following discussion does neither account for the psychological processes necessary to form an intention or attitude towards a change in behavior, nor does it treat the issue of linking attitude and behavior (cf. [95]).

Behavior change requires becoming aware of one's current and past behavior, as well as about the existence of possible past and future alternatives. One also needs a way to approve or disapprove of past behavior, as well as rate and rank planned future behavior, both against a previously defined norm or goal (for two examples, see Figure 1). The rating and ranking process of planned future behavior often becomes complex as various different and conflicting goals need to be integrated.

(a) Radar Speed Sign: Current speed vs. speed limit (Source: commons.wikimedia.org)

(b) Pedometer: Current step count vs. goal (Source: Authors)

Fig. 1: Examples of behavior comparison against a norm

There are several difficulties realizing behavior change, without the support of information technology. First, people are seldom aware of their routine behavior, because large parts are carried out subconsciously [77]. This makes it challenging to effectively self-monitor behavior. Second, it is difficult to become aware of alternatives to established behavior. People are biased by the availability [85] of their past routines and thus have difficulties mapping out the space of possibilities. Third, efficiently dealing with many goals at a time exceeds the cognitive capabilities of most people [19], and may be one reason why they often do not succeed in integrating “principle goals” [63] with daily necessities. Fourth, the rating and ranking of possible future behavior is difficult because it is often not possible to determine an activity’s metric and its impact, especially in a systemic context.

2.2 What can location-aware ICT contribute?

In this paper, we argue that location-aware ICT can effectively support people in dealing with these problems or at least mitigate them. Mobility has steadily been increasing, and so has the availability and people’s use of location-aware ICT. As a matter of fact, most people living in one of the privileged and developed parts of the world belong to a mobile information society. One prominent example of location-aware ICT are location based services [66], which exploit geospatial information about the user and her surroundings for providing spatio-temporal decision support [68,75].

Location-aware ICT can be utilized in two ways: for direct support in mobile decision-making and for evaluating various aspects of people's mobile behavior. The dynamic nature of mobility resulted in a shift of people's information needs because they often need to make quick decisions on the spot. The interaction between environments, individuals, and mobile devices is thereby critical for understanding how people make their decisions while on the move. Mobile decision-making involves a multitude of spatio-temporal constraints, relating not only to people's spatio-temporal behavior in large-scale space [51] but also to their interaction with mobile devices, and perceptual, cognitive, and social processes.

While on the move, (geo)-sensors can be utilized for recording both tracking and context information, such as weather, pollution indicators, or mode of travel. In addition, it has become possible for humans to annotate some performed mobility behavior themselves. For example, users can rate their own mobility performance and peers can tag each other's mobility behavior with "likes" (cf. [73]).

These data offer insights into people's mobility behavior and can be of use in analyzing, evaluating, and predicting human mobility patterns from both an individual and an urban perspective. For example, one can detect similarities and differences between travelers and their paths [92,93]. Furthermore, ICT can support context and location aware planning, e.g., through the integration of personal information such as calendars or to-do lists [1].

However, one of the major challenges from a Human-Computer-Interaction (HCI) perspective lies in how context sensitive information should effectively (i.e., timely and useful) be fed back to a person.

2.3 Persuasive vs. Supportive Technology

Persuasion can be defined as "an attempt to change attitudes or behaviors, or both (without using coercion or deception)" ([31], p. 15). It is worthy to note the differences between persuasion and coercion or deception. Coercion is defined as "the act to make (someone) do something by using force or threats", while deception is "the act of making someone believe something that is not true"[2]. In contrast, persuasion "implies voluntary change - in behavior, attitude, or both" ([31], p. 15). Thus, persuasive technologies are interactive technologies that intend to change a person's attitudes or behaviors [30].

Technology can persuade in various ways (see Figure 2), depending on its functional roles [31]. *Technology as a tool* can persuade through making some behavior easier to do, i.e., by increasing a user's capability for some task. *Technology as a social actor* can persuade through providing positive feedback (e.g., rewards), i.e., by creating a relationship between the user and the system.

[2] `www.merriam-webster.com`

Finally, *technology as a medium* can persuade by letting one explore cause and effect relationships (e.g., by means of simulation), i.e., by providing people with experience and helping them to develop an expertise.

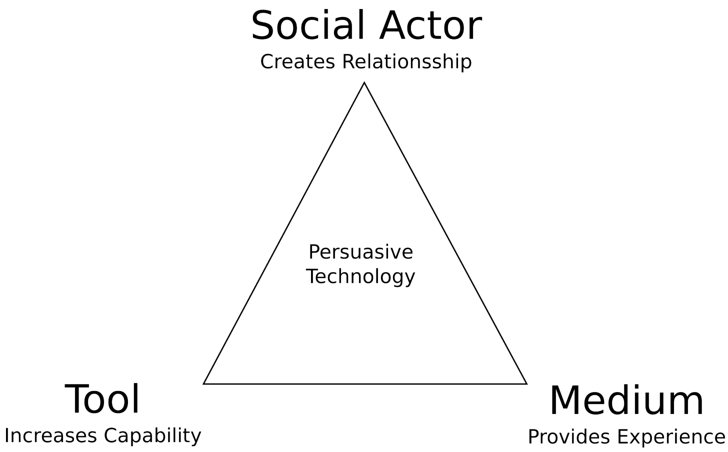

Fig. 2: Possible Functional Roles of Persuasive Technology (adapted from [31])

Persuasive technologies that aim at making people more sustainable, either through strong (behavior comparison against a norm) or passive (behavior presentation in a sustainable context) types of persuasion, form a very active field of research in the HCI community (cf. [27]). Despite its popularity the "persuasive sustainability" approach has recently spawned some critique questioning both its philosophical and practical implications (See for example [44, 15]).

