Intelligent Time Use Suggestions for Wellbeing Enhancement

Mario E. Marin, Julio C. Ponce

Universidad Autónoma de Aguascalientes,
Centro de Ciencias Básicas,
Mexico

marin@ia.org.mx, jcponce@correo.uaa.mx

Abstract. An intelligent application is developed to automatically suggest to users alternative time assignations to activities, based on data analysis of INEGI's ENUT (national time use survey), with the purpose of enhancing wellbeing. The predictive value of the datasets was ascertained with a comparative analysis of feedforward deep neural networks, support vector machines, logistic regressions and random forest assembles. Logistic regression used the less computational time, and the random forest assembles had the best accuracy. Respondents and users were profiled using K-means clustering, and a non-linear optimization model was developed to find the best datapoints to take suggestions from.

Keywords: Intelligent systems, data analytics, wellbeing, time use, clustering, optimization.

1 Introduction

Time can be considered a scarce resource "whose use largely determines the progress, achievement and wellbeing of individuals, families, communities and societies" [1], therefore managing it to put it to good use should be a priority for individuals and organizations. Despite most time management applications being focused on improving work performance, there is ample evidence that time management practices have a positive correlation with individual wellbeing [2]. However, the research in this field is scarce and distributed among many disciplines [3] and a review of the current applications resulted in very few automated or Artificial Intelligence (AI) approaches, with this field dominated by automated scheduling tools, and some tools for health assessments and wellness. No AI or automated tool was concerned with first suggesting what kind of activities, beyond the preexisting ones, could enhance wellbeing for the user except for tools specifically centered on wellness or health that can hardly take the place of current time management tools in organizations or workplaces where people spend most of their waking hours.

The question this work intended to answer was whether, given an adequate time use dataset, intelligent tools could be developed that automatically consider alternative activities in multiple areas of life from data of similarly positioned individuals in terms of roles and responsibilities, with a wellbeing enhancement criterion.

Using the datasets from a national time use survey that included subjective wellbeing data, the data was analyzed, and using a select subset of attributes and a clustering algorithm, 30 personal time use profiles were developed of which a user could be considered a member.

Then, a program was developed to suggest users to what activities they could give more or less time in their weekly routine to make a low-cost change in their membership from their original group to a similar one with a greater wellbeing average level. This was accomplished without resorting to data from most costly and cumbersome approaches like sensors and surveillance software.

The value of using time use survey datasets was proven by answering the question posited above in the affirmative; and by the success with predictive algorithms in estimating, from time use and demographic data, subjective attributes such as satisfaction and objective ones like gender or income.

These valuable time use datasets can not only be obtained from surveys, but also from other low cost, low nuisance methods like preexisting software calendars and Internet of Things (IoT) devices that can record the activities done in different time intervals.

2 Wellbeing Theory

A broad definition of wellbeing would be "an individual's ability to live the kind of life he or she values, on a sustainable basis" [4]. Wellbeing is a multifaceted concept, usually modeled by way of constructs that include both objective and subjective measures of wellbeing. It is difficult to obtain comprehensive datasets of objective wellbeing measures such as those indicating health, income, skills, job situation, and even characteristics of the environment in which a person lives.

Even then, a further problem remains: weighting each measure according to the subjective importance a user may give them. Subjective measures of wellbeing can be more convenient.

Subjective wellbeing is a "broad category of phenomena that includes people's emotional responses, domain satisfaction and global judgments of life satisfaction" [5] and it has been found to have positive correlations to various measures of objective wellbeing [6–8].

This makes subjective wellbeing a powerful proxy for overall wellbeing, and its being a self-reported measure [9] that has been shown to respond according to relevant circumstances [10], despite some of its components having correlation with personality traits [11], facilitates the generation of useful datasets.

The choice of time use datasets is because of the definition of wellbeing as an ability that people may have in relationship to the environment in which they act. Therefore, an agency based definition of wellbeing in relation to time use is more adequate [12].

