Well-Being's Predictive Value

A Gamified Approach to Managing Smart Communities

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Abstract. Well-being is a multifaceted concept, having intellectual origins in philosophy, psychology, economics, political science, and other disciplines. Its presence is correlated with a variety of institutional and business critical indicators. To date, methods to assess well-being are performed infrequently and superficially; resulting in highly aggregated observations. In this paper, we present well-being as a predictive entity for the management of a smart community. Our vision is a low latency method for the observation and measurement of well-being within a community or institution that enables different resolutions of data, e.g. at the level of an individual, a social or demographic group, or an institution. Using well-being in this manner enables realistic, faster and less expensive data collection in a smart system. However, as the data needed for assessing well-being is highly sensitive personal information, constituents require incentives and familiar settings to reveal this information, which we establish with Facebook and gamification. To evaluate the predictive value of well-being, we conducted a series of surveys to observe different self-reported psychological aspects of participants. Our key findings were that neuroticism and extroversion seem to have the highest predictive value of self-reported well-being levels. This information can be used to create expected trends of well-being for smart community management.

Keywords: Smart community management, well-being, social computing, gamification, human flourishing.

1 Introduction

Individual well-being is evaluated in a variety of ways: as subjective well-being, psychological well-being, or via economic calculation [1-5]. While each domain has different strengths, when used as complimentary systems they create a fitting proxy of personal and institutional well-being [1]. The relationship between personal and communal well-being is the fundamental base for using well-being data in smart community management. At the basest level, communities are made by personal interactions with other individuals, groups, institutions and events. Perceptions of these interactions drive personal perceptions of well-being, which among other indicators is a predictor of social cohesion [6], a necessary condition for progressive smart communities. According to former European Commission Directorate-General

for Information Society and Media Erastos Filos, smart communities are "understood to be both, internetworked and knowledge-driven, therefore able to adapt to new organizational challenges rapidly, and sufficiently agile to create and exploit knowledge in response to opportunities of the digital age" [7, p1]. One information development for exploitation in digital societies is general institutional wellness. Forward-looking smart communities find it in their best interest to both satisfy and maintain their constituent base, which in turn helps the community develop sustainably.

We argue that constituents, decision makers, stakeholders as well as human resource divisions lack adequate measures to determine the state of psychological or social health in their institution. Without access to such information, it can be challenging to make decisions that affect members of their institution. It is also not possible to inspect the after effect(s) of such decisions. This knowledge gap hinders key actors in decision making scenarios. To circumvent potentially significant gaps in knowledge, digital well-being measurement is needed as a "best practice" mechanism for thriving smart communities.

Our research goal is to establish a low latency method for the observation and measurement of well-being within a community or institution. However, as the data needed to measure well-being is often private and highly sensitive, we proposed a gamified approach to incentivize participants to reveal this information in [7]. In this paper, we build upon this vision and make the first steps to validate its feasibility by investigating the predictive value of different measures and indicators for the assessment of individual well-being. Our study is based upon a series of weekly surveys in which we inspect different self-reported psychological aspects of participants to determine if they can predict or indicate specific aspects of well-being. As a baseline, we use the ten Human Flourishing constructs proposed in [8]. This is an important first step, as without such insights we cannot appropriately structure an application for the individualized measurement of institutional well-being.

2   Related Work

Multiple studies indicate that well-being is closely linked to health, longevity, and community belonging [10-13]. Well-being also has applications in organizational spheres, where organizational design and human resources are two examples. Healthier, happier employees have both lower incidences of absenteeism, are more productive, and have lower organizational health care related costs [10,14]. Dissatisfied employees have higher turnover levels – especially significant when considering that the cost of losing an employee can range between 1.5 and 2.5 times the departing employee's annual salary [15]. These studies show that well-being data is powerful: just as manifestations of increases in well-being act as a proxy for increased livability, systematic decreases in self-reported well-being signify deep-seated institutional issues. As such, personal well-being measurement can function as a strategic progress indicator for assisting institutional managers in resource allocation [14].

In gamifying well-being, leaders take proactive steps towards smart community management. Acting as a thermometer by which to gauge institutional health, well-being data serves not only as a feedback mechanism between various actors and policy makers, but as a forward-looking decision making tool [16,17]. Thus there is widespread interest in tracking mechanisms with high popular acceptance. Until recently, attempts to collect well-being data as an institutional feedback mechanism have been scarce. The most frequent method of collecting well-being information, the Daily Reconstruction Method, is formulated to reconstruct the events and affective state of individuals [18-20]. This important work establishes well-being data collection in a more frequent interval, although it is not in a near to real time environment.

