Dear Dr. López-Ibáñez,

Thank you for giving us opportunity to submit a revised draft of our manuscript entitled, “Real-Time Detection of Internet Addiction Using Reinforcement Learning System” (wksp202s1) to *GECCO 2019*. We truly appreciate the time and effort you and the reviewer providing comments to our study. We have tried our best to complete all of the revisions according to the reviewer’s comments. To facilitate your review of our revisions, the following is a point-by-point response and related changes in our revised manuscript to the comments. We hope that our responses satisfy address all the issues the reviewer have noted. I’m more than happy to make any further changes that will improve our study.

Thank you once again for your time. I look forward to hearing from you.

Sincerely,
Tzu-Chien Hsiao, PhD
Associate Professor,
Department of Computer Science
Institute of Biomedical Engineering
College of Computer Science, National Chiao Tung University
Hsinchu, Taiwan
labview@cs.nctu.edu.tw

COMMENTS FOR THE AUTHOR and RESPONSES

Reviewer 1

1. **Why do you not use standard pinyin for your names? In this way it won't be pronounced correctly when we meet! :) is Hsiao pronounced Xiao?**

   Response: We appreciate the time and attention you gave to our study. Hsiao is used Wade Giles to pronounce. Wade Giles is a romanization system for Mandarin Chinese. Xiao is used Hanyu Pinyin to pronounce. The pronouncing of Hsiao and pronouncing of Xiao are the same.

2. **Please give a spellchecker pass to your document.**

   Response: Thank you for providing the suggestion. This revised manuscript have edited by native English-speaking. (Appendix 1)

3. **I'm surprised you haven't cited any of Butz or Bernardo's work on data mining with XCS, as it a building block of the papers you've cited.**

   Response: Many thanks to you for the comment. We will refer to these papers for the further study.

Reviewer 2

1. **The paper proposes a RL system to detect internet addition using an XCSR.**

   Response: We appreciate the time and attention you gave to our study.

2. **The authors mention a reward that changes depending on right and wrong answers: "The reward (p) setup for right and wrong answers are 1,000 and 0, respectively." I could not find what would be a correct and wrong answer. And provided that correct/wrong answers are given, why not use a supervised learning?**

   Response: Thank you for providing the comment. We have modified the description of reward. The reward (p) setup for HIA with IGD and LIA without IGD are 1,000 and 0, respectively. We expect to predict and alert patients to the severity of Internet addiction by monitoring their physiological signals in real time. However, the questionnaire score of the patient cannot be obtained in real time.

The patient is still required to fill out the questionnaire at a fixed time. Therefore, we choose to adopt RL.

Change in revised manuscript (p. 6, line 36-37 in 4.2 The Analysis Procedure; p. 7, line 6-7 in 5 Result and Discussion):
The reward (*p*) setup for HIA with IGD and LIA without IGD are 1,000 and 0, respectively.
we observed rules with HIA with IGD, p = 1000 in [P]

3. **It is also puzzling that the method finds so easily the solution to the problem. Either the problem is too easy (which is a little bit surprising given it is a reinforcement learning approach to a time dependent real problem) or there is something wrong.**

   Response: Many thanks to you for the comment. We distinguish LIA and HIA based on the cut-off point of CIAS questionnaire. XCSR can accurately distinguish between LIA and HIA easily based on respiratory signal which means that there is an obvious difference between the LIA and HIA. However, we don't know which respiratory index is the most important indicator. One of the aims of this study is to extract important respiratory indexes by XCSR.

4. **English has problems in some parts of the text. For example: "Since of one participant missing the respiratory signal,"**

   Response: Thank you for providing the suggestion. This revised manuscript have edited by native English-speaking. (Appendix 1)

5. **It would be interesting if the decomposition of the signals were discovered automatically.**

   Response: We appreciate the encouraging comment.

Reviewer 3

The authors report an intriguing application of XCSR to the validation of an existing instrument to determine the degree of addiction to the internet, based on physiologic signals (respiratory wall movement). While the application is certainly interesting, there are a number of issues that raise concern about the study.