Critiques have mainly challenged persuasive technologies because of their inherent concept of behaviorism. In particular, the sole focus on measurable effects, e.g., the amount of CO_2 produced for a given activity, neglects the semantics of the corresponding actions and their underlying causes, especially if put in a systemic context (See also [15]). The problem with many persuasive technologies is that their design is based on three erroneous assumptions:

- **Rationality:** There is strong empirical evidence that the notion of an agent who strives to optimize expected utility by using all available information does not hold up in reality [47]. Thus, we cannot assume that optimal information regarding sustainable alternatives (determined by means of computation) is necessarily used by a person to optimize her behavior.
- **Isolated Individuals and Behavior:** People are social actors and play different roles in different social contexts [29]. These roles are reflected by different information requirements. Thus, the concept of "one size fits all" cannot be applied to provide meaningful information.
- **Technological Paternalism:** Users can feel patronized, if the system designer specifies what sustainable behavior means in a top-down manner.

In this way, a system may violate an individual's psychological need for autonomy, i.e., to experience choice [96].

The system we envision as a result of our review takes this critique of persuasive systems into account. However, we prefer to call such a system *supportive technology* rather than persuasive technology. This does not imply, however, that such a supportive system does not have the means of persuading people of a behavior change. In fact, it may be more effective because it attempts to overcome the limiting aspects of behaviorism, as sketched above.

3 Information Requirements for Behavior Change

In this section, we identify relevant information processes that are involved in the analysis of current and past, as well as the planning of future mobility behavior. Processes together form a *feedback loop* which represents information requirements necessary to influence user behavior. This feedback loop involves (1) measuring behavior, (2) relating it to other behaviors or norms (relevance), (3) "illuminating the path ahead" (communication of consequences), and (4) user action, an approach often used in human computer interaction (Compare e.g. [36]). This approach helps us decide which processes should be supported by a behaviour influencing system and also allows identifying and discussing research gaps (See Section 4). Note that our process schema is preliminary and serves only to systematically structure our paper, not to simulate or represent the involved processes.

Figure 3 gives an overview of involved processes, which are depicted as rectangles. Their inputs and outputs are denoted by parallelograms and linked with directed arrows.

Consider the left part (*analysis*) of our model. People perform various activities as part of their daily routines. For example, Bob takes the train at 5 pm and then takes his car one hour later, while Alice takes her car at 8 am and at 6 pm. These *activities* (i.e., corresponding transport modes) need to be *detected* and collected in a user's individual *activity history.* Activity histories are one aspect required in order to score (rate) a user's past behavior.

However, meaningful activity scores depend on both "principle and specific" *goals* [63] that users want to pursue on their own, or the system designer intends to plant on them. For instance, Bob has the principle goal to "become more sustainable" and the specific goal to "take the car only once during the week". The *scoring process* therefore needs to take into account many goals on different hierarchical levels. Scoring activities in a context-dependent manner avoids to produce unrealistic suggestions that cannot be integrated into one's mobility life-style. For example, scores that account for motorized transport are not negative per se, but need to be generated as part of a systemic context, e.g., take into account that Bob cannot do without his car after 12 a.m. because where he lives there is only limited service of public transport.

The integration of different goals also requires taking into account different qualities of activities. For example, being on time for meetings is of highest

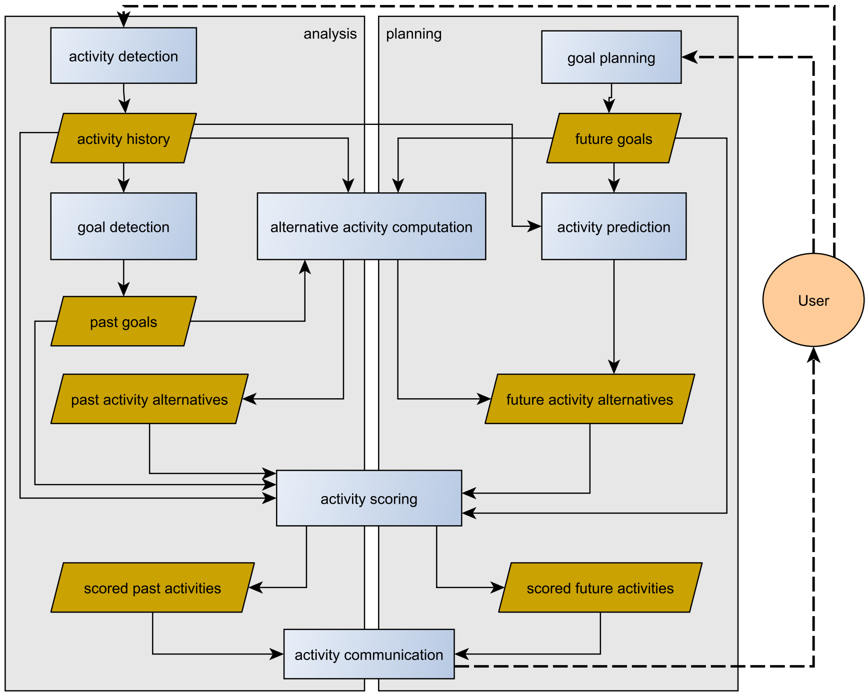

Fig. 3: Information processes required to provide meaningful suggestions for behavior change. Rectangular boxes are processes and parallelograms are inputs and outputs.

priority to Alice, while Bob would like to avoid using his car altogether whenever he runs his errands. Therefore, one major task is to detect the different goals (and their qualities) and to integrate them into the scoring process. Furthermore, scoring past behavior by taking into account realistic alternatives allows a user to develop personal benchmarks.

