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The utility of geographically-explicit ecological momentary assessment: from description to intervention

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Abstract

Kirchner and Shiffman do the field a service by summarizing the path from ecological momentary assessment (EMA) to what they term geographically-explicit ecological momentary assessment (GEMA). I will comment on a few things that struck me in their review, then add a few points about moving from assessment to intervention.

The E in GEMA

EMA has always been ecologically valid; in that researchers were always reasonably certain that the data were being collected outside the constricted "ecology" of their own laboratories. But that was as far as the certainty went. Additional ecological information had to rely on self-reported answers to questions like "where are you now?" or "who are you with?" With the addition of geographical data, as the authors note, we can "operationalize the 'ecological' aspect of EMA". Which is why I was struck by the authors' addition of the "explicit" to what had been termed geographical momentary assessment (GMA) [1]. Adding the 'E' to GMA highlights a key point for researchers who wish to adapt similar methods. Unless your interest is in a purely spatial measure such as distance traveled, it is not enough to simply add raw GPS points to your data set and call it a day. Those points in space need to be tied to clear and meaningful data describing the places they represent. The possibilities for what data one might use are broad. The authors point to excellent work looking at retail outlets, pollution, and disorder in the environment, but one can imagine linking all manner of traditionally geographical research (e.g. green spaces, crime, census tract data) to EMA assessments.

The review focuses on research assessing health/environment associations and how that research led to GEMA. When the authors cite Zajonc's work showing people's lack of awareness of their own cognitive motivations, I think again about the "explicit" in GEMA. When I have conducted geonarrative interviews with people in treatment for substance-use disorders, I have often been shocked by interviewees' unawareness of the impact of their environment, or their complete discounting of its role in their drug-related behaviors.

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Compliance with ethical standards

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Explicit geographical data can help uncover relationships between the environment and momentary states *even when participants lack the awareness to report it*.

Methodology

Kirchner and Shiffman wisely avoid being too restrictive in their assessment of what methodologies might come to be included in GEMA. Approaches that currently seem tangential to GEMA might turn out to add value to it. For investigators considering using a GEMA approach, Kirchner and Shiffman's comments on methodology provide a taste of the complexities that need to be anticipated. What types of geographical data will best fit the research question? How long a span of GPS data is needed, and how often should it be logged? What is the defining unit of geographical area? What is the range of participants' movement, and do your data on the environment cover that range? These questions have serious impact upon the resulting analyses.

The authors discuss spatial autocorrelation, which is the tendency for observations to be more similar to each other the closer they are. EMA data have always required consideration of temporal autocorrelation. This is compounded in GEMA because geographical proximity is typically accompanied by temporal proximity (or by temporal cyclicity, i.e., daily movements to the same space). The authors rightly note that GPS data should be assessed at times beyond when EMA entries are made, allowing researchers to examine EMA responses as a function of lengthier patterns of environmental exposure [1, 2]. Not only does this allow researchers access to the base rate information needed for clear conclusions, it also helps deal with the spatial autocorrelation and more accurately reflect the impact of the environment. In some instances, the effect of an environmental exposure might truly be momentary, as when a person abstaining from alcohol is exposed to a billboard advertising an alcoholic beverage. However, seminal works have shown that environmental exposures can also have cumulative effects. Kirchner et al. [2] showed that cumulative number of exposures to point-of-sale tobacco outlets predicted likelihood of lapse in low or no craving conditions. Similarly, Epstein et al. [1] showed that 4.5–5 hours of GPS data on exposure to disordered environments provided the best time frame over which to predict subsequent mood, stress, and craving.

Two more methodological concerns involve the spatial units one chooses for dividing geographical space [3]. The first is the modifiable areal unit problem, exemplified by the use of census-tract-level summaries for regions of space that could just as well have different boundaries. The second is the uncertain geographic context problem, referring to the difficulty of knowing the relevant spatial range over which to look for influences on an individual's behavior. One might simply choose to measure the environment with the smallest area that is statistically definable. However, when examining something such as the interaction of one's home with effects from the non-home environment, one must consider that a restricted space around the participant's home may not accurately reflect their causally relevant home environment.

Beyond description and to intervention

Kirchner and Shiffman show how GEMA can produce uniquely informative descriptions of relationships between environmental stimuli and health behavior. These descriptions can be a basis for the next step: using our knowledge about the environment to try to change health behavior. Because GEMA elucidates relationships between individual behavior and large-scale structural factors, it can inform interventions on both the individual and the community levels.

On the individual level, the authors touch on some of the work being completed using passive mobile sensing (of which location is a component) in machine learning algorithms to predict behaviors and moods. This is a growing field; we are seeing more and more attempts to predict stress [4, 5], mood [6], and drug craving [7] from passively collected data. These predictions could conceivably be used to trigger “just in time” interventions for a variety of health conditions. An effective mobile intervention to support people in recovery from alcoholism has incorporated location data [8] to alert end users when they are in a hotspot for risk, such as a bar they used to frequent. Currently, the end users have to provide the hotspot data themselves. Machine-learning algorithms might automate some of the hotspot inferencing, reducing both user burden and reliance on consciously available information.

We may be also able to think bigger than EMA-driven “just in time” ambulatory interventions—and we may need to, because people with chronic or lifelong health conditions might not want to “check in” regularly with an intervention app for years on end, even if they still need the intervention. In contrast, collection of geographical data places little or no burden on end users and could be used to intervene over extended periods of time, either with the end users themselves or at the level of the environment. Non-GEMA work examining the relationship of alcohol outlets to violence in Baltimore has directly led to policies impacting that environment [9]. GEMA work could have a similar impact. For example, one could take the work of Kirchner et al. [2] to suggest that limiting point of sale cigarette outlets could have a positive impact on smoking lapses. Further GEMA work could examine the effect of such a policy change.

GEMA holds promise as a tool to describe the relationships between health behaviors and environmental surroundings. Using rapidly advancing mobile technologies it is becoming possible to harness those descriptions into powerful tools for change on both the individual and community levels.

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