UNIVERSITÉ DE MONCTON
EDMUNDSTON MONCTON SHIPPAGAN

Research report

MOODIE PILOT

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Executive summary

- The results of the pilot study suggest that the Moodie app is likely working as intended
    - Strongly expected results are indeed found
    - Moods and activities are found to be more associated with well-being and related constructs than with academic motivation
- We faced significant challenges with GIMME analyses
    - GIMME analyses reject any participants for whom a variable is held constant
    - Most participants held at least one variable constant
- The non-directed psychometric network nevertheless shows some informative patterns
    - Sleep, family, home, relaxation and positivity play more central roles in the network
- It may be advantageous to explore alternative measurement strategies for daily activities
    - Introducing more variance in the measurements could benefit statistical explorations between variables
    - One potential strategy would be to focus on fewer “key activities” and assess them on a scale rather than through a yes-no decision

Report aims and scope

Amongst other functionalities, the Feeling Moodie App provides users with the opportunity to keep track of their daily activities and mood. Recently, the way in which moods are captured by the app was modified to be better aligned with the way moods are typically measured in the scientific literature. The aims of this report are to present the results of a pilot project conducted at the Université de Moncton in the wake of these modifications. Opportunities for further development are highlighted.

Pilot method and results

Université de Moncton students were recruited through the university's SONA platform. This platform allows students to participate in scientific studies in exchange for extra credit. To obtain full credits, participants had to respond to a preliminary questionnaire ("time 1"), complete 48 daily mood check-ins, and respond to a final questionnaire ("time 2"). Time 1 and time 2 questionnaires included the same instruments (see below). Data collection occurred over the period of October 4th to November 30th, 2021. We included a number of constructs in these questionnaires to permit a fairly wide-ranging exploration of patterns surrounding Moodie use. All questionnaires are free to use for research purposes.

Instruments

Academic motivation scale[1]
This questionnaire assesses motivation for making efforts in one's program of study. It identifies various types of motivation, that vary in their quality. Higher quality motivations are typically associated to more positive outcomes than lesser quality motivation. In order of increasing quality, we find:

- External extrinsic motivation (being motivated by external rewards or punishment, such as monetary earning potential).
- Introjected extrinsic motivation (being motivated by internal rewards or punishment, such as feelings of pride or shame).
- Identified extrinsic motivation (being motivated for something because it is associated with an important or valued goal).
- Intrinsic motivation for stimulation, accomplishment and knowledge (being motivated by the inherent pleasures of the stimulation, accomplishment and knowledge potential one can find in their programs of study).

Warwick-Edinburgh Mental Well-being Scale[2]
This questionnaire assesses general well-being. It includes questions about feelings of optimism, interests, energy, and connection with others.

Depression Anxiety Stress Scale ("DASS-21")[3]
This scale assesses the stated mental-health related variables over a week (i.e., participants are invited to rate their stress, depression, and anxiety feelings over the last week).

- Depression questions involve feelings of meaningless and lack of enthusiasm.
- Stress questions involve tendencies to over-react and having trouble relaxing.
- Anxiety questions involve awareness of bodily discomforts (e.g., trouble breathing, trembling), and feelings of panic and unexplained fear.

Scale of Positive and Negative Experience ("SPANE")[4]
This scale assesses the frequency of positive (e.g., feeling "good", "pleasant") and negative affect ("sad", "afraid") over a week. Items are combined into a single score, representing affect positivity.

Participants

Overall, 1504 mood points by a total of 33 participants were collected, although it should be noted that some participants participated more than once per day on days they participated. There were 40 responses to the time 1 questionnaire, and 27 responses to the time 2 questionnaire that could be matched to time 1 participants.

Statistical analyses
As this pilot had an exploratory focus, we selected a few analytical strategies that could permit an overview of general tendencies in the results. First, we explored correlation patterns (linear associations between constructs such that when one rises in quantity, so does another) between the psychological variables cited above and frequency of Moodie use. We continued with correlations between the psychological variables and participants' average moods and activities over the collection period. Finally, as a proof-of-concept, we explored the psychometric networks found across mood points.

Correlations with frequency of Moodie use
As seen in table 1 of the appendix, 3 correlations were statistically significant. People who reported more stress at time 1 used Moodie less. On the other hand, people who used Moodie more were less externally motivated and less anxious at time 2. The correlation with stress at time 1 is likely self-explanatory: stressed people probably had less psychological resources to spend on mood check-ins. The correlation with external motivation is more surprising but still logically plausible (people who are "in it for the money' may find less value in participating in a scientific study over a long term). The negative correlation is likely the most interesting one: there is a potential for a causal effect here where Moodie use decreases anxiety. Of course, all correlations discussed must be interpreted in light of the study limitations exposed further in the text.