However, analyzing the past alone is not sufficient to provide useful suggestions for behavior change. A user also needs a way to plan alternative future behavior (See the right, *planning* part of our model). *Future goals* are output of a *goal planning process*, and they are input of processes that schedule a concrete future activity (*activity scheduling*). However, in order to introduce behavior change, the space of possible activities must be analyzed and *alternatives* need to be computed and chosen. For the latter process, it is crucial that alternatives need to take account of the same goals. Similarly, the *scoring* of these planned alternatives needs to be based on future goals. For example, Bob plans to avoid the car for shopping groceries. In order to do so, he needs to figure out alternative transport possibilities that minimize CO_2 and enable him to get his errands done, for example, using the supermarket next to his school.

Finally, by communicating scored results, a user may or may not adjust her activity behavior and its associated planning, which results in a feedback loop.

4 Information technology for behavior change: a survey

In this section, we elaborate on the different components of our model, introduced in Section 3. In particular, we discuss the state-of-the-art concerning technical and theoretical approaches and identify open research gaps. We start with the challenges regarding the evaluation of activities, i.e, their scoring (See Section 4.1) and communicative aspects of providing feedback on a user's behavior (See Section 4.2.1). Section 4.3 discusses various aspects of activity, goal, and intention recognition. In Section 4.4 we elaborate on activity prediction and support for activity planning.

4.1 Activity Scoring

In our model (See Section 3), *activity scoring* depends on a user's concrete *activity history*, her *past and future goals*, as well as any *activity alternatives.* Goals include both external (i.e., the system designer's perspective) goals, as well as user goals, all of which may conflict on various hierarchical levels. Thus, the challenge is to integrate them such that a meaningful score can be generated [74], which is the basis for communicating alternatives or evaluations of past behavior.

Note, our wording *score* is influenced by recent attempts to *"use design elements characteristic for games in non-game contexts"* [25]. Other examples related to this "gamification" approach are to give users rewards for some performed activity, as well as high-score lists ranking users according to their score. One of the challenges in enabling *meaningful gamification* lies in designing scores which allow users to internalize externally intended behavior [60].

4.1.1 Domains and Qualities of Scoring

The first step in building a scoring framework (See Figure 4) is to select the *activity types* to be scored and assess which *qualities* of these activities should be taken into account. Qualities can come from activities themselves, as well as from activities' outcomes [73]. In our attempt to support sustainable mobility behavior, activities like "Bob takes the train at 8 am for 20 minutes", or "Alice drives her car at 5 pm for 10 minutes" are of particular interest. Qualities of those activities are, e.g., velocity, cost, or CO_2 emissions, while the qualities of their outcomes could take into account whether one arrived at the intended destination on time.

It should be noted, however, that the selection of qualities will often be restricted by the available technology. An activity's velocity can be measured in a relatively accurate and precise manner using accelerometers and GPS sensors [78] while monetary cost or CO_2 emissions will have to be approximated in some way.

4.1.2 Standardization

To allow for meaningful scores, selected qualities need to be standardized. This can be done in different ways, i.e., by comparing them to:

1. **A user's own past**. This allows to measure an individual user's change. For example, if Alice starts using public transport more often, her measured CO_2 emissions will drop, which can result in a higher score.
2. **The behavior of others**. An example would be the comparison of CO_2 emissions of a given transportation mode of Bob against Alice on a particular day.
3. **Established norms**. CO_2 emission contingents for a user or a group of users could, for instance, be based on the 2°C standard of temperature rise [3].
4. **Conceivable alternatives**. This standardization method compares an activity's quality with what a user might have done instead. For example, staying at home (cf. teleworker) instead of commuting to work would reduce CO_2 emissions, but is not an option for everyone. Likewise, using public transport instead of a car might be an alternative for urban dwellers but not for people living in rural areas.

The last point challenges a system designer to embed external goals into a user's context by providing alternatives that are favorable under these additional goals. This requires a detailed understanding of the user's goals as well as restrictions imposed upon the user.

4.1.3 Criteria and Score Construction

Once standardized, it needs to be determined how far qualities contribute to a goal. By doing so, qualities become concrete *criteria*. Contribution towards a goal can be analyzed by comparing values of qualities to a favored state implied by a goal. For example, keeping CO_2 emissions within internationally established contingents might be considered a favored state with respect to climate protection. However, it might make more sense to choose a personalized standard as a favored state, such as minimizing CO_2 savings with respect to one's own past or in competition with others, in order to keep a user's motivation alive.

[3] "Copenhagen Accord'. U.N. Framework Convention on Climate Change. United Nations. 18 December 2009.

After criteria have been established, they can be turned into a single score. Several strategies to integrate multiple criteria can be used, ranging from compensatory to non-compensatory multi-criteria decision making techniques [46]. For example, if we want to combine Alice's weekly activities into a single score, we have to integrate her criteria for being time-efficient with a possible system designer's criteria for green mobility (e.g., reduction of CO_2 emissions by some factor x). This is difficult given the fact that these criteria will often contradict each other.

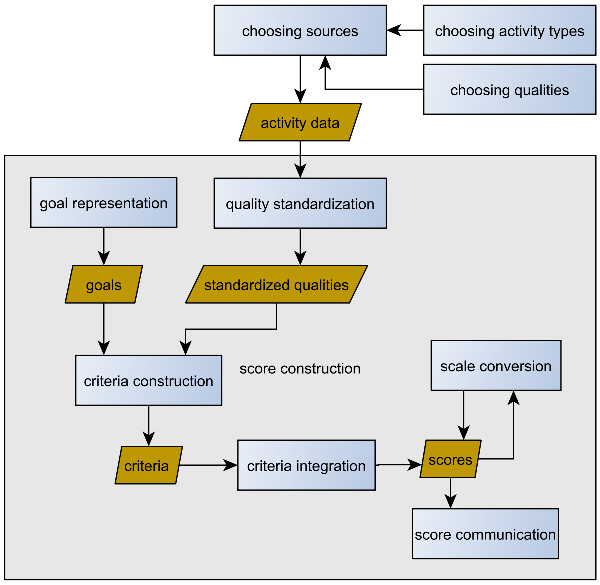

Fig. 4: Model of the scoring process. Rectangular boxes are processes, parallelograms are outputs. (Source: Authors)

4.2 Communication and Motivation

A major part of effectively influencing user behavior is to communicate sustainable activity alternatives in a meaningful way. This has to take into account psychological, sociological and technical aspects.