1. **It is not actually clear that signal detection took place in real-time- that is, that XCSR treated each input signal after decomposition, as it occurred. Instead, it appears that the physiologic data were obtained and analyzed en bloc.**

   Response: We appreciate the time and attention you gave to our study. In this study, the signals detection did not take place in real-time. The aim of this study is to extract important respiratory indexes by XCSR. We would like to measure physiological signals in real-time, and we combine the ensemble empirical mode decomposition method with XCSR for real-time physiological signal processing in the near future.

2. **Algorithm 1 is not clearly described.**

   Response: Thank you for providing the suggestion. We have modified the algorithm 1.

   Change in revised manuscript (p. 5, in 4.1 The Experimental Procedure):

Algorithm 1 Analysis procedure of the EMD

$x_1(t) \leftarrow x(t)$
$s(t) \leftarrow x(t)$
for $i = 1$ to N **do**
\\ sifting process
  while (SD($s(t)$) ≥ 0.02) do
    $p_u \leftarrow$ TheLocalMaxima($s(t)$)
    $p_l \leftarrow$ TheLocalMinima($s(t)$)
    $u(t) \leftarrow$InterpolatingTheLocalMaxima(p_u)
    $l(t) \leftarrow$InterpolatingTheLocalMinima(p_l)
    $m(t) \leftarrow (u(t) + l(t))/2$
    $s(t) \leftarrow s(t) - m(t)$
  end
  $IMF_i(t) \leftarrow s(t)$
  $x_{i+1}(t) \leftarrow x_i(t) - IMF_i(t)$
  $s(t) \leftarrow x(t) - s(t)$
end

SD($s(t)$): standard deviation of $s(t)$

3. **The sample size is very small.**

   Response: We thank the reviewer for this important comment. We agree that it is a potential limitation that the sample size is very small. Further study must recruit more participants.

4. **Figures 3 and 4 are very difficult to understand. Specifically, what is accuracy based on, and what is meant by "interaction number" is not at all clear.**

   Response: Thank you for providing the comment. In this study, participants will fill out a questionnaire before the experiment. There is a standard cut-off point of CIAS questionnaire to help us determine whether the participant is LIA or HIA. “Iteration number” refers to the number of training instances gave to the XCSR. Whenever a training instance is given to the XCSR, XCSR will use the exploration (random guess or learning) or exploitation (best result so far) to predict in turn. All accuracy is calculated by the moving average per 50 exploitations for XCSR. In manuscript, Figure 4 and Figure 5 display the classification accuracy. In Figure 4, XCSR predicts whether the subject is HIA or LIA based on the CIAS data. Accuracy was calculated by comparing the prediction of XCSR with the 63/64 cut-off score between LIA and HIA in the CIAS total score. In Figure 5**,** XCSR predicts whether the subject is HIA or LIA based on respiratory instantaneous frequency signals. The calculation is the same as in Figure 4. We have modified the Figure 4 and Figure 5.

   Change in revised manuscript (p. 6 and p. 7, in 5 Result and Discussion):

   All accuracy is calculated by the moving average per 50 exploitations for XCSR. Figs. 4 and 5 illustrate the classification accuracy (%) of the average of 30 replications for XCSR with iteration number of 1,950 by using CIAS data and IF values, respectively.