From this perspective, a clearer definition of wellbeing is that it is the state in which people can act while gaining greater ability to engage with their environments. Given the complexities of studying environmental and interpersonal factors of wellbeing, it is hoped that behavior of people obtained through time use datasets, and subjective wellbeing evaluations can offer insights into wellbeing enhancement in general.

3 Wellbeing Analytics

The analysis approach in this work is that of data analytics, which is a set of "theories, technologies, tools and processes that enable an in-depth understanding and discovery of actionable insight" [13]. In the context of wellbeing, the datasets available and necessary for an automated approach and for many kind of analyses are such that the implications of the model of the 5 Vs of big data must be considered: volume as in very big datasets; variety as in different kinds of data of which time use surveys are just a few slices; velocity, with many data even generated in real time from large groups of people; value [14], which in the case of wellbeing analytics must be linked to an agency based definition of wellbeing; and veracity, as in underlying accuracy of the data specifically impacting the ability to derive actionable insights and value out of it [15].

While this work is centered in time use datasets obtained through surveys, the same kind of data can be obtained from IoT devices, portable sensors [16], digital traces [17], and from data generating activities. Thought the interest of this work is mostly centered in data generated with a low cost, low nuisance approach, hence one-time surveys, the insights of this project can be carried over to analysis of other varieties of data.

This work can be considered as one of data analytics, and the analyses in the next sections as different levels of data analytics [14]. From the descriptive, with the correlation analyses, to the predictive with a comparative analysis of different methods of prediction; and to the prescriptive in which from the very beginning the user is aided by all the information and knowledge accumulated in the system developed.

4 Datasets and Methods

The datasets used for this work are from the microdata repository of the National Time Use Survey in Mexico performed by its National Institute of Statistics and Geography (INEGI) in 2014 (ENUT-2014) [18]. Respondents were asked about their weekly time use, meaning, their time allocations to different activities during a week; as well as some demographic data. This time use survey was the first in Mexico to also ask about subjective wellbeing. Eight ENUT-2014 datasets with data from Spanish speaking people were preprocessed, transformed, and unified into a single dataset.

The ENUT-2014 datasets had 58,187 entries considering 42,117 people who took the complete time use survey, 1,914 people not living in the same house but who donated their time in it, and data about other people who did not answer the time use survey as they were less than 12 years old or had a disability that prevented it. The 42,117 complete respondents were from among 15,500 homes or family units living in 15,058 houses, with some of these housing more than one home or family unit. Data from different sections of the survey went into different datasets as we see in Table 1.

The subjective wellbeing attribute "happiness" is the one being enhanced in this work, because of its simpler description and high correlation to some of the other options, but the model can work with any subjective wellbeing attribute in the dataset. Reindexing, ordering, transformation, and fusion procedures were made in the datasets to create a single unified dataset with 42,117 entries and 322 attributes which nonetheless had all the relevant data from the other datasets included in each entry. A diagram of this process can be seen in Fig. 1.

Table 1. Datasets from the ENUT-2014.

Dataset	Survey section	Data from	Entries	Features
TVivienda	I	Houses	15,058	24
THogar	II, III, VIII	Home or family units	15,500	51
TSDem	III	Sociodemographic data	56,273	7
TModulo1	IV	Time use	42,117	182
TModulo2	V, VII	Time use	42,117	192
TModulo3	VI, VII	Time use and subjective wellbeing	42,117	178
TNoResidente	VIII	Nonresidents	1,914	33
Metadatos	I-VIII	Entries	58,187	4

