Supplementary Appendix

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Table S1: Branched survey for collection of basic demographic information from users of the app.

Question	Responses	
About how long have you been using the app (in months)? (Select 0 if you are a new user.)	Range: 0-100	
What is your level of medical training?	Physician: Attending/Consultant Physician: Fellow/Resident/Registrar Anesthesia Assistant (PA) Nurse Anesthetist (CRNA) Nurse (RN) Technically Trained in Anesthesia Anesthesia Technician Student AA	Student Nurse Anesthetist Medical Student Paramedic/EMT I am not a medical practictioner Respiratory Therapist Pharmacist Other type of medical provider
What are your medical specialties?	Anesthesiology Pain Medicine Pediatric Anesthesiology Cardiothoracic Anesthesiology Obstetric Anesthesiology Adult Critical Care	Pediatric Critical Care Emergency Medicine Pediatrics Internal Medicine Other
How many years have you been in practice? (Not counting years in training)	Range: 0-50	
Please rate the importance of the app to your practice:	Not Important At All Of Little Importance Of Average Importance Very Important Absolutely Essential	
I have used the app as a reference under emergent/urgent circumstances:	True/False False	
We would appreciate knowing how the app was useful to you in an emergency:	Free Text Response	
I have used the Society for Pediatric Anesthesia Critical Events Checklist:	True/False	
We would appreciate knowing how the checklist was useful to you:	Free Text Response	
What are is your practice size?	I am the only practitioner for large area One of several practitioners in the area Group practice 1-5 members Group 5-10 members	Group 10-25 members Group 25-50 members Group > 50 members
What is your anesthesia practice model?	Physician only Physician supervised, anesthesiologist on site Physician supervised, non-anesthesiologist physician on site	Physician supervised, no physician on site No physician supervision Not an anesthesia provider
What is your primary practice environment?	Private clinic or office Local health clinic Ambulatory surgery center	Small community hospital Large community hospital Academic department/University hospital
What is community does your practice primarily serve?	Rural Suburban Urban	
I use of the app as a reference for which classes of patients/procedures?	Adult Pediatrics Obstetric Cardiothoracic Intensive Care	Regional Pain Emergency Room Other

Table S2: Healthcare providers consenting to participation in the study of the app. Percentages were rounded for clarity.

Role	Count	Percentage
Physician: Attending/Consultant	4840	28.4%
Physician: Fellow/Resident/Registrar	3682	21.6%
Anesthesia Assistant (PA)	2433	14.3%
Nurse Anesthetist (CRNA)	1703	10.0%
Anesthesia Technician	873	5.1%
Medical Student	750	4.4%
Nurse (RN)	521	3.1%
Paramedic/EMT	468	2.7%
Technically Trained in Anesthesia	417	2.4%
Student Nurse Anesthetist	356	2.1%
Student AA	346	2.0%
Other type of medical provider	245	1.4%
I am not a medical practitioner	133	0.8%
Pharmacist	131	0.8%
Respiratory Therapist	128	0.8%
	17026	100.0%

Table S3: Univariate negative binomial regression analysis testing the association of country income level with physician app adoption rate. Physician workforce estimates were obtained from the WHO and from Holmer et al [1]. The app adoption penetration index was calculated as the estimated number of physician app users per 1000 physicians in the country. As explored in the Discussion, due to the relatively small number of anesthesiologists and low total surgical physician workforce in many low-income countries, the apparent adoption rate of the app may be artificially high using the Holmer estimates. We adopt the nomenclature of app adoption penetration index to emphasize the differences between the country income levels over the usability of the raw estimate to predict the adoption rate in any given country.

Characteristic	N (Countries)	Estimated Penetration Index	95% CI for Estimate		Univariate P-Value	Directionality vs Reference Category
			Low	High		
Country Income	N = 158	Estimated Penetration Index Using WHO Estimates of Physician Workforce			Overall Variable p < 0.001	
High income	47	1.8	1.4	2.4	Reference Category	
Upper middle income	44	3.1	2.3	4.1	< 0.01	More Users
Lower middle income	44	2.7	2.0	3.8	0.044	More Users
Low income	23	8.0	5.3	12.5	< 0.001	More Users
Country Income	N = 132	Estimated Penetration Index Using Holmer Estimate of Anesthesiology Workforce			Overall Variable p < 0.001	
High income	45	43	31	62	Reference Category	
Upper middle income	32	96	64	150	< 0.01	More Users
Lower middle income	34	198	132	306	< 0.001	More Users
Low income	21	804	480	1,414	< 0.001	More Users
Country Income	N = 132	Estimated Penetration Index Using Holmer Estimate of Total Surgical Physician Workforce (Surgeons + Obstetricians + Anesthesiologists)			Overall Variable p < 0.001	
High income	45	9	7	13	Reference Category	
Upper middle income	32	17	12	26	< 0.01	More Users
Lower middle income	34	25	17	37	< 0.001	More Users
Low income	21	67	42	111	< 0.001	More Users