In particular, a system should strive for offering a high number of motivational affordances [96]. The concept of a motivational affordance comprises the actionable properties between a user and the system, and whether it can support a user's motivational needs (e.g., autonomy, competence, relatedness). Zhang [96] proposed a number of design principles for ICT that aim at offering high motivational affordances. For example, a user's need for autonomy should be supported by providing a personalized experience. Also, the need for feeling competent can be satisfied by providing challenges, e.g., in the form of games and learning systems.

4.2.1 Means of Feedback Communication

There are numerous ways to communicate feedback on a user's behavior. Yun et al. [94] distinguish between instructional, motivational, and supportive ways of encouraging a more sustainable life-style. Instructional approaches include education (i.e., "why"), advice (i.e., "how"), and self-monitoring (i.e., "what is"). Motivational approaches include setting goals, allowing for comparison (own and other's performance), keeping one engaged (e.g., to appeal to one's curiosity). Finally, supportive approaches encompass providing people with communicative tools (e.g., social networks), ways to self-control behavior (e.g., by reducing complex tasks into an automated one), and rewards for the accomplishment of some target behavior.

Froehlich [32], as well as Fogg [31] suggested a number of design dimensions relevant to the communication of feedback. Here we elaborate on four of them, i.e., the frequency, timing, measurement unit, and recommending action of a feedback.

The ideal *frequency* of feedback is difficult to determine because it depends on several context-related factors, including a user's motivational stage [43]. Fischer [28] found that frequently updated information on one's behavior increases the awareness between one's actions and their impact. However, on people like Alice who are still somewhat reluctant whether or not they should act upon feedback to become more sustainable high intensity feedback may have negative effects (cf. [59]).

Timing is equally important and the challenge is to find an opportune moment for feedback [31]. It often involves (a combination of) elements of the environment (e.g., location or social context), user characteristics (e.g., mood, motivation, self-worth, or feelings of connectedness to others), and the currently performed activity [31,84,22]. In general, feedback should be given timely in relation to the behavior that triggered the feedback to ensure a user perceives the consequences of her actions (cf. [96]).

A choice of *measurement units* can help to provide users with easily understandable feedback [28]. For example, scores can have different scale levels, ranging from nominal over ordinal and interval to ratio [81]. If Bob, for instance, received a badge (as a reward) for completing the challenge of using his car only 2 days of the week, this means that a ratio scale (CO_2 emission sums) was turned into a nominal scale (according to a minimal amount of CO_2 savings). An example for an ordinal scale are narrative progression icons as used by "UbiGreen" [33] which reflect individual mobility behavior during a week. Another possibility to simplify score communication is to change the scale level of a score depending on the user and context, e.g., through classification into understandable categories. Another possibility to ensure comprehension of feedback is to use analogies instead of quantitative measurements (e.g., “Bob, this week you saved the equivalent of a movies ticket by taking the train instead of the car!”).

Recommending actions is more effective if they are (perceived to be) highly personalized for a specific user in a given context (See Fogg [31] for an overview of relevant studies). In addition, the type of wording of a suggestion can determine whether or not it leads to desirable behavior. In one study, Schultz et al. [76] demonstrated a *boomerang effect* in the behavior of some of the participants to whom the researchers presented normative descriptive messages on average neighborhood energy usage. While participants above the average attempted to reduce consumption, those who were below the average increased consumption. Apparently those participants who were below the ”norm” felt they could increase consumption since they were better than the average. Schultz et al. (ibid.) argued that this boomerang effect does not occur if users are provided with an additional injunctive message, e.g., in the form of smileys indicating social approval or disapproval.

4.2.2 Motivation

Many theories on motivation advocate models that consist of several stages. For instance, the *transtheoretical model* [64] argues that one’s motivation undergoes five stages: precontemplation, contemplation, preparation, action and maintenance. During *precontemplation*, one is either unwilling to change or unaware of a problem in their behavior (cf. our character Alice). During *contemplation*, one knows that a behavior change is required and intends to change in the near future. During *preparation*, one is committed to change and works on a concrete plan on how to achieve this (cf. our character Bob). During *action*, one has actively and substantially changed their behavior over some longer period of time. During *maintenance*, one attempts to keep up with the new behavior. Note, it is possible for someone to be in different motivational stages for different forms of behavior.

Depending on a user’s current stage, different communication means should be applied in order to ensure progression to the next, or avoid relapsing to a prior stage. For example, early stages (where users are unwilling or are not aware of concrete alternatives to their behavior) need communication on an educational and informational level [43]. Users in the progress of changing their behavior need regular feedback and comparison to their previous behavior, while users in later stages need irregular reminders [43].

Another important distinction is whether a user is intrinsically or extrinsically motivated [71]. In general, intrinsic motivation is desired, as it allows long-lasting behavior change. In addition, people who are intrinsically motivated (e.g., interested, curious, feeling of competence and enjoyment) should not be exposed to extrinsic forms of motivation, e.g., by giving them rewards (cf. [24]) for their behavior. Instead, intrinsic motivation should be controlled by giving positive feedback [23], or alternatively letting a user experience “freedom” [45] and choice in terms of which goals she wants to pursue. In contrast, people who are extrinsically motivated can be presented with a variety of action choices to increase their sense of intrinsic motivation [45].