Correlations with average moods and activities
Results relevant to this section can be found in tables 2 to 4. Table 2 concerns correlations between extrinsic motivations and average moods and activities reported by participants. While we do see examples of potential spurious correlations here (correlations with weather and with the category "Other", for example), we also find some correlations that may be meaningful. People who reported more "active" moods on average also reported more external extrinsic motivation at time 2, suggesting a potential pattern where people who are at university mainly for the potential monetary fall out have more stress.

Table 3 concerns correlations between intrinsic motivations and average moods and activities. Few correlations reach statistical significance. People who relaxed more report lower motivation for stimulation at time 2. People who reported more active moods report higher motivation for accomplishment at time 2. It is rather difficult to find an overall meaningful pattern in this table. It is possible that day to day activities and states do not matter much for intrinsic motivation, and vice versa.

Table 4 presents the correlations with well-being and related constructs. Here we find a lot of statistically significant correlations that "make sense". People who felt more depressed at time 1 reported fewer positive moods on average. People who reported fewer positive moods on average reported being more depressed at time 2. Interestingly, we find generally stronger effects between positive moods and “time 2” variable than between positive moods and time 1 variables. This might suggest that mood positivity is better characterised as a cause than an effect with regards to these variables.

Psychometric networks

Two psychometric network approaches were attempted. The first approach is called “GIMME”, which stands for Group Iterative Multiple Model Estimation(5). The GIMME algorithm uses intensive (at least 60 repeated measures are recommended, with general agreement that results are quite stable with 100 measurement points) longitudinal data from fixed intervals (the time between measurements is assumed to be the same – in our case “daily” is stable enough, even if participants don’t answer exactly at the same time every day) to produce group (all participants in the analysis), subgroup (when there are at least 20 participants, the GIMME algorithm can find subsets of participants that show similar patterns) and individual level psychometric networks for as few 3 participants (upper range is limited only by computing power). GIMME has been shown to be reliable with up to 20 variables. In effect, longitudinal psychometric networks provide a map of the sequence in which variables occur. For example, if there were virtuous and vicious cycles surrounding daily activities and mood positivity, GIMME would be able to highlight these cycles whether they are true for all participants, groups of participants, or individual participants. While we were able to run GIMME on a subset of participants, we ran into issues which limited the potential for extensive findings using this method.

The main issue was that GIMME cannot run when some participants have constant values for a variable. As shown in table 5, there are very few participants who did not have at least one constant value for one or more activities (table 5 reports activity means for participants with at least 5 mood points). Moreover, there were no variables for which there was not at least one participant who had held it constant. The lack of variance issue was compounded by the fact that most participants did not participate on all 60 days. The average number of mood points for participants was 31.66. Nevertheless, we identified three participants with more than 50 mood points each and varied answer for a fairly extensive set of daily activities. The GIMME algorithm could not converge on a model for one participant (some of this participant’s activity variances were very low), and could therefore not converge on a group model. The algorithm did converge for two participants, and PDF files “Participant A” and “Participant B” presents the visual graphics illustrating the participants’ respective individual network.

In these graphics, dashed lines represent lagged relationships (values on one day predicts values the next day), and solid lines represent concomitant relationships (values on one day predicts values on the same day). Blue arrows represent positive relationships while red arrows represent negative relationships. Thicker lines represent stronger links. The direction of arrows is established based on “centrality”, a measure of how well a variable explains the relationships between two (or more) other variables. For example, in Participant A’s network, we see a solid blue line from activity to home, and a solid red line from home to activity. This apparent contradiction suggests that variables that are mostly correlated with activity were high when activity and home values were also both high, but that variables more strongly correlated with home had high values when home and activity were not aligned in value. Ultimately, because few participants were used in the analyses, and even these participants had lower numbers of mood points than what would really be recommended, these graphics should be interpreted with great caution, and are mostly provided as an illustration of what kinds of results GIMME analyses might provide in the future.

The second approach to psychometric networks that we used is a non-directed psychometric network across all mood points, all participants confounded. This approach permits the identification of the overall pattern of relationships between concomitant variables, all participants confounded. While we included next day values for positivity and activity to give us an idea of lagged effects on mood, this approach is not strictly speaking longitudinal.