Even though having been used earlier, the term "gamification" did not see widespread adoption before the second half of 2010 [21]. Since then it has been used with quite different scope and connotation. Antin and Churchill state that context sensitivity is often neglected with current, schematically imposed reward mechanisms [22]. Vessileva indicates that for gamification to work, it needs to take into account the users' different personalities [23]. However, this larger group of authors does not generally object gamification, but assumes that a reservoir of not yet used improvements does exist. Deterding subsumed "Gamification is the use of game design elements in non-game contexts [21]." Being generally more positive about its possible application, McGonigal proposes to construct games in the spirit of gamification that unlock the engagement and determination inherent in gaming to solve real-world problems [24]. She identifies gamers, while playing to be "super-empowered hopeful individuals" supported by an environment that provides superior abilities for blissful productivity, social fabric, urgent optimism, and epic meaning.

This too in turn is questioned by Huotari and Hamari who bring up that its perspective is too systemic [25]. They state that it depends on the individual perception of a user if a service is gameful, making it impossible for a service designer to identify the non-game context that is necessary for the above definition. Based on their background in service marketing, their suggestion to define gamification is as "a process of enhancing a service with affordances for gameful experiences in order to support user's overall value creation" – therefore setting priority on the goal of creating better experiences instead of the methods applied for achieving it.

2.1   Davies J-Curve and Social Disruption

In his book "Conditions of Happiness", Veenhoven wrote "The more healthy and active the citizens and the smoother their contacts, the greater the chance that society flourishes. Moreover, widespread dissatisfaction with life tends to act as a bomb under the social system [6, p 404]." We likewise hypothesize that significant issues of well-being manifest in (sub)groups of the population, and negative well-being will follow a Davies J-curve distribution [26]. This model indicates when social expectations have a large deviation from the actual outcomes of human well-being (relative deprivation), some form of social schism should be expected (Figure 1).
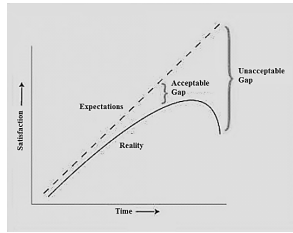
Fig. 1.   The Davies J-Curve

In other words, social unrest is a subjective response to a sudden reversal in fortunes after a long period of growth [26]. The strength of relative deprivation is evaluated by charting and changing the expected change of actual well-being levels against expected well-being figures. For a given attribute type, a lack of statistically significant differences between expected and actual well-being levels implies no discrepancy and no social unrest; significant differences implies the opposite.

2.2   Beyond the Vision: BeWell

In an endeavor to achieve near real time measurement of well-being with high user acceptance, a gamified survey collection method was proposed in Hall et al. [8]. Fully interactive, BeWell: a game of you, utilizes novel near real time data collection methods by using both the push method found in [18-20], and a gamified portal to entertain users [8] via smart devices. BeWell records personal well-being data over time as elicited in a series of responses based on gamified text and pictographs. Registration is completed with a series of short tests to assess users' personalities. This not only allows the program to assess the way the well-being levels are likely to change due to any given users baseline personality factors, but gives participants an additional facet with which to see their daily personal levels of flourishing holistically [8,9].

Badges and points gained through successful task completion can be used to level up, allow crowd-sourced (i.e. new) task suggestion, and permit community historical well-being badge achievement viewing rights [8]. Badging occurs in three states to incentivize further participation: low, moderate and exceptional mission completion. Anonymous data aggregation in turn allows smart community managers to use regionalized "well-being maps" in order to assist in decision-making when allocating resources, upgrading infrastructure, and/or engaging public political discourse.

3   Attributive Prediction and the J-Curve: A Use Case

To find expected and actual well-being, we propose that the historical characteristics of well-being create trends. From a combination of these trends and psychometric profiling, prediction of the aspects and existence of wellness can be completed. A proof of concept survey was propagated through the main authors' online social

networks[1] in order to validate if attribute-based prediction can be used in conjunction with the measurement of well-being. Surveys were administered once per week for four weeks on Wednesdays, in order to control for variance in weekly activities, such as subjective preferences for weekends. All surveys were conducted in English. Ten identical questions covering varying aspects of human flourishing were posed to facilitate prediction of said dimension [9]. Demographic questions, the 44-item scale Big Five Inventory personality test, the Maximizer/Satisficer scale test, and a fairness scale [27-29] were also added as additional attributes. Each was administered for one week only to test prediction abilities of well-being based on pre-existing personality traits. These psychometric tests have low variance, and thus can be tested once and still are considered valid for the length of this one month survey. Respondents were given the option to review their results at the end of the four weeks.