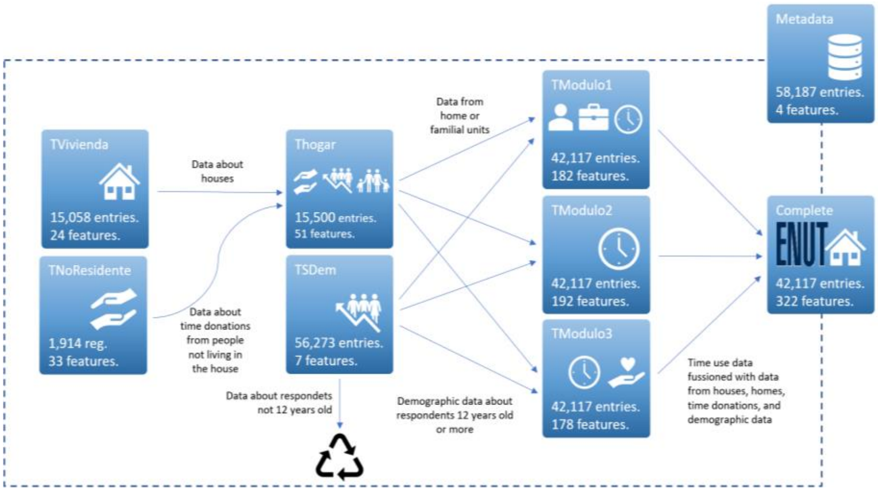

Fig. 1. Data preprocessing process.

In order to ascertain the value contained in the unified dataset, four different predictive algorithms were used to predict subjective wellbeing and other relevant attributes using the unified ENUT-2014 dataset and compared: feedforward deep neural networks, support vector machines (SVM), random forest assembles, and logistic regression.

The visualization technique for high dimensional data FreeViz [19] was used to evaluate the structure of the unified dataset and the K-means clustering algorithm [20] was used to create different clusters that could represent groups of people with similar time use assignations.

A non-linear optimization model was presented with two different objective functions for different approaches: change in minutes, and cost of these changes, whether they are increments or decrements.

Table 2. Predictive analysis comparison.

Attribute	**Method**	**Accuracy**	**Weighted F1**	**C. Time (s)**
Satisfaction with studying time use* (Values: 0,1)	Random forest	**0.9602**	**0.9601**	014.56
	SVM	0.8962	0.8961	016.15
	Neural Net	0.9158	0.9158	101.67
	Log. Regression	0.9130	0.9130	**000.55**
Satisfaction with work time use* (Values: 0,1)	Random forest	**0.8146**	**0.8082**	057.02
	SVM	0.7823	0.7800	254.73
	Neural Net	0.7698	0.7693	636.34
	Log. Regression	0.7471	0.7467	**001.37**
Satisfaction with life in general* (Values: 1-5)	Random forest	0.2448	0.2337	004.43
	SVM	**0.2750**	**0.2549**	001.57
	Neural Net	0.2467	0.2346	014.06
	Log. Regression	0.2957	0.2906	**000.15**
Income (Values: 1-5)	Random forest	**0.5716**	**0.5725**	004.71
	SVM	0.4159	0.3852	002.59
	Neural Net	0.3964	0.4022	015.4
	Log. Regression	0.4145	0.4061	**000.21**
Gender (Values: 0,1)	Random forest	**0.8872**	**0.8872**	070.57
	SVM	0.8302	0.8295	373.28
	Neural Net	0.8569	0.8569	850.42
	Log. Regression	0.8595	0.8594	**001.81**
Indigenous self-identification (Values: 0,1)	Random forest	**0.6604**	**0.6602**	079.32
	SVM	0.5710	0.5645	514.21
	Neural Net	0.5659	0.5656	736.62
	Log. Regression	0.5950	0.5949	**001.77**

*All subjective wellbeing attributes were dropped from the training dataset.

5 Predictive Value of the Dataset

As previously stated, in practice applications using time use datasets would fall into the big data analytics field; therefore, it is relevant to ascertain the value of the dataset [14] before using it in an application. The approach decided was to apply four different predictive algorithms to the dataset and evaluate their performance in predicting relevant attributes.