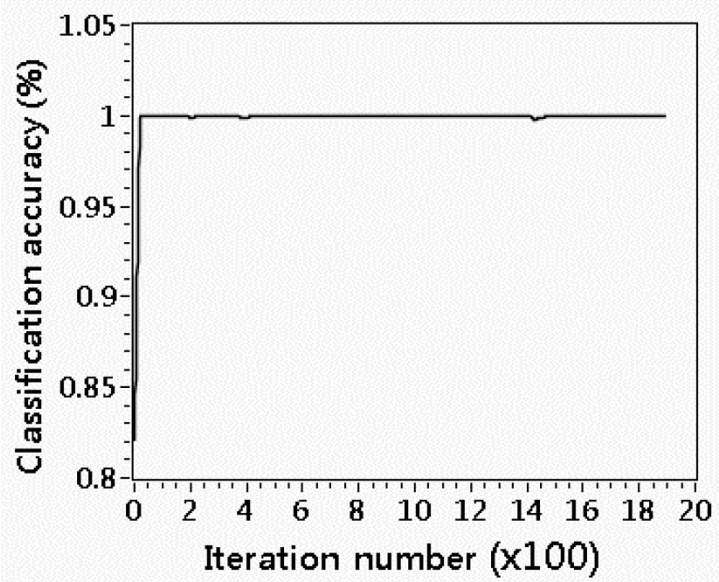

Figure 4: The classification accuracy of 30 replications of XCSR for CIAS data.

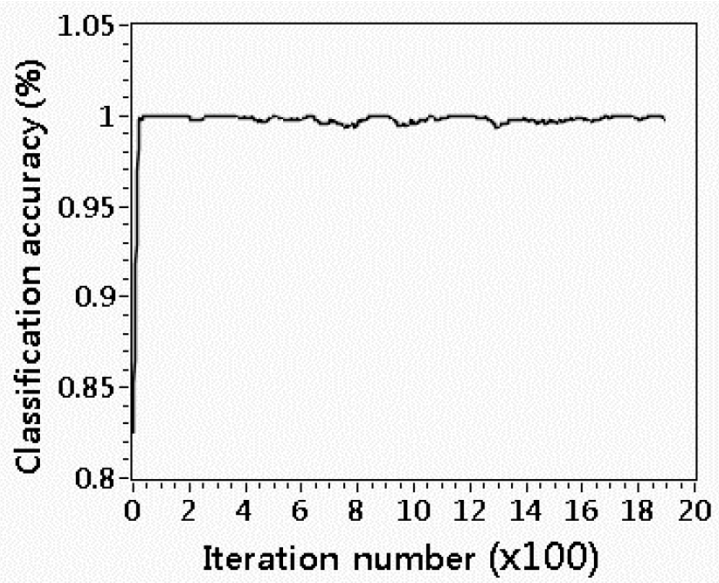

Figure 5: The classification accuracy of 30 replications of XCSR for respiratory instantaneous frequency signals.

5. **Tables 2 and 3: Pn (e.g., "P1" or "P2") is not defined- what do the numbers mean?**

Response: Thank you so much for catching the unclear definition. We have modified the Tables 2 and 3.

Change in revised manuscript (p. 7, in 5 Result and Discussion):

Table 2: The # probability for CIAS and IF data. (P*i*: IF component during positive emotional stimuli; N*i*: IF component during negative emotional stimuli; *i*: 1~8)

CIAS data (# probability, %)							
S_C	11th	14th	19th	20th	22nd		
	41.7	25.0	33.3	58.3	33.3		
S_W	2nd	4th	5th	10th	16th		
	41.7	25.0	50.0	16.7	25.0		
S_T	3rd	6th	9th	24th			
	50.0	41.7	66.7	58.3			
P_{IH}	7th	12th	13th	15th	17th	18th	21st
	58.3	33.3	8.3	25.0	41.7	33.3	16.7
P_{TM}	1st	8th	23rd	25th	26th		
	41.7	33.3	33.3	41.7	50.0		
IF data (# probability, %)							
Positive stimuli	P1	P2	P3	P4	P5	P6	P7	P8
	46.2	43.6	51.3	43.6	53.8	41.0	66.7	38.5
Negative stimuli	N1	N2	N3	N4	N5	N6	N7	N8
	30.8	51.3	51.3	41.0	69.2	46.2	46.2	51.3

Table 3: The AUC of ROC with 95% confidence interval for IF_P and IF_N predicting HIA with IGD and LIA without IGD. (P*i*: IF component during positive emotional stimuli; N*i*: IF component during negative emotional stimuli; *i*: 1~8)