Table S4: Raw app adoption rate by physicians broken down by country income level. Physician workforce estimates were obtained from the WHO and from Holmer et al [1].

Country Income Level	N (Countries)	Total App Users	Total Estimated Physican Workforce	Adoption Rate	p-value
WHO Total Physician Workforce					
High income	48	2997	3329658	0.09%	Referent
Upper middle income	45	2772	4248414	0.07%	< 0.001
Lower middle income	44	2526	2092425	0.12%	< 0.001
Low income	23	162	40966	0.40%	< 0.001
Holmer et al Anesthesiologist Physician Workforce Estimate					
High income	45	2788	150860	1.85%	Referent
Upper middle income	32	2466	296331	0.83%	< 0.001
Lower middle income	34	2126	39471	5.39%	< 0.001
Low income	21	160	646	24.77%	< 0.001
Holmer et al Total Surgical Physician Workforce Estimate					
High income	45	2788	673912	0.41%	Referent
Upper middle income	32	2466	917253	0.27%	< 0.001
Lower middle income	34	2126	181214	1.17%	< 0.001
Low income	21	160	3788	4.22%	< 0.001

Table S5: Breakdown of community served by provider based on country income level. Percentages were rounded for clarity. P-values were calculated using chi-square test of independence and applying post-hoc Bonferroni correction for multiple comparisons.

	Low income		Lower middle income		Upper middle income		High income		p-value vs Rural
	N	%	N	%	N	%	N	%	
Rural	54	37%	399	31%	282	24%	235	18%	-
Suburban	26	18%	244	19%	157	13%	301	23%	< 0.001
Urban	65	45%	628	49%	727	62%	772	59%	< 0.001
p-value vs Low income	-		NS		< 0.01		< 0.001		

Table S6: Breakdown of provider group size based on country income level. Percentages were rounded for clarity. p-values were calculated using chi-square test for independence and applying post-hoc Bonferroni correction for multiple comparisons.

	Low income		Lower middle income		Upper middle income		High income	
	N	%	N	%	N	%	N	%
Group > 50 members	16	6%	169	7%	234	9%	566	20%
Group 25-50 members	6	2%	122	5%	162	6%	391	14%
Group 10-25 members	13	5%	181	7%	239	10%	425	15%
Group 5-10 members	30	12%	260	10%	300	12%	274	10%
Group practice 1-5 members	35	14%	363	15%	372	15%	290	10%
One of several practitioners in the area	60	23%	616	25%	401	16%	476	17%
I am the only practitioner for large area	98	38%	768	31%	805	32%	416	15%
p-value vs Low income	-		NS		< 0.01		< 0.001	

Table S7: Breakdown of user provider role by country income level. Percentages were rounded for clarity. P-values were calculated using chi-square test of independence and applying post-hoc Bonferroni correction for multiple comparisons.

	Low income		Lower middle income		Upper middle income		High income		p-value vs Physician
	N	%	N	%	N	%	N	%	
Physician	163	32%	2543	51%	2773	53%	3035	54%	-
AA or CRNA	178	35%	1152	23%	1338	25%	1458	26%	< 0.001
Nurse (RN)	22	4%	149	3%	116	2%	234	4%	< 0.001
Technically Trained in Anesthesia	15	3%	185	4%	153	3%	63	1%	< 0.001
Anesthesia Technician	48	10%	396	8%	300	6%	129	2%	< 0.001
Anesthetist Trainee	44	9%	225	5%	233	4%	199	4%	< 0.001
Medical Student	28	6%	265	5%	279	5%	176	3%	< 0.001
Paramedic/EMT	6	1%	51	1%	82	2%	328	6%	< 0.001
p-value vs Low income	-		< 0.001		< 0.001		< 0.001		

Table S8: Breakdown of age of patients the app was used with by country income level. Percentages were rounded for clarity.