All subjective wellbeing attributes were dropped when predicting a subjective wellbeing attribute as some are highly correlated. This analysis was performed with an

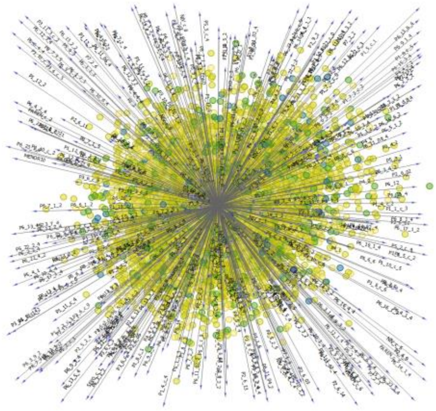

Fig. 2. FreeViz visualization of the completely unified dataset of the ENUT-2014.

Anaconda Python distribution in a laptop with an Intel Core i5-9300H processor, and 32GB in RAM.

Some relevant results are in Table 2, where the performance metrics confirm the value of the unified ENUT-2014 dataset. In almost every case, random forest assembles have the better accuracy, while logistic regression uses the less computational time. Because the dataset is unbalanced, undersampling was used taking an equal, or close to equal, number of entries for every class.

As can be seen, classifiers for satisfaction in specific domains related to time use in work and academic settings have high performance, whereas satisfaction in general just manages to be above a random classifier.

Other general subjective wellbeing attributes suffer from similar low performance too, and other domain specific time use satisfaction measures without as much related times use attributes as work and study have hover between 0.6 and 0.7 accuracy which is still notable for attributes with 5 classes.

It is also notable the high accuracy predicting gender and income, and a moderate one predicting indigenous self-identification which points to time use and demographic patterns linked to these attributes.

6 Time use Profiles Creation

Using the unified dataset, a FreeViz [19] visualization was generated, and it was clear from it that the dataset had no easily separable structure as can be seen in Fig. 2. Given this lack of structure, the K-means algorithm was used to partition the dataset in 30 clusters with the intention of having them represent groups with centroids well distanced from other groups' centroids and relatively little variance within groups which this clustering technique algorithm [20] is useful for.

Also, given the success of predictive algorithms with sociodemographic attributes, it was judged prudent to do a correlation analysis of the dataset with the class assigned by the K-means algorithm. If the groups were mainly defined by their

Table 3. First eight Pearson correlation of all attributes with the K-Means class.

Corr.	Attribute
0.818	Income by means of pension
0.294	User/respondent is retired
0.277	There are elderly people in need of special care at home.
0.253	Income by means of rent of some property
0.169	House has a landline.
0.157	Number of rooms in the house.
0.149	Age
0.142	Kitchen has a sink.

Table 4. First eight Pearson correlation of all attributes with happiness.

Corr.	Attribute
-0.15	Age
0.146	Toilet has running water.
0.144	Hours of checking e-mail, social networks, or chat apps.
0.141	Kitchen has a sink.
0.141	House has Internet connection.
0.141	There is a laptop computer in the house.
0.13	There is washing machine in the house.
0.128	Respondent has a car or pick-up truck.

sociodemographic attributes or others not easily changeable, this would mean that most suggestion to pass from one group to another would be problematic, impractical, or implausible.

6.1 Correlation Analysis

Various correlation analysis, using Pearson correlation as endorsed by the literature of wellbeing and quality of life studies [21], were done for the dataset and the class of the clusters generated. The first using all the attributes of the dataset showed that attributes with the highest correlation to the class of the group were indeed sociodemographic ones, such as the ones seen in Table 3. More worryingly, a correlation analysis with the happiness attribute shed light in that most of the attributes with high correlation with happiness were about having appliances and basic services available at home, age and just one time use attribute, as seen in Table 4.

If groups were allowed to be constructed in this way, the suggestions the application would give the user would be to change attributes like those shown in Table 3 and Table 4 and others like them, which would be of limited value in its context.

Table 5. First eight Pearson correlation of time use attributes and K-Means class.