4.2.3 A Note on Empirical Studies

Although there is a large number of studies that aim at supporting people to engage in a more sustainable life-style, many of them suffer from methodological issues (cf. [34,40,15,39]), which makes it difficult to evaluate their validity and reliability:

1. **Small Sample Size:** In an evaluation of 95 studies that tested persuasive technologies, Hamari et al. [39], found that the participants' sample sizes were rather small (median $N = 26$).
2. **Lack of Control Group:** Some of the studies reviewed by Hamari et al. [40,39] did not include control groups. Froehlich [34] specifically looked at 8 studies that included eco-feedback technologies and out of the 4 studies that reported behavior change none included a control group, and only one accounted for baseline data.
3. **Short Time-frame:** Only one of the 36 studies reviewed by Brynjardottir et al. [15] can be considered long-term (i.e., 3 months). In fact, only 2 studies were found to last longer than one month. The relatively short time frames typically found in such studies may lead to a novelty effect that "might have skewed the test subjects' experiences in a significant way" [39, p.127].
4. **Lack of Psychometric Measurements:** In many studies, no psychometric measurements about the subjects' experiences and attitudes were used [40].
5. **No Distinction between Motivational Affordances:** Often, the success of the persuasive system was evaluated as a whole [40], without testing the effects of motivational affordances (e.g., rewards, feedback, suggestions, etc.) individually.
6. **No Statistical Significance:** Most evaluations relied on descriptive statistics alone [39] and claim behavior changes but "without any statistically significant effect on the intended metric" [15].

4.3 Transparency of the past

In order to know how behavior could be changed in the future, one first needs to know how people have behaved in the past. However, past behavior can only become transparent once mobile applications can reliably recognize a user's activity pattern. Furthermore, evaluating and scoring past behavior (See Section 4.1) such that it is useful for personal feedback requires to take into account a user's underlying personal goals and constraints. Only in this case can behavior scoring become personal and integrated into a person's life routines. In the remainder of this section we explore state-of-the-art approaches and principle technical challenges for the recognition of a personal history of activities (See Section 4.3.1) and their underlying goals and intentions (See Section 4.3.2).

4.3.1 Activity recognition

As stated in Section 3, daily routines consist of a sequence of *activities* (which form the *activity history*). Take Bob for example, who boards the train in the morning, takes the ride, steps off, and walks to his school. The process of *activity detection* maps the current state of a person to an activity. Activity detection is difficult when performed algorithmically, especially if only little sensory information is available. For state-of-the-art activity detection using mobile phones or MSPs[4] the input consists of sensor readings such as location, acceleration, step count, or compass heading. Using various techniques, these inputs are mapped to a predefined set of activities. In the following, the technical challenges when inferring transportation activities are summarized:

- **Accurate, frequent, and energy-efficient sensor readings:** Activity detection can utilize a variety of sensors [61]. While GPS provides the most accurate location information, it also causes quick power drains and is unavailable indoors [57]. On the other hand, accelerometer data is always available and relatively cheap to read (in terms of the battery). It is therefore important to find sets of sensors to be used in different situations [91]. Parkka et al. [61] provide a comparison between different sensors and their suitability for activity detection. Actual implementations use a variety of sensors: accelerometer only [91], accelerometer and GSM location [78], accelerometer and GPS [57], GPS only [80] or a combination thereof, e.g., acceleromenter, barometer, and microphone [69]. While accelerometers yield the best overall results, new algorithms for GPS-based activity recognition are gaining momentum, especially in terms of accurate detection rates [14, 13].
  It is noteworthy that phone manufacturers start to integrate activity recognition using specialized hardware and operating system functions with the goal of reducing power consumption[5].
- **Models that capture the activity domains and yield high classification accuracy:** A number of models for activity detection is currently being analyzed. Liao et al. [53] test an unsupervised layered Markov model that is able to predict user goals and activities, and determines when a user diverges from a known or planned route. Stenneth et al. [80] examine and compare Bayesian net, decision tree, random forest, naïve Bayesian and multilayer perceptron algorithms on previously annotated data. Shin et al. [78] favor an approach with predefined thresholds in sensory data as well as time. Riboni and Bettini [69] propose an ontology that asserts activities that can be performed at a user's location. The prediction accuracy

[4] Mobile Sensing Platforms
[5] cf. `http://en.wikipedia.org/wiki/Apple_M7`

usually ranges from about 75% to 95% for various activities, depending on the sensor output difference.

- **User-dependent activity model:** While Berchtold et al. [11] built a user-specific classifier, a lot of research solely relies on sensory data and is user-agnostic [78]. As users have different patterns for certain activities, classification accuracy can be increased by building personalized classifiers, or at least by training with different data [11]. The use of ontologies can further decrease the set of possible activities for a single user, thus yielding a higher accuracy [69].
- **Training data for supervised learning:** While it is a common approach to have labeled data, i.e., users annotate data with corresponding activities [78], other approaches evaluate unsupervised learning. They enable learning important places and distinct activities, but are often not able to detect their semantics, e.g., activity type labels [53]. Because manually labeling data requires users to actively cultivate data, it can prevent scaling [48]. Thus, for supervised training it is always required to initially learn activity labels. One of the important questions is where one can get the necessary data from?
- **Integration with other knowledge sources.** Using additional data such a user's calendar entries [55], street-topology information [80], or ontologies [69], activities can be detected with higher accuracy. For example, past activities can be associated more easily with current ones using a calendar. Also, possible activities can be constrained by the restrictions given by an underlying road network. Furthermore, an ontology can be used to assert activities that are allowed in certain places.

