Communications-based early detection of gambling-related problems in online gambling

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Early detection items and responsible gambling features for online gambling (Häfeli, Lischer, Schwarz 2011)

This model was developed in an explorative study with the objective to generate guidelines which permit the development, implementation and validation of objective protocols for early detection of gambling issues based on customer communication behaviour.
# Early Detection

<table>
<thead>
<tr>
<th></th>
<th>Land-based Gambling</th>
<th>Internet Gambling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation of gambling behaviour</td>
<td>Typically not observable in an objective way (comprehensive usage of smart-cards may offer first approaches)</td>
<td>Stored and readily available for longitudinal analysis</td>
</tr>
<tr>
<td>Observation of social interaction behaviour</td>
<td>Available (quality of observations depends on standardisation of protocols and training of staff)</td>
<td>?</td>
</tr>
</tbody>
</table>

Date: 17/09/2014
Early Detection

Anonymity and the lack of social interaction are typically mentioned as inherent risks of Internet gambling.

Online gambling operators communicate with their customers as well; typically via email or telephone - amounting up to 150,000 customer contacts per month per operator.

Assumption that these qualitative indicators could be used for early detection of problem gamblers.
Overview First Study

**Literature Review:**
Social behaviour as a predictor of gambling-related problems in land-based gambling

**Semi-structured interviews:**
Senior customer-services staff (EGBA members)

**Prospective Analysis:**
Email Customer Communication
150 Self-excluders
150 Controls
→ 1008 Emails
→ 2 independent Raters
Study part I: Method

Findings
- Customer **communication does contain indicators** for future gambling problems
- This **indicators cannot be** solely based **on discrete key words**.
Hypothetized risk-indicators

**Content-based Indicators:**
- Chasing losses
- Financial problems
- Loss of control
- Social situation
- Criminal acts
- Health issues
- Results of games/bets
- Higher Limits
- Lower limits
- Partial blocking
- Account reopening
- Technical problems

**Tonality-based Indicators:**
- Complaining
- Threatening

**Other Indicators:**
- Frequency of customer contacts
- Immediate repeats
Customer Communication

“Tonight I placed a live-bet at 21.20 pm. I bet there won’t be another yellow card until the end of the match. By that time M already had a yellow card and after that there wasn’t another card given. So my bet must be correct.”

“I ask you to immediately remove my limitation to 100 EURO, because else I will go public with it and this will certainly not be good PR for your brand.”
Study part II: Method

Sample
N = 150 self-excluders
N = 150 controls

Data set contained 1008 e-mails
All e-mail correspondence since registration from both groups

- 163 e-mails (16.2%) did not contain any indicators
- 747 e-mails (74.1%) contained one indicator
- 98 e-mails (9.7%) contained two indicators
## Results: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Controls</th>
<th>Self-Excluders</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td>91.3 %</td>
<td>94.6 %</td>
<td>0.366</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>32.9</td>
<td>31.5</td>
<td>0.235</td>
</tr>
<tr>
<td><strong>Communication available</strong></td>
<td>39.3 %</td>
<td>52.7 %</td>
<td><strong>0.028</strong></td>
</tr>
<tr>
<td>(at least one E-Mail)</td>
<td>(N=59)</td>
<td>(N=79)</td>
<td></td>
</tr>
<tr>
<td><strong>Nr. of Mails</strong></td>
<td>3.3</td>
<td>8.3</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>
## Results: Univariate Analysis

<table>
<thead>
<tr>
<th></th>
<th>Controls</th>
<th></th>
<th>Self-Excluders</th>
<th></th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td></td>
</tr>
<tr>
<td>Results of game</td>
<td>11.0</td>
<td>20.5</td>
<td>16.9</td>
<td>22.4</td>
<td>ns</td>
</tr>
<tr>
<td>Increase limits</td>
<td>0.3</td>
<td>2.2</td>
<td>1.3</td>
<td>6.3</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td><strong>Account reopening</strong></td>
<td>2.7</td>
<td>14.5</td>
<td>8.6</td>
<td>19.3</td>
<td><strong>&lt; 0.001</strong></td>
</tr>
<tr>
<td><strong>Account administration</strong></td>
<td>23.3</td>
<td>35.4</td>
<td>20.0</td>
<td>28.5</td>
<td><strong>&lt; 0.05</strong></td>
</tr>
<tr>
<td><strong>Financial transaction</strong></td>
<td>30.9</td>
<td>38.7</td>
<td>35.1</td>
<td>31.8</td>
<td><strong>&lt; 0.05</strong></td>
</tr>
<tr>
<td>Request for bonus</td>
<td>7.9</td>
<td>20.1</td>
<td>5.0</td>
<td>14.8</td>
<td><strong>&lt; 0.05</strong></td>
</tr>
</tbody>
</table>
## Results: Univariate Analysis

<table>
<thead>
<tr>
<th></th>
<th>Controls</th>
<th>Self-excluders</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neutral</strong></td>
<td>61.3</td>
<td>44.5</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td><strong>Complaining</strong></td>
<td>35.0</td>
<td>40.0</td>
<td>ns</td>
</tr>
<tr>
<td><strong>Threatening</strong></td>
<td><strong>3.8</strong></td>
<td><strong>12.9</strong></td>
<td>&lt;0.05</td>
</tr>
<tr>
<td><strong>Other</strong></td>
<td>0</td>
<td>2.6</td>
<td>ns</td>
</tr>
</tbody>
</table>
Results: Multivariate Analysis

- Optimal Prediction rate was achieved by a logistic model
  ⇒ No comparable DSM-5 criteria found!