Corr.	**Attribute**
0.13	Time taking care of kids while doing something else (weekdays)
0.12	Time taking care of kids while doing something else (weekends)
0.079	Time dedicated to eating meals (weekdays)
0.078	Time dedicated to work (weekends)
0.077	Time dedicated to commutes (weekdays)
0.075	Time dedicated to work (weekdays)
0.068	Time dedicated to cleaning the interior of the house
0.067	Time taking care of babies or toddlers (weekdays)

6.2 Profile Generation

To avoid generating unusable groups for current purposes, they were generated only considering time use attributes. The correlations of the attributes of these groups with the class assigned by the clustering algorithm were analyzed and the attributes with high correlation to the class are time use assignations as can be seen in Table 5.

These attributes tend to distinguish different people with different roles; for example, parents or children's tutors do have big time use assignations of childcare, whereas people without children do with far less regularity. The same happens with students having time assignments for classes and homework, and so on. This is the kind of groups that were sought: people with similar roles and responsibilities.

6.3 Characterization of Profiles and Users

As can be seen in Table 6, the 30 groups generated have been characterized by happiness level, age group, work situation and the distance they have to travel to their work or school, and whether they have children under their responsibility or not. The average of each attribute was used as per practices used by the Organization for Economic Cooperation and Development (OECD) [22] and then converted to a label.

It is to be noted that some users may be assigned, or suggested to change, to a group with certain roles and responsibilities that do not exactly match their own. However, as the groups were calculated using only time use attributes, this only means that some users may have similar time use assignments to those of people with different roles or may have "something to learn" from people with different roles or responsibilities.

7 Optimization Model

So far, the model has users grouped with other similarly positioned people in terms of roles and responsibilities as indicated by their time use assignations. The issue remains of how to suggest to users a low-cost change in their weekly activities that is backed by the data to have a probable wellbeing enhancement.

Table 6. Characterization of groups, 5 selected attribute.

Group	Happiness	Age	Children	Work	Commutes
1	Low	Medium	No	Part time	Far
2	High	Y. Adults	Yes	Full time	Very far
3	Medium	Y. Adults	No	Full time	Very far
4	High	Teenagers	No	No	Very close
5	High	Y. Adults	Yes	No	Close
6	Medium	Y. Adults	No	Extra hours	Very far
7	Low	Medium	No	No	Very close
8	High	Y. Adults	No	Full time	Ver far
9	High	Y. Adults	Yes	No	Close
10	High	Teenagers	No	No	Very close
11	Low	Medium	No	No	Ver close
12	Low	Medium	No	No	Close
13	Low	Medium	No	Few hours	Close
14	High	Y. Adults	No	Full time	Very far
15	Medium	Medium	No	No	Close
16	High	Y. Adults	Yes	No	Very close
17	Low	Medium	No	No	Very close
18	High	Teenagers	No	No	Very close
19	High	Teenagers	No	Part time	Far
20	Medium	Medium	No	Part time	Very far
21	High	Y. Adults	No	Full time	Very far
22	Medium	Medium	No	Part time	Far
23	High	Medium	No	Full time	Very far
24	High	Y. Adults	Yes	Full time	Far
25	Very low	Medium	Yes	Few hours	Close
26	Medium	Y. Adults	No	Extra hours	Very far
27	Medium	Medium	No	No	Very close
28	Very high	Teenagers	No	No	Very close
29	High	Y. Adults	No	Extra hours	Very far
30	Medium	Y. Adults	No	Full time	Adjacent

There are two approaches. To minimize the changes suggested in minutes assigned to certain activities, and to minimize the costs of such increases or decreases. The cost of increasing a particular activity may be different from that of decreasing it, and big costs to decrease can be associated to activities deemed essential by the user.

These costs would need to be asked to the user. Therefore, an optimization model is presented that has two options for objective function: one for change and one for costs of change.

For both approaches, the easiest path would be to suggest the time use assignation of a close datapoint with better wellbeing level in the same group as the user. This would have the advantage of taking the suggested changes from a person similarly positioned in terms of roles and responsibilities. However, there is no reason to think that just recommending another person's time use assignments, even if that persons has better wellbeing levels, will do something to improve wellbeing levels for the user.