In summary, to be able to deduce higher-level goals, a solid detection and classification of activities is needed. Accuracy can be increased by choosing suitable sensors depending on the current activity, a model that both captures the problem domain and allows user specific adjustments, and the integration of external knowledge. However, there is a lack of a combined solution that optimizes all the noted points. Furthermore, there is only little research that evaluates how and which *external knowledge sources* can be integrated with existing detection models.

4.3.2 Goal and intention recognition

In order to put an activity into a person's context and to help her evaluating it from her own perspective, it is necessary to know about the goals and intentions underlying the history of activities. How can we find out about these goals?

Children and adults are adept at guessing why someone has done something, i.e., inferring a person's intention from perceptions of his or her behavior, while computers are not [42]. The underlying inference problem was called *inverse planning* by Baker et al. [10]. Observers invert a probabilistic generative model of plans to infer their goals starting from their behavior. This is a typical example of *abductive reasoning*, i.e., inferring probable causes given the results and a set of explanatory models.

If inverse planning is an abductive reasoning task, then one could use abductive reasoning techniques to solve it technically. Logically, abduction can be split into two subtasks [5]: (1) inference strategy (infer activities from goals), and (2) search strategy (for probable goals given an activity). For example, inferring a goal's probability from an action can be estimated based on Bayes' rule, i.e., using a prior probability of acting in this way given a goal plus a prior probability of this goal [10]. However, how can we know about the probability of the goals? While search strategies in standard abduction techniques are based on "fixed" global goal probabilities, they may be unknown for a specific person. There are also "learning" approaches which incorporate the *history of explanation*, for example, based on case-based reasoning [52]. However, if goals are learned that way, then we need a training data set[6], which may be difficult to get.

The challenge seems to be that a goal search strategy (goal probability) needs to take into account the goal history of a person, which does not only change from one person to the next but (for a given person) also in time. Thus, there is a need to know about higher level goals in order to estimate which low-level intention of a user is most probable given an activity. For example, if we know that Bob is doing workouts, then his car ride to a gym after work has an obvious purpose. Thus, similar to our discussion about activity inference, we come to the conclusion that we require top-down information to correctly and reliably use bottom-up inference techniques. A complementary

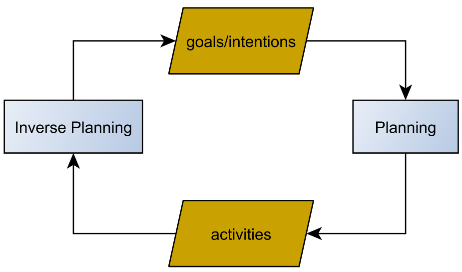

Fig. 5: How can inverse planning and planning be tightly integrated?

approach to learning about goals (as well as about types of activities) is based on combining bottom-up techniques with top-down user generated input. In this case, we use some form of interaction with a user to learn about his or her past goals. For example, if Alice travels a lot between meetings, then being present at a meeting can be inferred as a goal from her calendar, while hooking

[6] Unsupervised learning, e.g. clustering, does not require training data, but leaves open what kind of goal was detected in a set of activities.

up this calendar to measured locations and times allows intermediate travel events to be automatically added to it [20]. Fusing calendar events with sensor events has been used by Lovett et al. [55], in order to improve the quality of both, calendar completeness and consistency, as well as sensor-based event detection and labeling. Results show that calendars alone are not a reliable source for detecting meeting events, however, fusing sensor-based detection with calendar information can be such a source.

Thus, an obvious way to address these research challenges is to combine *inverse planning* with ordinary *planning* in a tight loop. The question is how this loop can be technically realized (See Figure 5)?

4.4 Transparency of the future

Influencing or changing one's behavior is a matter of *actionable* knowledge. It is a matter of how one's own prospect on the immediate future deviates from one's own old habits. If Bob knew that there was a way of easily getting to a nearby gym in a colleague's car directly from his work place (saving him time as well as resources), then he might choose against returning home and taking his own car to the gym, as he was used to. And similarly, if Alice knew that while on a business trip to the U.S. the newly built airport train took her to downtown Dallas more easily, quickly and cheaply, she would not rent a car at the airport. The question is how we can be made aware of our future prospects and how they deviate from our old habits, opening up a space of practical opportunities for behavior change.

4.4.1 Activity planning and computation of alternatives

Eco-feedback tools, such as [33], have primarily focused on giving feedback on past behavior. The idea is that feedback lets people control their behavior without any need to reflect on future decisions. However, we have argued in the last sections that meaningfully scoring and evaluating behavior as well as reliably detecting behavior needs top-down information about intentions and goals, and that a primary information source for the latter are calendars or other planning tools. Furthermore, feedback on past behavior is not yet actionable knowledge, because it misses the part of *decision support*, and thus a chance of recommending activities that change behavior.

Which kinds of mobility planning tools are available? (See also [65]):

– Web calendar services (e.g., Google calendar).
– Spatio-Temporal Personal Information Management Tools (cf. [2]).
– Mobile guides, which allow users to select tourist destinations or short trips to surrounding places. This can involve sophisticated optimization problems [87].
– Driver assistance and navigation systems.
– Multi-modal trip planning.
– Activity planning microsimulation models (see e.g. [9])

– Ride sharing systems (cf. [58]).

Activity planning primarily involves the *computation of feasible alternatives*. This includes the consideration of *alternative activity types* as well as *alternative activity schedules* (temporal sequences of activities). Regarding the latter problem, one way is to use multicriteria optimization technology (e.g., the branch-and-bound algorithm to solve linear programs) in order to schedule sequences of activities with space time constraints (see [21]), as envisioned by space-time geography [38]. Regarding the former problem, it is necessary to keep a plan library of possible activities and goals which allows for substitutions of activity types. Here, one could rely on classical planning algorithms in Artificial Intelligence, see [70]. Recent transport microsimulation approaches, such as ADAPTS [9], integrate empirically tested algorithms for activity planning, destination selection and activity scheduling into a single decision model which adapts to a particular planning situation.

