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Factors influencing healthcare provider respondent fatigue answering a globally administered in-app survey

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Background: Respondent fatigue, also known as survey fatigue, is a common problem in the collection of survey data. Factors that are known to influence respondent fatigue include survey length, survey topic, question complexity, and open-ended question type. There is a great deal of interest in understanding the drivers of physician survey responsiveness due to the value of information received from these practitioners. With the recent explosion of mobile smartphone technology, it has been possible to obtain survey data from users of mobile applications (apps) on a question-by-question basis. We obtained basic demographic survey data as well as survey data related to an anesthesiology-specific drug called sugammadex and leveraged nonresponse rates to examine factors that influenced respondent fatigue.

Methods: Primary data were collected between December 2015 and February 2017. Surveys and in-app analytics were collected from global users of a mobile anesthesia calculator app. Key independent variables were user country, healthcare provider role, rating of importance of the app to personal practice, length of time in practice, and frequency of app use. Key dependent variable was the metric of respondent fatigue.

Results: Provider role and World Bank country income level were predictive of the rate of respondent fatigue for this in-app survey. Importance of the app to the provider and length of time in practice were moderately associated with fatigue. Frequency of app use was not associated. This study focused on a survey with a topic closely related to the subject area of the app. Respondent fatigue rates will likely change dramatically if the topic does not align closely.

Discussion: Although apps may serve as powerful platforms for data collection, responses rates to in-app surveys may differ on the basis of important respondent characteristics.
Studies should be carefully designed to mitigate fatigue as well as powered with the understanding of the respondent characteristics that may have higher rates of respondent fatigue.
Title

Factors influencing healthcare provider respondent fatigue answering a globally administered in-app survey

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Abstract

Background: Respondent fatigue, also known as survey fatigue, is a common problem in the collection of survey data. Factors that are known to influence respondent fatigue include survey length, survey topic, question complexity, and open-ended question type. There is a great deal of interest in understanding the drivers of physician survey responsiveness due to the value of information received from these practitioners. With the recent explosion of mobile smartphone technology, it has been possible to obtain survey data from users of mobile applications (apps) on a question-by-question basis. We obtained basic demographic survey data as well as survey data related to an anesthesiology-specific drug called sugammadex and leveraged nonresponse rates to examine factors that influenced respondent fatigue.

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*Keywords:* respondent fatigue, surveys, mobile applications, smartphones, mHealth
Introduction

Respondent fatigue, also known as survey fatigue, is a common problem in the collection of survey data. It refers to the situation in which respondents give less thoughtful answers to questions in the later parts of a survey, or preliminarily terminate participation. Factors that are known to influence respondent fatigue include survey length, survey topic, question complexity, and question type (open-ended questions tend to induce more fatigue). Respondent fatigue lowers the quality of data collected for later questions in the survey and can introduce bias into studies, including nonresponse bias.

There is a great deal of interest in understanding the drivers of physician survey responsiveness due to the value of information received from these practitioners. These studies typically looked at overall response rate rather than respondent fatigue. However, with the recent explosion of mobile smartphone technology, it has been possible to obtain survey data from users of mobile applications (apps) on a question-by-question basis. While this increases the amount of data available to researchers, it also increases the risk of obtaining incomplete survey data.

While incomplete survey data reduces the quality of a dataset, it also provides an opportunity to study respondent fatigue directly. In the course of a study of more than 10,000 global users of a mobile anesthesia calculator app, we obtained basic demographic survey data as well as survey data related to an anesthesiology-specific drug called sugammadex. We leveraged nonresponse rates to examine factors that influenced respondent fatigue.

Methods

As described elsewhere, we have deployed a mobile anesthesia calculator app fitted with the Survalytics platform. Survalytics enables cloud-based delivery of survey questions and storage of both
survey responses and app "analytics" using an Amazon (Seattle, WA) Web Services database. Here, analytics is used to mean collected and derived metadata including app use frequency, in-app activity, device location and language, and time of use. Two surveys were deployed: one to collect basic user demographic information, and another to characterize attitudes and adverse event rates related to the drug sugammadex. Although data collection is ongoing, the study period for this work is limited to data collected between December 2015 and February 2017. The results of the sugammadex survey itself are beyond the scope of the present analysis.

Raw data from the DynamoDB database were downloaded and processed using CRAN R v3.3. User country was categorized using public World Bank classification of country income level. In cases where users were active in more than one country, the country in which the most app uses were logged was taken as the primary country. Detailed information about the Survalytics package, the data collected for this study, and the approach to calculation of frequency of app use can be found in the Supplementary Appendix.

