An Integrated Neural Network and Structural Equation Modeling Approach for Modeling Activity Trackers Use

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Abstract: The objective of this study is to enhance a Technology Acceptance Model (TAM) with an Artificial Neural Network (ANN) approach in order to obtain substantially accurate results when compared to Structural Equation Modeling (SEM). This study looked at another paper that created a TAM dedicated to activity trackers (AT) obtained via SEM from a questionnaire to 247 participants. This study uses the constructs of that paper in an ANN as the input units and the Root Mean Square of Errors to indicate that the ANN method achieves high prediction accuracy. The results provide conclusive evidence that Perceived Usefulness is the most significant factor affecting AT acceptance. Perceived Ease of Use and Image affect acceptance, however their impact is much lower. Hedonic Motivation and Habit were found to have a significant relationship with TAM while Self-Efficacy showed mixed results. This confirmation can be useful for future designs of activity trackers.

1 INTRODUCTION

Wearable devices such as activity trackers have become important in monitoring health behavior, for recreation, and socialization, and thus are a viable and significant research topic in Human Computer Interaction. Confirming this trend is the International Data Corporation in a press release, stating that worldwide shipments of wearables grew 9.9% throughout the third quarter of 2021 reaching 138.4 million units (IDC 2021). The improvement and the commercialization of activity trackers have helped many users to reach the recommended goal of ten thousand steps per day in order to maintain or improve their health (Akers 2012). However, a study on the acceptance of a particular activity tracker device discovered that half of the users stop using the device after two weeks (Shih 2015).

One possibility, to help solve design issues that lead to loss of interest or decrease od device usage, is the use of models. Even though some researchers think of them as excessively theoretical. In fact, researchers working with interfaces who had often been skeptical, started to acknowledge that models could be helpful in the design of interfaces (Myers 2000). Since Li et al.'s seminal work, researchers have been trying to describe the use of trackers through a model (Li 2010). Li et al. presented a model with five iterative stages: preparation, collection, integration, reflection, and action; later the model was refined by these authors. Also, Epstein et al. looked at that model and expanded on it by including the lapses and interruptions of tracking, and highlighting the intricacy of integration, collection and reflection (Epstein 2015). Narrowing the scrutiny, Sol and Baras obtained a model dedicated to activity trackers use (Sol 2016) that is used in this paper. The most important advantage of this model is that it is quantitative. It was obtained by expanding the Technology Acceptance Model (TAM), with health oriented, data control, and other constructs. TAM assumes that user acceptance can be described by two ideas: Perceived Usefulness (PU), and Perceived Ease of Use (PEoU) which determine Intention to Use through Attitude (Davis 1989).

A TAM based model for activity trackers, as most of the research on technology acceptance models is done simply with Structural Equation Modeling

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(SEM) methods, or other models, for example, the Ubiquitous Computing Acceptance Model (Spiekermann 2007), and the Health Information Technology Acceptance Model (Kim 2013). SEM is a sophisticated multivariate technique that can be used to scrutinize multiple dependence associations between variables simultaneously. It is useful for hypothesis specification and testing, can suggest novel hypotheses that were not considered initially. Nevertheless, SEM may lead frequently to an oversimplification of the complexities involved as it is simply detecting linear relationships (Ringle 2012). To address this issue, undertaking a second step using an Artificial Neural Network (ANN) allows for further scrutiny and examination.

An ANN is "a massively parallel distributed processor made up of simple processing units, which have a neural propensity for storing experimental knowledge and making it available for use" (Haykin 2004). Contrary to SEM an ANN is not suitable for hypotheses testing, but further to linear relationships can also deal with non-liner relationships. Moreover, an ANN has the capability to assess non-compensatory processes (Svozil 1997). Additionally, an ANN is more robust and can offer greater prediction accuracy than linear models (Tan 2014). This study uses the constructs of the TAM based model for activity trackers as the input units of an ANN in order to obtain a more accurate view of the acceptance and use of these devices.