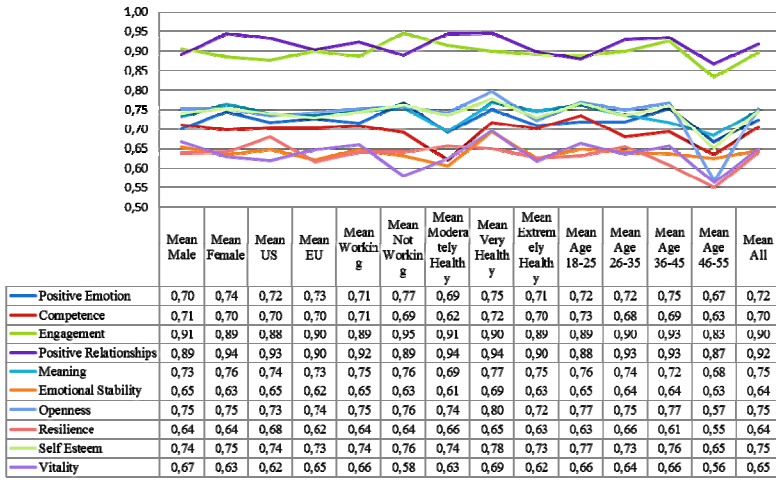## 3.1   Establishment of a Baseline

After four weeks, 65 of 85 participants completed all four iterations of the survey, with an overall loss of 14% of the participants across four weeks. Self-reported gender revealed a 50-50% female-male split, with one non-response. Three participants who completed the surveys self-reported being located in Asia; 22 from the United States; and 34 self-reported locations within Europe, with four declining to respond. 78% self-report being age 35 or under. 85% of respondents reported being currently employed. 81% of the respondents self-reported completing at least a master's degree. 86% of respondents refer to themselves as "moderately healthy" or "very healthy."

The self-defined subpopulations have telling normalized means which help to confirm the viability of this feasibility study. Perhaps unsurprisingly, there are not significant deviations between gender profiles and the normalized population mean across all human flourishing constructs. Overall, the regions of the United States and Europe are also quite similar, with the exception of the construct Resilience. In this area, Americans report higher average resiliency of 0.68, compared to the European mean of 0.62. Quite counter-intuitively, those whom report being unemployed score themselves significantly higher than the mean on the constructs Positive Emotion and Engagement, whereas those who reporting being employed are significantly higher for the constructs Positive Relationships and Vitality. Across the Health subcategory, those who rate themselves as "Very Healthy" are higher in almost all constructs than those who rate themselves in higher and lower health categories. Across age groups, there is an overall tendency towards growing less content through the middle-aged group, which is consistent with existing literature. We can expect that if the over 56 population engages the game, overall human flourishing trends for this group will rise again through the end of life. The effect is however unnoticeable for the construct Emotional Stability. A full listing of results can be seen in Table 1.

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[1] Primarily the propagation was done with direct emails and Facebook, but also a smaller effort was place on LinkedIn and Google+.

Table 1. Human Flourishing Construct Means across Subpopulations

	Mean Male	Mean Female	Mean US	Mean EU	Mean Working	Mean Not Working	Mean Moderately Healthy	Mean Very Healthy	Mean Extremely Healthy	Mean Age 18-25	Mean Age 26-35	Mean Age 36-45	Mean Age 46-55	Mean All
Positive Emotion	0,70	0,74	0,72	0,73	0,71	0,77	0,69	0,75	0,71	0,72	0,72	0,75	0,67	0,72
Competence	0,71	0,70	0,70	0,70	0,71	0,69	0,62	0,72	0,70	0,73	0,68	0,69	0,63	0,70
Engagement	0,91	0,89	0,88	0,90	0,89	0,95	0,91	0,90	0,89	0,89	0,90	0,93	0,83	0,90
Positive Relationships	0,89	0,94	0,93	0,90	0,92	0,89	0,94	0,94	0,90	0,88	0,93	0,93	0,87	0,92
Meaning	0,73	0,76	0,74	0,73	0,75	0,76	0,69	0,77	0,75	0,76	0,74	0,72	0,68	0,75
Emotional Stability	0,65	0,63	0,65	0,62	0,65	0,63	0,61	0,69	0,63	0,65	0,64	0,64	0,63	0,64
Openness	0,75	0,75	0,73	0,74	0,75	0,76	0,74	0,80	0,72	0,77	0,75	0,77	0,57	0,75
Resilience	0,64	0,64	0,68	0,62	0,64	0,64	0,66	0,65	0,63	0,63	0,66	0,61	0,55	0,64
Self Esteem	0,74	0,75	0,74	0,73	0,74	0,76	0,74	0,78	0,73	0,77	0,73	0,76	0,65	0,75
Vitality	0,67	0,63	0,62	0,65	0,66	0,58	0,63	0,69	0,62	0,66	0,64	0,66	0,56	0,65