However, despite the diversity of tools and solutions available, current technology still has a number of shortcomings in order to serve as *goal-aware and feedback friendly mobile planning tools* which are needed to close the various feedback loops in our model of Figure 3:

1. **Missing decision support**: As Raubal [67] has argued, current tools seldomly incorporate personal preferences and multiple criteria (e.g., multicriteria decision making approaches) to select a goal or a mode of action. However, the latter is needed in order to support activity scorings and evaluations of future activities.
2. **Missing calendar integration**: To date calendars are not integrated with spatial or location aware planning tools [3, 1]. For example, when Alice plans to attend a meeting overseas, she cannot schedule her flight in the calendar such that the calendar is aware of any associated spatial constraints. Calendars do only allow integrating time constraints into trip planning [56].
3. **Missing abstract goal representation**: Planning tools often have a too narrow notion of a *goal* (if at all). Either it is assumed that a goal is given (trip planning, driver and navigation assistance systems) or that a goal is simply a target location that a user selects. A location-independent and abstract goal such as Bob's need to perform regular workouts cannot be taken into account. Goals can be abstract and can be reached by different means and at different locations. One way to integrate abstract goal hierarchies into planning are *ontologies* [83].
4. **Missing goal inference from past behavior**: Planning tools often do not make use of learning about past habits and frequent behavior and the corresponding goals. For example, if Bob goes to the gym frequently, he can infer his own health goal and take it into account in planning support.
5. **Missing collaborative scheduling tools**. Collaboration can broaden alternatives and thus the possibilities of planning, as it generates new mobility options [58]. This, however, requires tools that facilitate collaboration beyond the sharing of data, and beyond established solutions such as car

sharing or couch surfing, incorporating many aspects of daily life. Collaboration may, e.g., be embedded into calendars and may involve activities such as running errands together or jogging together. Furthermore, it needs a way of generating trust and privacy, because collaboration requires the sharing of personal details.

One way to meet these requirements is based on an *integrated activity calendar*, which we will sketch in our research agenda (See Section 5).

4.4.2 Activity prediction

Closely interconnecting the activity past with the future can be done by basing recommendations on probable behavior as observed in the past. Predicting activities can be used to fill empty calendar slots, to make conservative recommendations, or to deliberately deviate from choices of the past in activity planning.

In transportation science, daily activities are commonly predicted based on logistic regression and models of choice for the purpose of travel demand modelling [12]. We focus here more on data driven machine learning approaches.

Predicting a user's next activity can be modeled as a problem of reasoning under uncertainty, given the user's (most recent) activity history [54]. Activity prediction identifies future activity candidates, assigns probabilities to them, and returns the most likely one. In case several candidates are assigned similar probabilities we are facing a problem of ambiguity. For the case of mobility prediction, ambiguity occurs on several levels [49, p.6]: there may be several locations the user will go to next, a location may belong to several places (spatial context ambiguity), and a place may have several actions a user might plan to perform there (affordance ambiguity). Some application domains may have a higher intrinsic ambiguity than others. Alices' activities at the airport, for instance, will be more structured (check-in, drop luggage, pass through security, etc.), and thus easier to predict, than her freetime activities on a Saturday afternoon.

The challenge for the system designer consists in designing a prediction algorithm which reduces ambiguity, given the domain at hand [50]. Methodologically, prediction algorithms are closely related to recognition algorithms (see Section 4.3.1), sharing the same algorithmic foundations, e.g., multi-layer DBN [62] and machine learning [7]. However, activity prediction algorithms are the more challenging problem because they always have to cope with incomplete activity histories and offering predictions that need to be made on the spot (time constraints). In addition, it also requires the accurate detection of previous activities and/or goals. If an activity history on which we base the inference has been recognized with a high uncertainty value, the result is that the uncertainty propagates to the future activity candidates, leading to higher ambiguity and incorrect predictions. It may also become necessary to revise recognition attempts made previously.

In the most simple case, activity prediction uses a history of size 1, e.g., using a first-order Markov model [8]. This is often very effective. For instance, if Alice is walking towards her car on a Monday morning, we can infer that her most likely next activity will be driving to work (based on an individual user model and a user-independent plan library). While in principle, a larger activity history may help to reduce ambiguity, it is often unavailable [6], or the size of the activity history needed to capture a certain activity pattern is too large to be modeled with formalisms that provide an efficient inference [49, pp.63ff]. For instance, if Bob visited a public library at some point during the last 4 weeks, the likelihood of re-visiting that library is higher than the base probability for library visits (because he needs to return the borrowed items at some point). Making probabilistic inference on an activity history of 4 weeks (e.g., with a DBN), however, is not feasible without the introduction of a belief state aggregating the past before a certain point, which however may require exponential memory for complex domains [18].

5 Conclusion and Research agenda

In this paper we explored research challenges for location-aware ICT that provide users with suggestions of sustainable activity alternatives. We structured research challenges according to information processes that illustrate the information requirements for changing one's behavior both from an analysis (current and past behavior) as well as a planning (future behavior) perspective. In particular, we distinguished activity scoring (rating) and challenges that arise during meaningful communication (through feedback) of activity alternatives. In addition, we talked about activity recognition, as well as goal and intention recognition, and identified open research gaps.

In the remainder, we outline a research agenda as the summary of our literature review (See Section 4) and related to the model we introduced in Section 3. The following subsections are ordered in terms of priority with respect to a typical design process of ICT, starting from the definition of requirements and design principles for such a system and ending with an empirical large-scale user evaluation. Note, in Table 1 we give an overview of our suggestions for future research and the associated challenges. For better reference, we link each suggestion with its corresponding section in our paper.