In the following sections, we contextualize the study with the literature review, and present the model. Next, we describe the methodology, and discuss the results of ANN analysis. Finally, we conclude, and envision the possibility of future research.

2 LITERATURE REVIEW

In this section we primarily review the literature related to activity trackers. We also look into Artificial Neural Networks research to understand its relations, importance and classifications. The acceptance and use of activity trackers is due to many reasons and motives, several of which seem to clash. Users may begin tracking their activity since they have a certain goal in mind (Epstein 2015). Still, there are users who start to use activity trackers with no goal in mind and use the device to help them set an objective. This objective becomes clearer as the usage changes after transitioning from the discovery phase to the maintenance phase of pondering (Li 2010). Other users start tracking merely moved by concern and curiosity of the quantitative data (Lindqvist 2011). Nonetheless, goal seating is just one notion to help and persuade health-related behavior change.

For example, when the user wants to implement a habit in daily life, one of the best ways is for the activity tracker to help implementing routines (Lazar 2015).

An egocentric perspective for these devices (Elsden 2015) can be looked at as a form of hedonic motivation, as is individual encouragement (Patel 2015), the acknowledgement of effort (Kim 2016), and giving credit (Consolvo 2006).

When looking at image one can look into the lifestyle of the user (Consolvo 2006) or to the aesthetics and form of the devices (Harrison 2015). Other notions embrace social comparison (Harrison 2015), social competition and collaboration (Patel 2015).

Users manage to change their goals, habits, and devices; however, the applications or dashboards are ill equipped to allocate this change. For tracking, users tend to change devices often or even use several devices in parallel, which leads to complications in measuring and associating data (Rooksby 2014). This issue has many impacts as it increases the difficulty to provide a tailored efficacy evaluation (Klasnja 2011) that is important for the users' self-efficacy.

When one approaches to data control the information that activity trackers are gathering can be extremely sensitive (Lupton 2017) and the risk of third-party recording is real (Elsden 2015).

When looking at how to improve the usefulness of activity trackers different researchers produced several design ideas, one of which was the facilitating of micro-plans (Gouveia 2018), another was to give meaningfulness in context (Rooksby 2014), yet another was to provide a wide variety of adjustable goals (Clawson 2015), or to appeal to identity (Lazar 2015), and another was the idea of adherence (Tang 2018).

The idea that the devices have to "speak" the language of the users (Lazar 2015) because users are not data scientists (Rooksby 2014), and the need for devices to remind them (Shih 2015) are ways to improve the usability of activity trackers. Nevertheless, these devices are still being used in a rather limited manner (Didziokaite 2017).

Numerous statistical techniques are parametric, such as SEM and Multiple Regression Analysis (MRA), requiring a great statistic background, while artificial neural networks are non-parametric models, which can provide higher prediction accuracy (Tan 2014). An ANN uses a considerable interconnection of simple computing units called neurons or nodes as inputs, hidden, and outputs layers with connection values called synaptic weights that are adaptable via an iterative process. A classic ANN consists of several layers: one input layer, one or more hidden layers and one output layer (Negnevitsky 2011). In ANNs for technology acceptance typically only one hidden layer is used (Tan 2014). There are several types of ANNs, but the most common is feed forward back propagation multilayer perceptron (BPFF). In this kind of network, belonging to supervised learning ANNs, the knowledge stored in the network by iteratively subjecting it to patterns of known inputs and outputs (Negnevitsky 2011). The difference between desired and actual output, is calculated and propagated back, in order to change the synaptic weights and by doing so minimize the estimation error (Haykin 2004).

A node uses a function f defined as a weighted sum of its inputs based on equation 1 where the w are the weights, and the x are the inputs, the bias is b and the output is Z (Haykin 2004).

$$Z = f(w_1 x_1 + w_2 x_2 + b) \quad (1)$$

There are many activation functions for the output layer, however Sigmoid, shown in equation 2, is generally used in a technology acceptance context (Tan 2014).