Overall, Positive Relationships and Engagement are the most highly rated constructs, meaning these are the areas in which people see themselves most fulfilled. This relationship is significant at the 0.01 level in a two-tailed Pearson correlation test, as seen in Table 2. Emotional Stability and Vitality are the lowest of the ten total constructs, which are also significantly correlated at the 0.01 level as seen in Table 3.

Table 2. Pearson correlation, Positive Emotion (PE) and Engagement (En);.

		PE	En
PE	Pearson Correlation	1	,372**
	Sig. (2-tailed)		,002
	N	65	65
En	Pearson Correlation	,372**	1
	Sig. (2-tailed)	,002	
	N	65	65

**. Correlation is significant at the 0.01 level (2-tailed).
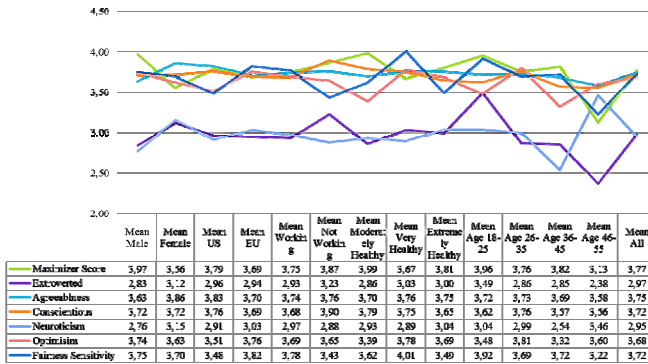
Table 3. Emotional Stability (ES) and Vitality (V)

		ES	V
ES	Pearson Correlation	1	,664**
	Sig. (2-tailed)		,000
	N	65	65
V	Pearson Correlation	,664**	1
	Sig. (2-tailed)	,000	
	N	65	65

**. Correlation is significant at the 0.01 level (2-tailed).

3.2   Predicting Human Flourishing

When considering the seven attributes tested throughout the survey (fairness, maximization, extroversion, neuroticism, optimism, agreeableness, conscientiousness), we see much more varied results across subpopulations than are found throughout the human flourishing constructs (Table 4). This is encouraging, as the attributes here are the basis of how the gamified survey predicts wellness based on

Table 4. Attribute Predictor Means across Subpopulations

	Mean Male	Mean Female	Mean US	Mean EU	Mean Working	Mean Not Working	Mean Moderately Healthy	Mean Very Healthy	Mean Extremely Healthy	Mean Age 18-25	Mean Age 26-35	Mean Age 36-45	Mean Age 46-55	Mean All
Maximizer Score	3,97	3,56	3,79	3,69	3,75	3,87	3,99	3,67	3,81	3,96	3,76	3,82	3,13	3,77
Extroverted	2,83	3,12	2,96	2,94	2,93	3,23	2,86	3,03	3,00	3,49	2,86	2,85	2,38	2,97
Agreeableness	3,63	3,86	3,83	3,70	3,74	3,76	3,70	3,76	3,75	3,72	3,73	3,69	3,58	3,75
Conscientiousn	3,72	3,72	3,76	3,69	3,68	3,90	3,79	3,75	3,65	3,62	3,76	3,57	3,56	3,72
Neuroticism	2,76	3,15	2,91	3,03	2,97	2,88	2,93	2,89	3,04	3,04	2,99	2,54	5,46	2,95
Optimism	3,74	3,63	3,51	3,76	3,69	3,65	3,39	3,78	3,69	3,48	3,81	3,32	3,60	3,68
Fairness Sensitivity	3,75	3,70	3,48	3,82	3,78	3,43	3,62	4,01	3,49	3,92	3,69	3,72	3,22	3,72

subpopulations. After calculating human flourishing as based on the calculation of Huppert and So [8,9], we modeled a simple liner regression, with the human flourishing score as a dependent variable and the psychometric attributes as predictors.