	Age <= 1 month		Age <= 1 year		Age <= 3 years		Age <= 12 years		Total	
	N	%	N	%	N	%	N	%	N	%
Low income	1,364	22%	2,423	39%	3,061	50%	4,543	74%	6,164	100%
Lower middle income	14,408	20%	25,297	36%	33,046	47%	51,409	73%	70,502	100%
Upper middle income	15,788	18%	28,755	32%	38,461	43%	63,315	71%	88,755	100%
High income	18,352	21%	28,560	32%	39,126	44%	65,588	74%	89,013	100%
Total	49,912	20%	85,035	33%	113,694	45%	184,855	73%	254,434	100%

Figure S1: Screenshot of the app.

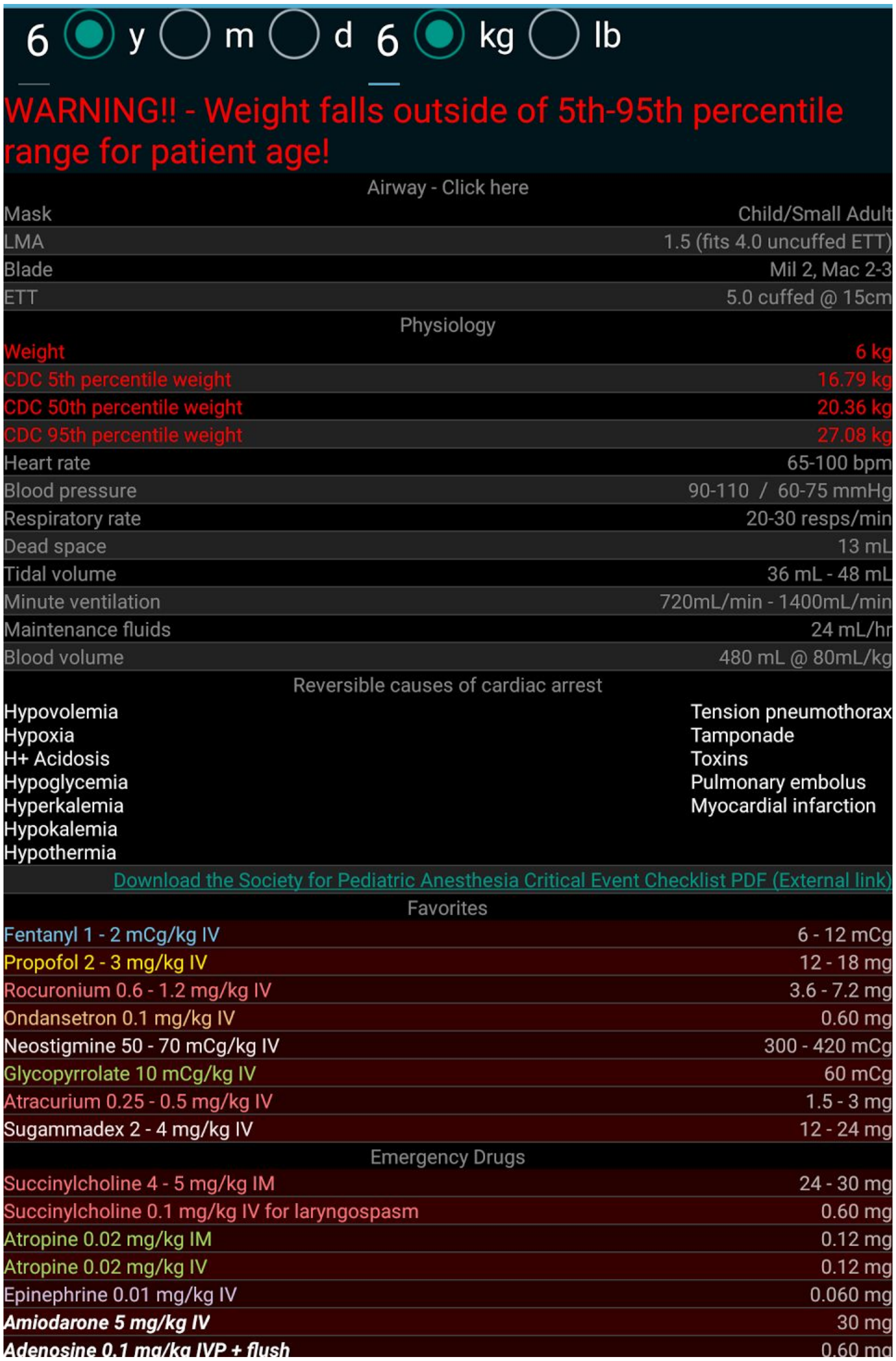
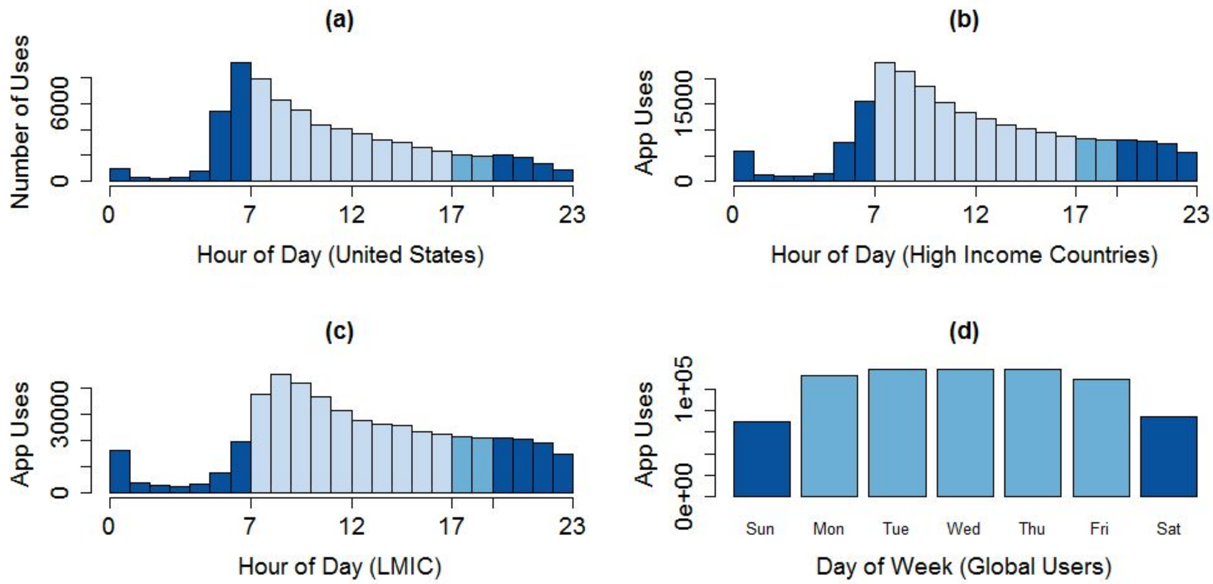