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \quad (2)$$

The root mean square of errors (RMSE) is used to predict accuracy and is calculated using equation 3 and 4 (Tan 2014), where SSE is the sum of squared error, and MSE is the mean squared prediction error.

$$MSE = \frac{SSE}{n} \quad (3)$$

$$RMSE = \sqrt{MSE} \quad (4)$$

3 MODEL OBTAINED VIA SEM

In order to obtain the model for activity tracking use, via Structural Equation Modeling, the paper targets a population of actual activity trackers users. These users were recruited from social media and on a micro work site. A survey with 80 questions adapted from prior research was deployed. The items of the survey were considered using a seven-point Likert scale, amid between "Strongly Disagree" and "Strongly Agree." Specifically, the strength and significance of direct effect of nineteen independent variables on behavioral intention were determined. From a total of 17 tested relationships, 11 were statistically significant.

There were a total of 247 users, mostly from Western Europe and North America, that completed

Table 1: Definitions of the constructs present in the model.

	Definition
Perceived Susceptibility of Disease	"The perception of the likelihood of experiencing a condition that would adversely affect one's health" (Jayanti 1998)
Perceived Severity of Disease	"The beliefs a person holds concerning the effects a given disease or condition would have on one's state of affairs" (Hochbaum 1952)
Habit	"The extent to which people tend to perform behaviors automatically because of learning" (Limayem, 2007)
Health Consciousness	"The degree to which health concerns are integrated into a person's daily activities" (Jayanti, 1998)
Hedonic Motivation	"The fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use" (Brown, 2005)
Image	"The degree to which use of an innovation is perceived to enhance one's image or status in one's social system" (Moore, 1991)
Self-Efficacy	"The judgment of one's ability to use a technology (e.g., computer) to accomplish a particular job or task" (Compeau 1995)
Perceived Data Control	"The degree to which a person feels they have control over the use of, and access to, the data collected" (Lindqvist 2011)
Perceived Usefulness	"The degree to which a person believes that using a particular system would enhance his or her job performance" (Davis 1989)
Perceived Ease of Use	"The degree to which a person believes that using a particular system would be free of effort" (Davis 1989)

the survey, from these 144 were male (58.3 percent) and 103 were female (41.7 percent). The average age was 33 with a standard deviation of 10.6.

The sample size of 247 has exceeded the recommended minimum sample size of 111 obtained from G*Power with an effect size of 0.3, an alpha level of 0.05 and a power of 0.95 (Faul 2009). In Table 1 we display the definitions of the constructs that make up the model.

The previously found model was obtained using maximum likelihood parameter estimation. Descriptive statistics, and Exploratory Factor Analysis were conducted using IBM SPSS version 23. The structural equation model was built-in with maximum likelihood estimation routines in IBM SPSS Amos 23.

The Kurtosis analysis found normality issues, with values higher that 2, in item 2 of the construct Perceived Usefulness, item 2 of the construct Perceived Ease of Use, item 1 of the construct Intention to Use, and in all items of the construct Behavioral Intention. However, these constructs passed in the Exploratory Factor Analysis. In Figure 1 we show the path diagram of the activity tracker acceptance model with the respective path coefficients.

4 METHODOLOGY

In this work, an Artificial Neural Network is applied to analyze, complement and verify the SEM approach and measure the effectiveness of the constructs that prevailed for the acceptance of activity trackers.

We used a Multilayer Perceptron (MLP) back propagation feed-forward (BPFF) method. The MLP is the most used and widespread ANN method (Liébana-Cabanillas 2017). The ANN contains three layers: the input layer, the hidden layer, and the output layer. In this work, the ANN is created using SPSS 24. The model obtained from SEM is divided into four ANN models with one output variable. Model A has the output as the construct Health Consciousness and has three inputs Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit. Model B has the output as the construct Perceived Usefulness and has five inputs Health Consciousness, Hedonic Motivation, Image, Self-Efficacy, Perceived Ease of Use. Model C has the output as the construct Perceived Ease of Use and has three inputs Image, Self-Efficacy, and Perceived Data Control. Model D has the output as the construct Behavioral Intention to Use (BIU)/ Acceptance and has three inputs Perceived Usefulness, Image, Perceived Ease of Use. The four models ANN are shown in Figure 2. The nodes (hidden neurons) are