<table>
<thead>
<tr>
<th>Indicator</th>
<th>odds-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>1.034</td>
<td>0.003</td>
</tr>
<tr>
<td>Account reopening</td>
<td>1.029</td>
<td>0.024</td>
</tr>
<tr>
<td>Account administration</td>
<td>1.012</td>
<td>0.057</td>
</tr>
<tr>
<td>Financial transaction</td>
<td>1.012</td>
<td>0.094</td>
</tr>
<tr>
<td>Threatening Tonality</td>
<td>2.596</td>
<td>0.095</td>
</tr>
</tbody>
</table>
Practical Impact and Shortcomings

Customer communication does indeed contain information about whether or not gamblers are at-risk of developing gambling related problems.

Problems manifest primarily indirectly over high emotional involvement & distress, heavy complaining and failure to cope with arising problems.

Communication behaviour should not be the sole source of information, but instead be combined with other objective methods of behavioural analysis.
Practical Impact and Shortcomings

Analysis of customer email correspondence is in practical use as a method of behavioural tracking with several European online gambling operators.
Practical Impact and Shortcomings

Analysis of customer correspondence is in practical use as a method of behavioral tracking with several European online gambling operators. In practical application it appears especially useful, where latent indicators can be used to clarify an ambiguous situation.

Problems
- Rating of customer communication requires a considerable amount of training to conduct the analysis in a standardized manner
- Insufficient as solitary from the analysis – relevant subgroup does not communicate at all
- Practical processes for the escalation of RG cases lead to backlogs which might be undesirably long.
Study part III: Automated text analysis

Linguistic Inquiry and Word Count (LIWC) (Tausczik & Pennebaker 2010)

- Not necessarily about reading and understanding a text like a human rater would
- Style words are largely unaffected by the content of the text of the text and can be counted without understanding its meaning
- However automated text analysis can be affected by a number of mistakes

➔“Mad” will load on the anger scale
➔“I’m mad about her” however has absolutely nothing to do with anger.
LIWC Scale Selection

**Affect**
- Positive emotion  
  *nice, sweet, ...*
- Anxiety  
  *worried, nervous, ...*
- Anger  
  *hate, annoyed, ...*
- Sadness  
  *grief, sad, ...*

**Cognition**
- Insight  
  *think, consider, ...*
- Causation  
  *because, hence, ...*
- Discrepancy  
  *should, would, ...*
- Tentative  
  *maybe, perhaps, ...*
- Certainty  
  *always, never, ...*
- Inhibition

**Topic areas related to gambling consequences**
- Money  
  *cash, owe, ...*
- Time  
  *end, until, ...*
- Work  
  *job, majors, ...*
- Family  
  *wife, husband, ...*
Hypotheses 1: Automated text analyses to replace human raters

Replacing human assessors by automated text analysis?

Criterion: self-exclusion
Predictors: text analysis only

Validity: 0.42
Classification Rate: 76.4%

<table>
<thead>
<tr>
<th>Indicator</th>
<th>B</th>
<th>odds-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>0.256</td>
<td>1.291</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Instable prediction, hinging on one predictor. Not applicable in practice
Hypotheses 2: Combined Prediction

Criterion: self-exclusion
Predictors: Rater analysis and text analysis

Validity: 0.69
Classification Rate: 79.1%

<table>
<thead>
<tr>
<th>Indicator</th>
<th>B</th>
<th>odds-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rater Prediction</td>
<td>4.853</td>
<td>128.1</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Anger</td>
<td>209</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>Time</td>
<td>0.141</td>
<td>1.151</td>
<td>0.080</td>
</tr>
<tr>
<td>Causation</td>
<td>-0.397</td>
<td>0.673</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Considerable incremental validity on top of human rating. **Combining both factors would noticeably improve the prediction.**
Hypotheses 3:
Automated Pre-Calculation

Criterion: self-exclusion
Predictors: Relative Frequency and text analysis

Validity: 0.63
Classification Rate: 78.3%

<table>
<thead>
<tr>
<th>Indicator</th>
<th>B</th>
<th>odds-ratio</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Frequency</td>
<td>0.027</td>
<td>1.027</td>
<td>0.023</td>
</tr>
<tr>
<td>Anger</td>
<td>208</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>Time</td>
<td>0.179</td>
<td>1.196</td>
<td>0.020</td>
</tr>
<tr>
<td>Causation</td>
<td>-0.336</td>
<td>0.714</td>
<td>0.031</td>
</tr>
</tbody>
</table>

Slightly weaker than combined prediction but relatively close. Can serve as a screening if balanced in a way that the screening would not miss any self-excluders the full prediction would capture.
Automated text analysis

- Inbox
  - Automatic Rating
    - Customer Service Inbox
    - Responsible Gaming Team Inbox
  - Customer Service Handling
  - Combined Rating
    - Responsible Gaming Team Handling
Discussion

The combination of automated and human assessment is able to streamline customer services processes.

- Increase the validity of the prediction
- Reduce the response delay for a given customer services backlog

The tested automated text analysis methods were unable to replace human assessors.

➡ Processes for the detection of potential risk-behaviour, based on customer correspondence, require a high degree of training.
Limitation

- All effects observed could be specific to the sample.

- The choice to use LIWC as a text analysis tool is arbitrary and primarily based on the extensive validation and the existence of equivalent dictionaries in German and English.
**Acknowledgments**

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I also would like to thank my colleagues Jörg Häfeli, Jürg Schwarz and Joachim Häusler, who conducted this research with me.
Thank you very much for your attention.