Figure S2: Counts of app activations broken down by the hour of the day (local time): (a) in the US, (b) in non-US high income countries, and (c) in LMICs. These were significantly different using a Chi-square test of independence ($p < 0.001$). (d) Counts of app activations broken down by day of week. Colors highlight (a-c) daytime vs evening vs night uses and (d) weekday vs weekend.



Survalytics Detailed Description

The Survalytics platform is designed to send survey questions to the app and to retrieve survey responses and other analytic metadata from the app. These surveying capabilities are not one-time or static. New survey questions can be delivered via the Internet to the installed base of mobile devices at any time, with the questions being presented to the app users the next time that the app is opened. Survey data and app usage information are transmitted to and from the app utilizing services provided “in the cloud” by Amazon Web Services (Amazon Seattle, WA).

A detailed schema for the survey and analytic data collection was developed. The Survalytics platform allows for the surveys to have a branched structure. Such a branched survey was used to collect basic demographic information from the user after initial installation and agreement by the user to participate in the study. The survey questions are summarized in Table S1. Users had the ability to opt in or opt out of the study at any time.

Location of the device was determined using three different approaches, as described below. For all of the approaches, only the country and “administrative region” were determined and stored, even when more precise determination of location was possible. Here “administrative region” refers to the largest geographical subdivision within the country such as the state in the U.S. or province in India. The precision of the location determination was limited to granularity no more defined than administrative region in order to provide Health Insurance Portability and Accountability Act (HIPAA) compliant de-identification of data. Healthcare providers were entering into the app a patient age and weight. If the location information stored were more precise, patient age and weight information entered into the app might be combined with the specific location and date in a manner that could potentially comprise protected health information (PHI) as defined by HIPAA.