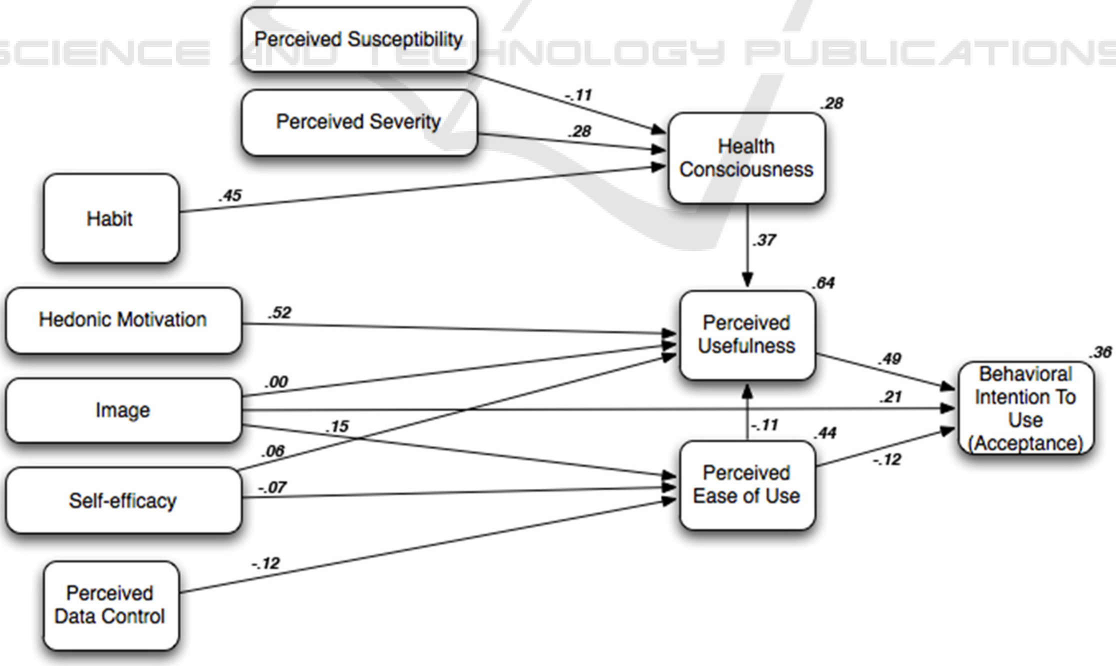

Figure 1: Path Diagram of the Activity Trackers Acceptance Model obtained via SEM with respective path coefficients (Sol 2016).

automatically generated by SPSS and the activation function used for both hidden and output layers was Sigmoid Function. We assigned 90 % of the samples to the training procedure and the remaining 10% were used for the testing procedure. To avoid the risk of over-fitting, we employed a ten-fold cross-validating process. The root mean square of errors (RMSE) was used to assure the predictive accuracy of the four ANNs. The next section analyzes the results of the ANN.

5 ARTIFICIAL NEURAL NETWORK RESULTS

An ANN is helpful in discovering both linear and non-linear relationships without requiring any distribution assumptions like linearity, normality, or homoscedasticity as in Structural Equation Modeling (Leong 2013). By doing so, an ANN can provide higher prediction accuracy (Tan 2014).

Table 2: RMSE values of ten artificial neural networks.