A better path is to have information about a group of thousands of people with similar time use patterns linked to a greater average wellbeing level than that of the user, then we would have reason to recommend a datapoint within this group. Provided that the user does not have a maximum level of wellbeing already, this is exactly what the model shown in this work already provides. The process would be to find the closest datapoints, using Manhattan distance, with greater wellbeing level that belong to groups with greater average wellbeing than the current level of the user. This set of datapoints then can be presented ordered as recommendations to the user to decide between them.

The optimization model is proposed thus:

Indexes:

$$i \in \{1, \dots, n\},$$

n: Number of groups.

$$j \in \{1, \dots, m\}.$$

m: Number of activities considered.

Sets

Dataset composed of n groups:

$$D = \{G_1, \dots, G_n\}.$$

Parameters:

Current time use assignment to activity *j*:

$$u_j \in \mathbb{N}_o.$$

Current wellbeing level of user/decision maker:

$$f \in \mathbb{N}_o.$$

Cost/Value of increasing time assignment to activity *j:*

$$a_j \in \mathbb{R}.$$

Cost/Value of decreasing time assignment to activity *j:*

$$b_j \in \mathbb{R}.$$

Time use assignment for the centroid of group *i* in activity *j*:

$$c_{ij} \in \mathbb{R}_0^+.$$

Average wellbeing of group *i*:

$$h_i \in \mathbb{R}_0^+.$$

Original group to which the user/decisor was assigned to:

$$g \in \{1,2, \ldots n\}.$$

Variables:
Time use assignment recommended for activity j taken from data from group i:

$$x_{ij} \in \mathbb{N}_o.$$

Recommended group to switch to:

$$y_i \in \{0,1\}.$$

Restrictions:
A group must be selected:

$$\sum_{i=1}^{n} y_i = 1\,.$$

Time use assignments for all activities must not exceed minutes in a week:

$$\sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \leq 10080.$$

Recommended time assignments for all activities must be a datapoint belonging to the group being considered:

$$\{x_{i1}, x_{i2}, \ldots, x_{im}\} \subseteq \{G_i | y_i = 1\}.$$

Objective function for minimizing change:

$$C(y_i, x_{ij}) = \sum_{i \in \{1,\ldots,n | f < h_i\}} \sum_{j=1}^{m} y_i \left| x_{ij} - u_j \right|.$$

Objective function for minimizing cost:

$$C(y_i, x_{ij}) = \sum_{i \in \{1,\ldots,n | f < h_i\}} \sum_{j=1}^{m} y_i \left\{ \frac{a_j}{2} \left[sign(x_{ij} - u_j) + 1 \right] (x_{ij} - u_j) + \frac{b_j}{2} \left[sign(u_j - x_{ij}) + 1 \right] (u_j - x_{ij}) \right\}.$$

8 Results

The correlation and predictive analysis done demonstrate the value contained in the ENUT-2014 dataset, not only as it provides insights about differences in time use by different demographic groups, but also about their relationship to subjective wellbeing. Therefore, it is possible to extract knowledge about how time use patterns affect

Table 7. Suggestions summary for 5 randomly selected respondents.

# ID	Change in minutes	Group change	Wellbeing difference	Greatest increase	Greatest decrease
40902	9308	8 → 5	+0.214304	Taking classes	Caring for adults
	9323	8 → 5	+0.214304	Taking classes	Caring for kids*
	9494	8 → 5	+0.214304	Taking classes	Caring for adults
7815	4725	12 → 5	+0.214304	Taking classes	Growing food
	4935	12 → 5	+0.214304	Taking classes	Growing food
	4990	12 → 5	+0.214304	Taking classes	Growing food
5091	5679	15 → 9	+0.165179	Caring for kids*	Collecting firewood
	5729	15 → 9	+0.165179	Caring for kids*	Cooking
	5929	15 → 9	+0.165179	Caring for kids*	Collecting firewood
99	4275	0 → 5	+0.214304	Sleep, weekdays	Homework
	4445	0 → 5	+ 0.214304	Sleep, weekdays	Listening to audio
	4795	0 → 4	+0.301020	Sleep, weekend	Listening to audio
27055	6250	17 → 25	+0.168627	Caring for kids*	Tend to livestock
	6315	17 → 25	+0.168627	Caring for babies*	Tend to livestock
	6340	17 → 5	+ 0.214304	Taking classes	Tend to livestock