The study was reviewed and approved by the Emory University Institutional Review Board #IRB00082571. This review included a finding by the FDA that Anesthesiologist falls into the category of "enforcement discretion" as a medical device, meaning that, at present, the FDA does not intend to enforce requirements under the FD&C Act.

Statistical Methods

Subjects were categorized as "fatigued" or "not fatigued" according to whether they responded to the first unbranched sugammadex survey question but did not complete the survey to the last question. This classification was used to perform binomial regression analysis against several independent
variables, including provider role, frequency of app use, country income level, rating of app importance, and length of time in practice.

**Results**

We saw a consistent rate of data collection throughout the study period (Figure 1). Following successful study launch in December 2015, the sugammadex survey was put into the field in March 2016. Responses to this survey were consistently collected throughout the study period, at a rate of approximately 179 total responses per day (green line, magnified 10x). There was a demonstrable and consistent rate of respondent fatigue, leading to the observed decrease in the rate of responses to the first unbranched question of the sugammadex survey (Q-03, blue line, magnified 50x, 16 responses collected per day) versus the last (Q-10, purple line, magnified 50x, 11 per day).

The overall rate of respondent fatigue was 34.3% (N = 5991). Respondent fatigue then analyzed by several respondent characteristics. Some of these characteristics were based on self-reported data collected in the baseline survey (provider type, importance of app to personal practice), while others were based on objective data (user location, frequency of app use). Results of univariable binomial regression analysis are shown in Table 1.

Provider role was an excellent predictor of the rate of respondent fatigue (Figure 2, N = 5333, p < 0.001). Physicians and physician trainees were most likely to complete the sugammadex survey, while technicians and respiratory therapists were least likely to do so. Main country income level was also an excellent predictor (Figure 3, N = 5986, p < 0.001); respondents from low income countries were less likely to complete the survey than those from high income countries.

Rating of the app's importance to the provider's practice was a moderate predictor of respondent fatigue (Figure 4, N = 3642, p = 0.009), although the relationship between app importance and
respondent fatigue was unusual (see Discussion). Although length of time in practice had a statistically significant association with respondent fatigue (Figure 5, N = 2518, p = 0.02), the length of time in practice did not have monotonic directionality with regards to respondent fatigue. There was no association between the frequency of app use and respondent fatigue (Figure 6, N = 4659, p = NS).

**Discussion**

Overall, we determined that several provider characteristics, primarily provider role and World Bank country income level, were associated with the rate of respondent fatigue for an in-app survey. Other factors that would have been assumed to be associated with less respondent fatigue, such as higher frequency of app use, turned out not to be associated. Length of time in practice and rating of importance of the app were associated with respondent fatigue, but in unusual ways.

The association between provider role and fatigue rate is valuable because it demonstrates that we are likely to get a higher rate of complete response from users for whom the app and survey are well aligned. Physicians and anesthetists had the lowest rate of fatigue, and were users most likely to interact with the subject of the survey (sugammadex) on a frequent basis. Anesthesia techs and respiratory therapists are far less likely to use this drug or have knowledge of it, and so the high rate of observed respondent fatigue in these user groups is logical.

Our findings related to country income level are somewhat disheartening, in that the ability to reach and obtain feedback from users in resource-limited settings is a powerful promise of the global adoption of smartphones and mobile apps. Perhaps resource-limitations contributed the relatively high rate of respondent fatigue in users from lower-income countries: lack of access to reliable Wi-Fi, more expensive mobile data, and perhaps more time spent on patient care rather than in-app surveys. Another factor may be related to the expense of sugammadex itself; users from low-income countries were less
likely to indicate access to sugammadex (Table 2, low = 46%, lower middle = 56%, high income = 57%), and perhaps even users with access to it in lower-income countries did not feel they had enough experience with the drug to complete the survey.

The association of app importance to fatigue rate is interesting because it does not follow a monotonic trend, nor does it follow a pattern that would fit standard assumptions (Figure 4). It is predictable that those viewing the app as "Not important at all" would have the highest rate of respondent fatigue, consistent with our observation. Not intuitive, however, is the finding that users who rate the app as having average/little importance have the lowest rates of fatigue. Perhaps those users who rate the app as more important to their practice take less time to complete the in-app survey because when they are using the app, they generally launch it for practical purposes.

Likewise the association between length of practice and respondent fatigue does not follow a monotonic trend, which perhaps limits the usefulness of this finding in practice. It does suggest that the rate of responsiveness from providers early in their practice or with many years in practice may be reduced.