	Model A		**Model B**		**Model C**		**Model D**	
Input Neuron	Perceived Susceptibility to Disease (PSusD), Perceived Severity to Disease (PSevD), Habit		HC, Hedonic Motivation (HM), Image, Self-Efficacy, Perceived Ease of Use		Image (I), Self-Efficacy (SE), Perceived Data Control (PDC)		Perceived Usefulness, Image, Perceived Ease of Use	
Output Neuron	Health Consciousness (HC)		Perceived Usefulness (PU)		Perceived Ease of Use (PEoU)		Behavioral Intention to Use (BIU)/ Acceptance	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN 1	0.114	0.134	0.072	0.073	0.104	0.096	0.075	0.057
ANN 2	0.117	0.107	0.077	0.077	0.101	0.099	0.072	0.058
ANN 3	0.118	0.116	0.083	0.055	0.100	0.120	0.072	0.067
ANN 4	0.119	0.106	0.076	0.056	0.104	0.094	0.074	0.076
ANN 5	0.119	0.104	0.078	0.077	0.105	0.102	0.087	0.054
ANN 6	0.115	0.129	0.087	0.072	0.102	0.104	0.073	0.071
ANN 7	0.117	0.080	0.080	0.063	0.105	0.159	0.071	0.062
ANN 8	0.116	0.107	0.079	0.049	0.111	0.130	0.079	0.053
ANN 9	0.130	0.108	0.073	0.066	0.100	0.114	0.069	0.083
ANN 10	0.117	0.072	0.069	0.067	0.103	0.079	0.078	0.057
Mean RMSE	0.118	0.106	0.077	0.066	0.103	0.110	0.075	0.064
Standard Deviation	0.005	0.019	0.005	0.010	0.003	0.022	0.005	0.010

Table 3: Neural network sensitivity analysis.

	Model A			**Model B**					**Model C**			**Model D**		
Output	Health Consciousness (HC)			Perceived Usefulness (PU)					Perceived Ease of Use (PEoU)			Behavioral Intention to Use (BIU)/ Acceptance		
	Relative Importance			Relative Importance					Relative Importance			Relative Importance		
ANN	PSusD	PSevD	H	HC	HM	I	SE	PEoU	I	SE	PDC	PU	I	PEoU
1	0.324	0.240	0.437	0.040	0.671	0.065	0.113	0.112	0.301	0.429	0.270	0.730	0.218	0.052
2	0.326	0.256	0.417	0.070	0.603	0.050	0.123	0.154	0.352	0.356	0.291	0.731	0.166	0.103
3	0.298	0.238	0.464	0.237	0.514	0.025	0.097	0.127	0.358	0.306	0.336	0.690	0.174	0.136
4	0.350	0.161	0.488	0.062	0.603	0.035	0.071	0.229	0.411	0.331	0.258	0.651	0.213	0.136
5	0.298	0.248	0.454	0.091	0.584	0.023	0.052	0.250	0.311	0.423	0.266	0.360	0.188	0.453
6	0.379	0.251	0.370	0.168	0.367	0.033	0.170	0.264	0.324	0.419	0.257	0.694	0.149	0.157
7	0.315	0.217	0.467	0.060	0.567	0.096	0.117	0.161	0.335	0.376	0.289	0.754	0.193	0.053
8	0.311	0.252	0.437	0.039	0.601	0.041	0.029	0.289	0.237	0.503	0.260	0.579	0.174	0.247
9	0.223	0.106	0.671	0.023	0.651	0.018	0.102	0.205	0.304	0.299	0.397	0.723	0.195	0.082
10	0.255	0.275	0.470	0.049	0.604	0.054	0.146	0.146	0.380	0.353	0.267	0.525	0.405	0.070
Average	0.308	0.224	0.468	0.084	0.577	0.044	0.102	0.194	0.331	0.380	0.289	0.644	0.208	0.149
Average	68%	50%	99.8%	16.4%	100%	7.7%	18.9%	35.2%	83.3%	93.4%	72.5%	97.9%	33.3%	25.9%

As shown in Table 2, the RMSE values for the training data and the testing data are low, representing a higher predictive accuracy and better data fit.

In Table 3, we show the results of the sensitivity analysis that assessed the strength of the predictive power of each of the input neurons. In order to have the normalized importance of these neurons in percentage we divided the relative importance by the maximum importance.