5.1 Conceptual Requirements

5.1.1 Design Principles For Meaningful Recommendations

A set of cognitively and psychologically sound design principles that can guide system developers in choosing the appropriate use of motivational affordances (see Section 4.2.1) for a given user context is urgently needed (cf. [88]). These principles must be grounded in research on the psychology of motivation to increase user acceptance and the likelihood that the system's suggestions are actually carried out.

Table 1: Overview of suggestions and corresponding research challenges as discussed in this article.

Agenda section	Agenda suggestion		Challenge	Section
Conceptual requirement	Design principles		Strategies f. feedback communication	4.2.1
			Design for motivational stages	4.2.2
	Ontologies		Missing abstract goal representation	4.4.1
	Collaborative planning		Missing collaborative scheduling	
System components	Activity calendar	Activity recognition	Accurate, frequent, energy-efficient sensor readings	4.3.1
			Model that capture activity domains	
			User-dependent activity model	
			Acquisition of training data	
			Integration with other knowledge sources	
		Goal and intention recognition	Integration of *inverse planning* and *planning*	4.3.2
		Planning	Missing decision support	4.4.1
			Missing calendar integration	
			Missing goal inference from past behavior	
			Activity prediction	4.4.2
	Activity scoring		Score standardization	4.1.2
			Score construction	4.1.3
Evaluation	Empirical studies		Small sample sizes	4.2.3
			Lack of control group	
			Short time-frame	
			Lack of psychometric measurements	
			No distinction between motivational affordances	
			Statistical significance	

For example, the fact that people typically undergo different motivation stages for behavior (see for example Section 4.2.2) is often not explicitly considered in the design process. Someone who contemplates behavior change needs different forms of feedback (in type, magnitude, and frequency) than one who is actively preparing to change (cf. [43]). In addition, people's motivational needs [72] such as the innate needs for autonomy, competence, and relatedness can act as guiding principles on how and what type of information is provided. For instance, systems let users define their own goals may be less patronizing than systems that "dictate" external goals set by the system's designer (see Section 2.3).

5.1.2 Ontologies for goal and activity representation

Because goals and activities are tightly interlinked, both causally (e.g., in order to get to the gym, some form of transport has to be used), as well as conceptually ("working out" is an abstraction of "going to the gym"), a way of modeling such dependencies is needed. This will be one requirement for using goals and activities in reasoning. The use of ontologies and rules for representing abstract goals in planning, as well as for activity recognition and prediction could fill this gap and enable users to specify goals on a higher level of abstraction (cf. [35]), leaving their spatio-temporal realization in terms of activities up to recommendation. One major challenge is to find a level of abstraction that fits well with user specific goals and allows for the activity calendar integration (see Section 5.2.1).

5.1.3 Methods For Collaborative Planning

Planning tools that can automatically take into account several users, offer decision support for multiple goals, provide calendar integration, as well as knowledge integration with past behavior are still missing. The conceptual foundation for such a tool is an open and extensible infrastructure to support both communication and matching of potential collaborators [16,17,37]. This will broaden the range of activity options, e.g. the improved access to shared resources. In addition, it will be one way to empirically test all involved planning conditions and the limits of cooperation towards a common goal (cf. [58, 90]).

5.2 System Components

5.2.1 The integrated activity calendar

Tools that attempt to integrate personal information (e.g., to-do-lists) with spatio-temporal information [1] are required to connect higher-level goals (e.g., intentions) with low-level activities such as navigation. The integration of *planning* with *inverse planning*, as sketched in Section 4.3.2, would allow a more reliable detection of (especially user-specific) types of activities (See Section 4.3.1), as well as their specific goals and goal probabilities. The benefit will be an external knowledge source and thus training data for the recognition of the past, but also a reliable platform for planning support. However, it remains an open question how both planning and inverse planning and activity detection can be technically integrated.

5.2.2 Meaningful Personal Activity Scoring

Goals of a user and external goals both need to be taken into account in scoring a user's activities (see Section 4.1). This enables the development of intrinsic motivation [60, 72] and allows to plant external goals on somebody. In addition, personal scoring of activities relative to alternative activities is needed. The space of alternatives is then determined by personal goals. This also motivates people to change behavior inside the boundaries of their personal possibilities. However, how should score and criteria construction, standardization, goal integration and score communication be carried out technically?

5.3 System Evaluation

5.3.1 Empirical Evaluation of Behavior Change

In order to make valid and reliable empirical claims on the effectiveness of technologies that support people in a sustainable mobility life-style, it will be necessary to conduct long-term and large-scale user studies that overcome the methodological issues mentioned in Section 4.2.3. The design of large-scale and long-term studies are challenging but can give valuable feedback on whether the design principles (see Section 5.1.1) initially selected led to the intended results. It will thus be required to carry out an iterative system design in which the design and evaluation of a system (for specific user groups in a given context) are mutual inputs.

Large-scale and long-term empirical studies, however, will face new emerging challenges. For example, how can people be motivated to use such a system for longer periods? What are effective mechanisms that can keep users motivated once the novelty effect of such a system has worn off [40]? Recent studies have pointed at the long-term motivating potential of gamification, i.e., "the use of design elements characteristic for games in non-game contexts" [p.9][25]. Leaderboards, social comparison and peer pressure, as well as setting objectives and goals, can influence a user's motivation both towards using the system and changing her behavior. Yet, similarly to the necessary design principles for information feedback (See Section 5.1.1) it is still unclear how much potential "gamified" systems have for the purpose of behavior change.

In addition, tracking users over longer periods will yield very detailed and extensive user profiles, especially if spatio-temporal information is connected to a user's preferences and attitudes. How can we assure the user's right to geoprivacy [89] and, (how) do we sufficiently address ethical concerns, if we design systems intended to change behavior?

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