With an R score of .727 and R Square of .528, we validate the feasibility of making predictions of human flourishing to be reasonably accurate. This is further confirmed by the results of an ANOVA on the linear model (Table 5) which confirms that at least one of the predictors has a highly significant correlation to human flourishing.

Table 5. Analysis of Variance (ANOVA), Human Flourishing and psychometric attributes

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,899	7	,128	9,116	,000^b
	Residual	,803	57	,014		
	Total	1,701	64			

Of the seven predictors it was found that neuroticism and extroversion have the highest predictor importance. Neuroticism is the single most important predictor, representing 44% of the predictor weight. It is highly significant at 0.001 as an effect and a negative coefficient estimate. This indicates that higher levels of neuroticism predict lower flourishing levels. As an effect and a coefficient, extroversion is also highly significant at the 0.001 level with a positive coefficient estimate. As a single attribute, it contributes 27% of the prediction weight. High extroversion is predictive of high flourishing levels.

The strength of these two relationships to overall human flourishing scores is notable, as it suggests that inferences about the population can be made. This must however be further tested for interaction effects, which is to say that the existence of other attributes contribute to the overall human flourishing score and thus moderate the absolute impact of neuroticism and extroversion. This is especially noticeable in the case of gender per subpopulation (Table 4). Overall, women report lower human flourishing levels. Accordingly, this subpopulation rates itself with higher over

overall levels of neuroticism. However, women also rate themselves to be more extroverted as a subpopulation than men. While this confounds the information above, this result also proves that a multi-faceted approach to defining and tracking well-being as an indicator is necessary, as the approach cannot be watered down into a pair of psychometric properties from which all attributes can be predicted.

3.3   Towards Validating the J-Curve

Our feasibility study has confirmed the ability of psychometric properties to predict levels of wellness. These results support the creation of attribute based tracking for the establishment of baseline well-being expectations. Using these attributes, we can create well-being profiles across subpopulations and use them to predict future well-being values; the expected trend line of the Davies J-Curve. By then considering current well-being information, we can inspect the deviation of reality from expectation. This can be performed either on an individual basis, institutional basis or somewhere in between, for example a social or demographic group. Per attribute group, these two lines are the measurement of policy impact, public debate, and institutional wellness. Manifestations of the absence of well-being or a change from its expected level are predictable when plotted, thus facilitating evaluation and stakeholder discussions. Our vision revolves around the use of smart devices, in the context of a familiar setting (Facebook), which should facilitate the construction of a smart community portfolio: a stakeholder feedback loop of community wellness and overall satisfaction. However, further research is needed to confirm if Facebook is a viable platform.

4   Conclusions and Future Work

This paper presents a methodology that utilizes attributive predications in order to analyze and evaluate data obtained in gamified human computer interaction systems for smart community management. We observed from our study, that two factors of the Big Five Inventory, namely neuroticism and extroversion, seem to have the highest predictive value. The outcomes from our analysis illustrate the ability to predict communal vigor for progressive and active management. These results aid in the realization of BeWell in that they provide a guideline for the development of future predictive models. This responsively tracks trends in noisy data of personal well-being, continually updates given new data points, and highlights otherwise hidden attribute-based well-being forecasting.

   With respect to the calculation and measurement thereof, in the next instantiation machine-learning methodologies will be utilized to both calculate the current data input, and create a forecast of expected future input [30]. The real time community of BeWell could be further leveraged if combined with a data-mining approach that investigates the existence of positive or negative affect in data such as Facebook status updates, or Tweets. From the additional data points gained, more sensitive trending can be made in connecting the levels of well-being.

This aspect of popularly sourced well-being information is ripe for adaptation into the smart community spectrum. By utilizing this multi-faceted picture of the individual, BeWell encourages communities to proactively manage the components causing agency loss (e.g. cheating, lack of transparency, ill-health) as a form of adaptive people management. Such an elastic measure can be repurposed as both a diagnostic and predicative model for diverse participation-based movements and institutions when populated with well-being data. Well-being can be "mapped" to communities, regions, and institutions to illustrate policy effectiveness and enhance participative debates. Through the observation of a decrease in well-being, participatory approaches could be a reactive measure as a means to reengage previously content constituent-users, and engage new constituent-users throughout the community. Gamified well-being measurement is a progressive step in smart community management.

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