Habit (H) was found to be the key determinant in predicting Health Consciousness (HC) followed by Perceived Susceptibility to Disease (PSusD) and lastly Perceived Severity to Disease (PSevD) in model A. In model B, the order of importance towards Perceived Usefulness (PU) in descending order is Hedonic Motivation (HM), followed by Perceived Ease of Use (PEoU) and Self-Efficacy (SE) and the least important were Health Consciousness (HC) and Image (I). For model C, Self-Efficacy (SE) is the most prominent predictor for Perceived Ease of Use (PEoU), followed by Image (I) and lastly Perceived Data Control (PDC). Finally, Perceived Usefulness (PU) constituted the most effective in term of predicting Behavioral Intention to Use (BIU)/ Acceptance, followed by Image (I) and lastly Perceived Ease of Use (PEoU).

All constructs in all ten ANNs for each model had at least one non-zero synaptic weight connected to the hidden neurons which validates the relevance of the constructs as variables as Figures 2 to 5 show.

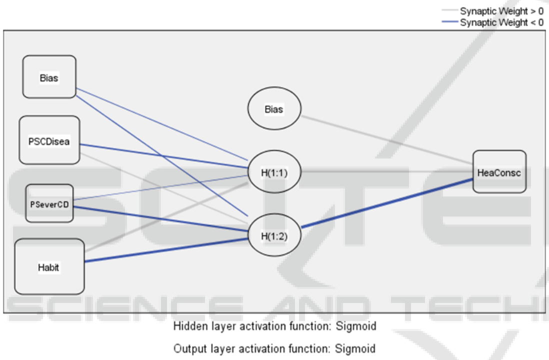

Figure 2: Neural Network between Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit with Health Consciousness.

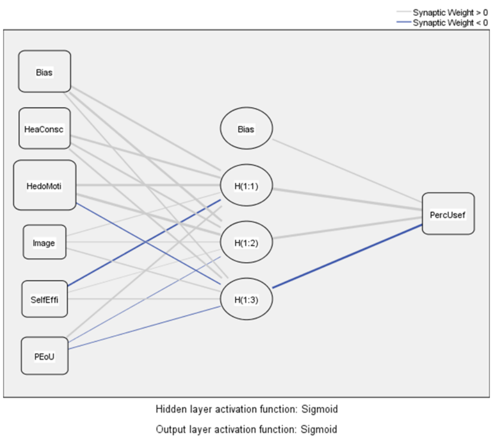

Figure 3: Artificial Neural Network between Health Consciousness, Hedonic Motivation, Image, Self-Efficacy, and Perceived Ease of Use with Perceived Usefulness.

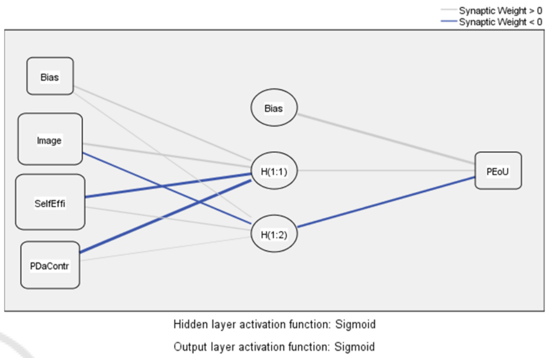

Figure 4: Artificial Neural Network between Image, Self-Efficacy, and Perceived Data Control with Perceived Ease of Use.

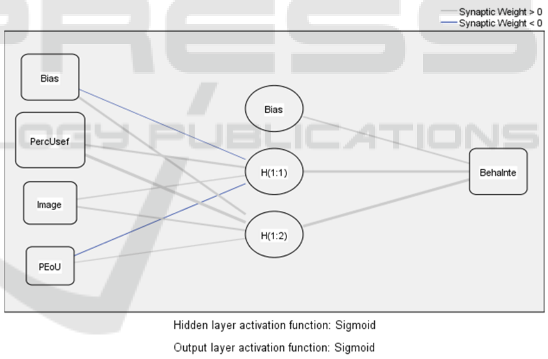

Figure 5: Artificial Neural Network between Perceived Usefulness, Image, and Perceived Ease of Use with Behavioral Intention to Use / Acceptance.