The first of the three approaches to determining the country and administrative region data was based on GPS coordinates which were reverse geocoded using Google's Geocoding API[2]. “Reverse geocoding” refers to the process of converting longitude and latitude coordinates, such as those provided by GPS, into human-interpretable geographic descriptions such as country, state/province, or address. The second approach was based on using the mobile device’s Internet Protocol (IP) address. The IP address was reverse geocoded using a web-based service provided by ip-api.com[3]. The last approach was based on the country code stored in the memory chip used to uniquely identify the device (the Subscriber Identity Module or SIM card). Only country information is available via this last approach.

During analysis, the country and administrative region from GPS reverse geocoding was preferentially used. However, GPS coordinates were not always available for a variety of reasons including GPS reception problems, GPS sensor failure, or the device user not consenting to sharing GPS location information. If GPS data were not available, the country and administrative region from IP address was used. Sometimes, this information was not available due to lack of Internet connectivity at the time of data collection. If not, the country from the SIM card (felt to be the least accurate) was used.

The Survalytics platform stores each "event" (e.g. consent, a survey response, an in-app click, or closure of the app) in a local database on the device. When Internet connectivity is detected, one data packet is transmitted from the app at a time, with each packet representing a single "event". Each packet contains relevant details of the event (e.g. what was clicked), as well as a generic set of information including an anonymous globally unique identifier (generated when the app is first opened on the device), time information (specifically, timestamp, time zone, and local time), location information (from the three sources outlined above), and device language. Transmitted packets are stored as records in an Amazon Web Services DynamoDB database. See the publication describing Survalytics[4] for even further additional technical details.

The anonymous user identifier allows for all of the data from one device to be tied together. Together with the time stamps, this allows the sequence of app usage events and survey responses for each mobile device to be reconstructed from the database.

Mobile Healthcare App Study JSON Document Schema

I. Survey/demographics central database tables

The overall architecture is designed to simplify the codebase by using JSON primarily as a transport vehicle and limiting the number of database fields to those that need to be known by the database in question. For example, the AWS source database for downloading questions only needs to know questionguid (for a hash key) and the json_str containing the meat of the question. Telling it ordinal position simplifies other areas of the Android code and so that was included. Otherwise, the content remains unparsed until downloaded by the Android app.

On device, the database is again limited to guid, ordinal position, and jsonstr. The additional fields are flags for internal tracking use. Parsed JSON supplies fields for the generation of the question on-device and for the uploaded response.

http://www.jsoneditoronline.org/
https://www.guidgenerator.com/online-guid-generator.aspx

On AWS: Question Table:

```
    questionguid_str      : STRING, PRIMARY HASH KEY
    ordinalposition_int   : INT, RANGE KEY
    json_str              : STRING
```

json_str JSON Schema: Question

```
{
    surveyname_str        : STRING
    surveyguid_str: STRING
    ordinalposition_int   : INT
    questionguid_str      : STRING
    questionprompt_str    : STRING
    questiontype_str      : STRING
    responses_arr  : ARRAY
        [
            {
            responseid_int          :INTEGER
            response_str            :STRING
            },
            {
            responseid_int          :INTEGER
            response_str            :STRING
            },
            ....
        ]
OPTIONALLY
    conditional_upon_questionguid_str   : STRING // questionguid to check*
```

```
conditional_upon_responseid_int       : INTEGER // responseid to check*
        //*-above two work together and both required to be specified

conditional_upon_datemsid_int         : INTEGER
        // date (in UTC Unix epoch ms) after which to administer this question

conditionalbycountry_str              : STRING // use ISO 3166 alpha-2 codes

delaybydays_int                       : INTEGER
        //wait this many days after the question is first downloaded to ask this question

ongoingquestion_arr                   : ARRAY //array of day of week+time as follows
        [
                {
                notificationtime_str    : STRING
                },
                {
                notificationtime_str    : STRING
                },
                ...
                //notificationtime formatted as follows:  EEEHHmm
                // EEE = three letter day of week (Mon, Tue, Wed, Thu, Fri, Sat, Sun,
Dly)
                //                                      Dly = daily
                // HH = military time hours 00-23
                // mm = minutes 00-59
                //  Examples:      Tue0900, Thu1400, Dly1200
        ]

deletequestion_str                    : STRING //questionguid of ongoing question to
                                              // delete from local SQLite db

}
```

<u>Local DB on Android</u>

<u>Table questions</u>
questionguid_str
json_str
ordinalposition_int   //Primary key
final_responseid_int
final_response_str
answered_bool
uploaded_bool //unused