It is important to note that this survey topic was closely aligned with the subject area of the app. Respondent fatigue rates are likely to change dramatically if the topic does not align closely. This is supported in some ways even by our data; as noted above, users who had less interaction with a drug were observed to have a much higher rate of respondent fatigue. The effect on response rates was dramatic; fatigue rates climbed to 60% for respiratory therapists who would not have cause to interact with or administer sugammadex.

Conclusions
These findings extend previous work in the area of respondent fatigue in two ways. First, to our knowledge, this is the first study to examine respondent fatigue for in-app mHealth surveys. Given how much easier it is to quickly click through a survey on a mobile device as compared to filling out a pen-and-paper survey, or even sit down to a web survey provided via weblink, there would be no \textit{a priori} reason to assume that respondent fatigue rates would be comparable. Two-thirds of time spent in the digital realm is time spent in mobile apps\textsuperscript{17}. On the other hand, mobile apps are typically used in very short bursts, 2-8 minutes per session\textsuperscript{18}. Apps, small programs with very specialized functions, are likely to be launched only when practically needed, potentially limiting the likelihood of participation in extraneous tasks such as in-app surveys.

Second, this study examines the rates of respondent fatigue during the course of a single survey, administered one question at a time, with full participant control over when to cease answering questions. Existing studies have primarily looked at global respondent fatigue in terms of e.g. rates of survey return. By allowing participants full control, we were able to observe in the metadata a more complete picture of the associations with respondent fatigue during the course of a single survey, without needing to isolate phenomena such as straight-line answering.

This study demonstrates some of the advantages and limitations of collected data from mobile apps, which can serve as powerful platforms for reaching a global set of users, studying practice patterns and usage habits. Studies should be carefully designed to mitigate fatigue as well as powered with the understanding of the respondent characteristics that may have higher rates of respondent fatigue. Variable rates of respondent fatigue across different categories of providers should be expected. We expect that the crowdsourcing of information to uncover epidemiological hotspots or outcomes
information will only continue to grow as medicine grapples with these new opportunities and technologies.

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Conflict of Interest Statement

Authors declare: no support from any organisation for the submitted work; no financial relationships with any organisations that might have an interest in the submitted work in the previous three years; no other relationships or activities that could appear to have influenced the submitted work. The app was initially released in 2011 by Vikas O'Reilly-Shah with advertising in the free version and a paid companion app to remove the ads. The app intellectual property was transferred to Emory University in 2015 and advertisements were subsequently removed, and the companion app to remove ads made freely available for legacy users not updating to the ad-free version. Following review by the Emory University Research Conflict of Interest Committee, Vikas O'Reilly-Shah has been released from any conflict of interest management plan or oversight.

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Table 1: Univariable binomial regression results examining the association between various independent variables and the presence of respondent fatigue. The association of respondent fatigue with provider role, country income level, rating of app importance, length of time in practice, and frequency of app use are discussed in greater detail in the text.
Table 2: Percentage of responses from users of each country income category within each category of responses regarding access to sugammadex.

| Low income | Lower middle income | Upper middle income | High income |
|------------|---------------------|---------------------|-------------|
| No or unsure, but not relevant to my practice | 10.30 | 10.70 | 6.82 | 8.50 |
| No, not approved in my country | 22.20 | 22.20 | 14.40 | 9.13 |
| No, not on formulary | 33.00 | 22.70 | 16.30 | 20.00 |
| Yes | 46.30 | 37.90 | 55.90 | 57.50 |
| Yes, but not relevant to my practice | 6.08 | 6.47 | 6.63 | 4.88 |
Figure 1: Data collected over the study period, including visualization of the difference between rates of response to the first unbranched sugammadex survey question (Q-03) and the final sugammadex survey question (Q-10).
Figure 2: Observed fatigue rate versus provider role. Top number is the number of participants with respondent fatigue (see Methods). Bottom number is the total number of participants in the category.
Figure 3: Observed fatigue rate versus primary country World Bank income level. Top number is the number of participants with respondent fatigue (see Methods). Bottom number is the total number of participants in the category.
Figure 4: Observed fatigue rate versus provider rating of app importance. Top number is the number of participants with respondent fatigue (see Methods). Bottom number is the total number of participants in the category.
Figure 5: Observed fatigue rate versus provider length of time in practice. Top number is the number of participants with respondent fatigue (see Methods). Bottom number is the total number of participants in the category.
Figure 6: Observed fatigue rate versus normalized frequency of app use. R-squared = 0.007.