6 DISCUSSION

The Technology Acceptance Model (TAM) is based on many theories and grounded in many studies. In this work, the determinants of activity trackers use include TAM constructs and other constructs such as Image, Hedonic Motivation, Habit and Self-Efficacy. The results show that the research model studied in this work is acceptable. Next, we discuss the findings in more detail.

6.1 Relationships between Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit with Health Consciousness

As shown in Table 4, the construct Habit showed a significant relationship with Health Consciousness with a path coefficient of 0.451 obtained during the Structural Equation Modeling and has the highest normalized importance according to the Model A of the Artificial Neural Network analysis. While to our knowledge this relation is not found in the literature, the fact that both approaches ranked Habit in first place makes one ponder that a Health Conscious person has health habits.

The findings in this study also show that the construct Perceived Severity to Disease with 50% normalized importance is positively related to Health Consciousness. Looking at this result one might consider that if a person is Health Conscious, then that person should have a high degree of awareness of disease and related issues. Nevertheless, the construct Perceived Susceptibility of Disease showed mixed results within the two approaches.

6.2 Relationships between Health Consciousness, Hedonic Motivation, Image, Self-Efficacy, and Perceived Ease of Use with Perceived Usefulness

During to the SEM the path coefficient between Hedonic Motivation and Perceived Usefulness is 0.515, which is a significant positive correlation with the highest normalized importance given by model B of the ANN. For many studies, the perception of Hedonic Motivation has been viewed as egocentric (Elsden 2015) and an important issue for individual encouragement (Patel 2015), provide motivation (Lazar 2015), acknowledgement of effort (Kim 2016) or giving credit (Consolvo 2016).

The construct Perceived Ease of Use was promoted by the ANN when compared to SEM approach, however, the normalized importance was only 35.2%. This result is in line with previous work that demanded for reminders to be added to the devices (Shih 2015).

Table 4: Comparison between SEM and ANN analysis (output: Health Consciousness).

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Perceived Susceptibility to Disease	-0.114	3	68%	2	No
Perceived Severity of Disease	0.283	2	50%	3	No
Habit	0.451	1	99.8%	1	Yes

Table 5: Comparison between SEM and ANN analysis (output: Perceived Usefulness).

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Health Consciousness	0.372	2	16.4%	4	No
Hedonic Motivation	0.515	1	100%	1	Yes
Image	-0.013	3	7.7%	5	No
Self-Efficacy	-0.060	4	18.9%	3	No
Perceived Ease of Use	-0.110	5	35.2%	2	No

Table 6: Comparison between SEM and ANN analysis (output: Perceived Ease of Use).

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Image	0.146	1	83.3%	2	No
Self-Efficacy	-0.067	2	93.4%	1	No
Perceived Data Control	-0.115	3	72.5%	3	Yes

Table 7: Comparison between SEM and ANN analysis (output: Behavioral Intention to Use / Acceptance).

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Perceived Usefulness	0.492	1	97.9%	1	Yes
Image	0.207	2	33.3%	2	Yes
Perceived Ease of Use	-0.115	3	25.9%	3	Yes

Regarding the construct Sell-Efficacy, the weak influence is corroborated by model B of the ANN. To some extent, this result is partially contradicted by earlier studies that ask for a tailored efficacy evaluation (Klasnja 2011).

The ANN demoted Health Consciousness giving a low normalized importance that shows a weak influence in Perceived Usefulness.

Since the normalized importance for Image is less than 10%, we may conclude that the effect of Image in Perceived Usefulness is very small in comparison to Hedonic Motivation. This result seems to contradict past research (Harrison 2015) however one should keep in mind that here we are relating Image to Perceived Usefulness.

6.3 Relationships between Image, Self-Efficacy, and Perceived Data Control with Perceived Ease of Use

The construct Image showed a significant relationship with Perceived Ease of Use obtained during the SEM and even though it does not have the highest normalized importance it is a high value according to Model A of the Artificial Neural Networks analysis. This finding of this research is compatible with the findings of existing studies that state that Image is present as a component of social tracking (Rooksby 2014) and that it exists as both social competition and social comparison (Patel 2015).