Furthermore, because our focus was on moods, we only included variables that were significantly correlated with positivity and/or activity in the analysis (fewer variables help model convergence). The results of this analysis are provided in the “Mood points network’ PDF file. Again, line colours are indicative of positive or negative relationships, and line thickness of relationship strength in the network graphic. Some general patterns that can be found in said graphic include the fact that overall, participants chose the “relax” and “home” activities on the same days, likewise with “friends” and “family”. Positivity and next-day positivity (“pos_t2” in the graphic) were strongly associated, suggesting that the positivity and negativity of moods tends to be recurrent over a period of one day.

Sleep, family, home, relaxation and positivity gave the highest centrality values overall (all 3 centrality indices are variations of ways to calculate how well a variable can be used to explain the relationship between two or more other variables). These are the variables that are most connected to other variables in the network. They can be considered “more important” to the network only insofar as we can accept the idea that the removal of these variables would also remove a large part of the associations between other variables. The “Expected Influence” graph indicates whether a variable is more positively or negatively related to other variables in the network. These values should be interpreted with caution, as the averages can hide very different patterns of association. For example, while the average “expected influence” of family is negative, one only has to look at the network graphic to see that the main negative relationship involving family is with sleep – family is otherwise mostly positively related to other variables in the network.

Pilot study limitations and opportunities for further development

All of the results presented must be considered in light of the limitations of the pilot study. First, our approach was correlational, not experimental. For example, while we find that Moodie use was associated with lower anxiety at time 2, we cannot conclude that Moodie use *caused* lower anxiety. While correlation is a necessary condition for causation, it does not imply it. The same can be said of psychometric networks (which at their core are ultimately representations of multi-variate correlation patterns) – just because one variable frequently precedes another does not necessarily imply that it causes it. Without randomized controlled experiments, relationships between variables can only be interpreted as associations. Second, our sample of participants is rather small – many analyses are made with 27 participants only, for example. Small samples carry the risk of not being particularly representative of a population (by giving too much weight to potential individuals who may be very different from the norm) and of permitting spurious statistical significance in correlational analyses. Correlation values tend to stabilize with larger sample size, such that some correlations that reached statistical significance may have done so only randomly. We cannot know which of our correlations are spurious, unfortunately. The best we can do is make informed guesses based on theory, judgment, and the statistical information that we have.

Nonetheless, the informed guesses to be made on the base of the pilot study can be informative, especially from an app development perspective. The fact that mood positivity is related to positive emotional states, for example, makes too much sense to be ignored. Likewise, the fact that sleep, family, and food are all related to mood positivity can only be seen as confirmation that Moodie finds expected patterns. Finding otherwise would have indicated serious issues with the app – and we can report that we do not find serious issues with the app.

We do find some potential areas of opportunities for further app development, depending on desired outcomes.

If the GIMME approach is to be implemented, major modifications would need to be made to the "daily activities" measurement approach. Because most inferential statistics are based on analyzing which variables vary together, variance is a baseline necessity for most analyses. GIMME results would be optimized if there is at least 20% variance in measurements (i.e., for yes-no decisions, the least chosen decision would have to be chosen at least 20% of the time, for 1 to 5 scales, standard deviation would ideally reach 1), although having a few variances at a 10% level would likely be perfectly workable. While the idea of providing detailed individualized reports of directed and longitudinal patterns surrounding moods may be enticing, GIMME requirements may be too strict for actual implementation. Other individualized reports could be made (for example, non-directed and non-longitudinal networks assessing which activities are most often associated with positive or negative moods, or the chi-square approach taken in the Dalhousie University report), even if they may not be quite as rich.

In any case, however, more variance in the daily activity measurement results would still improve the potential impacts of these other types of report. One potential strategy would be to focus on key activities and make the assessment method a scale (for example, instead of a yes or no decision for "sleep", "sleep quality" could be assessed on a 1 to 5 scale). The challenge here would be to decide on the key activities (and, potentially, on a relevant measurement scale or measurement scales). This approach would involve a trade-off: because ratings on a scale take more time than yes-no decisions, it may be necessary to assess fewer activities to maintain user engagement. With this in mind, this proposed approach may help to solve another issue; the meaning of certain activities may be quite different from one person to the next (for example, while some users may find the "other" category useful, it is difficult to interpret scientifically). Perhaps the best approach to this issue would be to take a step back and consider these questions based on the goal of Feeling Moodie. If the main goal is to help therapists and clients communicate, perhaps therapists might be the best source to help identify "key activities". On the other hand, if the goal is to have an app that can apply to everybody, careful consideration of the literature on daily activities and their relationships with well-being may be necessary.

References

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