			95% Confidence Interval	
IF	AUC	p-value	lower bound	upper bound
P1	0.52	0.82	0.33	0.71
P2	0.52	0.80	0.33	0.71
P3	0.58	0.41	0.39	0.76
P4	0.53	0.74	0.35	0.72
P5	0.56	0.55	0.37	0.74
P6	0.49	0.96	0.31	0.68
P7	0.63	0.17	0.45	0.81
P8	0.50	0.98	0.31	0.68
N1	0.54	0.63	0.36	0.73
N2	0.70	0.03	0.51	0.89
N3	0.67	0.07	0.48	0.86
N4	0.64	0.14	0.45	0.82
N5	0.52	0.87	0.32	0.71
N6	0.67	0.07	0.50	0.84
N7	0.58	0.41	0.39	0.76
N8	0.52	0.82	0.33	0.71

6. **Overall, the writing is very confusing, with a very large number of grammatical errors. The authors would benefit from a native English-speaking editor.**

Response: We are grateful for this comment. This manuscript have edited by native English-speaking. (Appendix 1)

Reviewer 4

The topic of Internet Addiction (and indeed smartphone addiction) is of great relevance in modern times; it is a new and growing concern to all economies and this paper addresses an extension to methods using traditional questionnaires and proposes a step forward by understanding the risk of IA and tackling it in real-time. In this analysis it makes sense to incorporate physiological measurements taken while the subject is engaged in the Internet activity (experience sampling method) because addicts do not typically accept their dependency and describe honestly their symptoms whether it is 6 months after (narrative survey) or shortly after (activity survey).

XCSR is an attractive choice to classify low and high-risk IA and results showing that it learns to classify with high accuracy fairly quickly. In addition –and particularly interesting- is that P# probabilities (although in this paper the variance is not significantly large) can help in the design of better ESM questionnaires as interrelationships and relevance of the different factors can be easily extracted and analysed due to the native rule-based structure of XCS. Here the explanatory power adds value compared to other methodologies such as neural networks/deep learning where results could show accurate classifications, but would unlikely provide feedback with regards to the decisions made and which factors are more relevant than others.

In future work, it would be useful to compare/validate against simple XCS by discretizing the input data, and to extend the analysis with varying parameter settings (i.e. N, P#..) to assess the robustness of the approach.

The organization, sentence structure and mechanics of your paper are good. However the spelling can significantly improve to increase the clarity of this paper and the message.

Response: We really appreciate the time and attention you gave to our study and the encouraging comment. This manuscript have edited by native English-speaking. We hope the modified version is suitable for readers.

Appendix 1

CERTIFICATE OF ENGLISH EDITING

This document certifies that the paper listed below has been edited to ensure that the language is clear and free of errors. The edit was performed by professional editors at Editage, a division of Cactus Communications.The intent of the author's message was not altered in any way during the editing process. The quality of the edit has been guaranteed, with the assumption that our suggested changes have been accepted and have not been further altered without the knowledge of our editors.

TITLE OF THE PAPER

Real-Time Detection of Internet Addiction Using Reinforcement Learning System

AUTHORS

Hong-Ming Ji, Liang-Yu Chen, and Tzu-Chien Hsiao

JOB CODE

WKKFQ_1

Signature

Vikas Narang

Vikas Narang,
Senior Vice President,
Operations-Author Services, Editage

Date of Issue
April 24, 2019

Editage, a brand of Cactus Communications, offers professional English language editing and publication support services to authors engaged in over 500 areas of research. Through its community of experienced editors, which includes doctors, engineers, published scientists, and researchers with peer review experience, Editage has successfully helped authors get published in internationally reputed journals. Authors who work with Editage are guaranteed excellent language quality and timely delivery.

Contact Editage

Worldwide	Japan	Korea	China	Brazil	Taiwan
request@editage.com	submissions@editage.com	submit-korea@editage.com	fabiao@editage.cn	contato@editage.com	submitjobs@editage.com
+1 877-334-8243	+81 03-6868-3348	1544-9241	400-005-6055	0800-892-20-97	02 2657 0306
www.editage.com	www.editage.jp	www.editage.co.kr	www.editage.cn	www.editage.com.br	www.editage.com.tw