The ANN came to empower Self-Efficacy as a relevant construct in its relationship with Perceived Ease of Use opposing a path coefficient of -0.067 that SEM found. The ANN result corroborates with previous research that demanded for good inter-device reliability (Dontje 2015). Nevertheless, one has to take into consideration that an ANN measure with high predictive accuracy has both a linear and non-linear relationship among variables.

During the SEM the path coefficient between Perceived Data Control and Perceived Ease of Use is -0.115, which is in accordance with the lowest normalized importance ranking but a high value of 72.5% given by model B of the ANN. To some extent, this result is partially supported by earlier studies which emphasize that the personal information collected by self-tracking can be highly sensitive (Lupton 2017).

One should note that these results are influenced by the fact that in Model C the Average RMSE value of the testing is higher than the Average RMSE for training.

6.4 Relationships between Perceived Usefulness, Image, and Perceived Ease of Use with Behavioral Intention to Use / Acceptance

Perceived Usefulness with the highest normalized importance (97.9%) given by Model D of the Artificial Neural Networks approach was found in the Structural Equation Modeling to have a significant relationship in predicting Behavioral Intention to Use / Acceptance. This finding supports prior research, as the suggestions for the designers of activity trackers to facilitate micro-plans (Gouveia 2018), add a wide variety of adjustable goals (Clawson 2015), and have adjustable tracking goals (Epstein 2015).

The construct Image shows a significant influence in predicting Acceptance in both approaches. The finding of this research is compatible with the findings of existing studies as the influence of activity trackers on lifestyle (Consolvo 2006) and the importance of aesthetics and form (Harrison 2015).

Concerning the SEM, the path coefficient from Perceived Ease of use to Acceptance is -0.115, nevertheless the normalized importance given by model D of the ANN was 25.9%. This result is in line with previous work which points out that people are using activity trackers in a rather limited manner (Didziokaite 2017).

7 CONCLUSIONS

This research aimed to study beliefs and behavioral variables that impact the acceptance and use of activity trackers. It looked to an established technology acceptance model dedicated to activity trackers that was obtained via Structural Equation

Modeling. These constructs of the model are used in an Artificial Neural Network as the input units of four ANN. The Root Mean Square of Errors with the highest value of 0.118 indicates that the ANN method achieves high prediction accuracy.

The constructs of the model were divided in four ANNs. Model A had as inputs the constructs: Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit, while the output was the construct Health Consciousness. Model B had as inputs Hedonic Motivation, Image, Self-Efficacy, Health Consciousness, and Perceived Ease of Use, while the output was Perceived Usefulness. Model C had as inputs Image, Self-Efficacy, and Perceived Data Control, while the output was Perceived Ease of Use. Model D had as inputs Perceived Usefulness, Image, and Perceived Ease of Use, while the output was Behavioral Intention to Use (BIU) / Acceptance.

When comparing the results of SEM and ANN analysis, the main disparity lies in the strength of the effect of the construct Self-Efficacy with regards to Perceived Ease of Use. The ANN analysis increases the importance of Self-Efficacy in the Perceived Ease of Use of activity trackers. Even though with a lower impact, the ANN also increases the importance of Perceived Susceptibility of Disease when related to Health Consciousness. On the other hand, it also decreases, with a not so high impact the importance of Health Consciousness in Perceived Usefulness.

The ANN were able to emphasize the strengths and weaknesses of the model obtained via SEM. Furthermore, this research shows the relevance of the two-stage approach integrating SEM and ANN techniques to fine-tune this technology acceptance models and to present valuable information that can be utilized to increase the acceptance and usability of activity trackers as well as to enhance device designs. This research is restricted in the sense that it would be interesting to include control variables such as age and gender and compare the results. Also, it used a cross-sectional approach to obtain the responses of the activity trackers users at one point in time. Hence, in a future study one may repeat the questionnaire to the same users in a longitudinal approach to examine the temporal effects.

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