*Activity done while doing something else.

subjective wellbeing. The clustering, and subsequent characterization of the groups of people similarly positioned in terms of roles and responsibilities that dictate their time use patterns, allow the use of this knowledge to develop applications to enhance wellbeing by recommending behavior changes with no prior data of the user before the input of its weekly time use data, as well as some sociodemographic data.

The optimization model was solved for randomly chosen datapoints within the ENUT-2014 dataset by exhaustive search to guarantee the results for this test, and to obtain a set of ordered recommendations of theoretically actionable suggestions to change time use assignation to activities, as can be seen in Table 7 with three options presented to five respondents from the ENUT-2014.

Also, by asking the user information to generate a vector of costs for increasing or decreasing time assignations, the model can take into consideration activities that the user thinks are more easily changeable or those that are essential, thus including information about the agency limitations of the user. As the ENUT-2014 does not contain data of this kind, no attempt was done to use the model to minimize cost. But as we see in Table 7, some users could label tasks such as “caring for adults” or “caring for kids” as essential and therefore assign high costs for reducing them. This would alter the changes suggested by considering the agency limitations of the users such as those that preclude a particular change in time use that would enhance subjective wellbeing because, overall, the capacity to change environment and conditions is limited, and thus overall wellbeing is limited as well.

9 Conclusions, Discussion, and Future Work

There are two main interests that directed this work. The first was to stablish the possibility and value of working with time use datasets in the context of developing intelligent applications to enhance wellbeing, despite established links of some subjective wellbeing components to personality [11]. If wellbeing enhancement applications can work with behavior change instead of personality traits, the task of creating these intelligent applications would be easier, as behaviors in the context of organizations, but also individually, can create data automatically that can more easily be recovered to form the datasets to power the applications. Also, data obtained from behaviors is less subject to distorted interpretations. The conclusion is that this work is indeed possible and valuable, and a data analytics approach is useful, particularly in the context of big datasets that can lead to prescriptive analysis automated applications that aid users backed by knowledge obtained from these datasets.

The other interest is about finding sources of data that are low cost, low nuisance to users. As we have seen, useful time use datasets can be created with one-time surveys like the ENUT-2014, but they can also be created by time management applications already in wide use in organizations as well as by the increasing number of everyday objects that are part of the IoT ecosystem. This means that in many organizations and households there is already a wealth of data waiting to be used for applications of wellbeing enhancement and time management.

Future work can consist of obtaining new time use datasets with a more streamlined set of attributes, datasets that include costs of increasing or decreasing each time commitment to an activity in order to apply and study the results of the optimization model which takes into account the cost of the changes. It remains to be seen if new indicators of wellbeing can be inferred from patterns in the time use and subjective wellbeing datasets that link to the definition of wellbeing based on agency and if these result in better suggestions. Also, the agency of the users, their capabilities to change their time use and wellbeing levels if they decide so, should be given a bigger role in the model and have the impact of these modifications ascertained. Linking an application like the one presented to a time management one is also an option, as well as analyzing other varieties of data, such as emotional analyses in text and images.

Finally, care should be taken to treat the datasets of time use as already describing organizational and societal biases that might need to be addressed before an application can be in use. Some of these biases can be inferred from the prediction algorithms used having high accuracy levels for linking time use patterns to sociodemographic attributes such as gender or indigenous self-identification, as well as to income.

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