Table responses
_id
json
uploaded

II. Responses: Generic schema

The generic schema serves as the basic information passed with all types of uploaded data. The additional overhead is minimal and the presence of this information in each of uploaded packet simplifies future analysis against unnecessary complexity in terms of crossreferences and joins.

```
{
        userguid_str                    : STRING      PRIMARY RANGE INDEX
        localtime_ms_int                : INTEGER     PRIMARY HASH INDEX
        localtime_hrsmilitary_int       : INTEGER
        localtime_dayofweek_str         : STRING
        localtimezone_str               : STRING
        country_tm_str                              : STRING
        lo_lang_str                     : STRING      //locale lang
        app_lang_str                    : STRING
        region_ipapi_str                : STRING      //www.ip-api.com/json
        regionname_ipapi_str            : STRING
        country_ipapi_str               : STRING
        region_gc_str                   : STRING      //geocoding
        country_gc_str                  : STRING
        entrytype_str                   : STRING      LSI // included in all section III items
        ...
}
```

III. Responses: Specific added fields to generic document schema

Survey/demographics data

```
…
entrytype_str           : “survey”,
surveyguid_str          : STRING
questionguid_str        : STRING
questionprompt_str      : STRING
response_str            : STRING
responseid_str : STRING //questionguid & "-" Integer.toString(respid)
responses_arr  : ARRAY [if type is multiple response eg checkbox)
        [
                {
                responseid_str          :STRING
                                //questionguid & "-" Integer.toString(respid)
                response_str            :STRING
                },
                {
                responseid_str          :STRING
                                //questionguid & "-" Integer.toString(respid)
                response_str            :STRING
                },
                ....
        ]
```

Consent/Consent Change

```
...
entrytype_str           : “consentcode_int/consentchange_int”
“consentcode_int”       : INTEGER
“consentchange_int”     : INTEGER

                        1 - do not consent
                        2 - consent
                        3 - exit study
                        4 - re-enter study
```

On Start

```
...
entrytype_str                   : “onstart”
“age_yrs_fra”                   : FRACTION
```

```
“weight_kg_fra”                   : FRACTION
```

Age/weight entered by app user (age over 89 to be reported as 89+)

```
...
entrytype_str                     : “ageweight”,
“age_yrs_fra”                     : FRACTION
“weight_kg_fra”                   : FRACTION
```

Total time using the app

```
...
entrytype_str                     : “totaltimeofuse”,
“timeinapp_ms_int”                : INTEGER,
"ageweightmodified_int            : INTEGER //0=no 1=yes
```

Drugs favorited and changes to favorites

```
…
entrytype_str                     : “favoriteslist”,
“favoriteslist_arr”               : ARRAY
        [
                {       “drugid_int” : drug.get_id(),            INTEGER
                        “name_str”: drug.getDrugName(),          STRING
                        “position_int” : favepos                 INTEGER
                } ,
                {       “drugid_int” : drug.get_id(),            INTEGER
                        “name_str”: drug.getDrugName(),          STRING
                        “position_int” : favepos                 INTEGER
                } ,
                ....
        ]
```

In-app clicks (drugs, Epocrates, airway setup guide, critical events checklist, externally linked nerve blocks)

```
...
entrytype_str   :       See the click types below

Entrytype_str click types:
        “drugclick”,
        “epocrates”,
        “linkline_str”,
        “airwaysetupguide”
```

Extra JSON for drug/epocrates

“drugid_int”	: drug.get_id()
“name_str”	: drug.getDrugName()

Extra JSON for linkline:

“linkline_str”	: STRING == name //nerveblock and spachecklist
“linklineurl_str”	: STRING == link //nerveblock and spachecklist

Detailed Statistical Approach

The primary dependent variables examined in this study are: (1) provider rating of the importance of the app to their practice; (2) the frequency of app use; and (3) rate of physician adoption of the app per country. App importance was measured via a 5-point Likert scale survey item. App use frequency was calculated based on the assumption that app usage is a Poisson process. This approach was taken to reduce bias that would occur as a result of a naïve calculation of the usage rate (i.e. dividing the number of app uses by the span of time app uses were observed). The method is described in detail ("Methodology for Calculation of App Use Frequency").

Rate of physician app adoption by country was calculated. For the denominator, we needed to obtain an estimated physician count per country. We used three estimates from two sources. First, we used public World Health Organization Global Health Observatory data [5]. A limitation of the data from this source is the age of the information. In a small number of instances, the data was more than 10 years old. Second, we used estimates published by Holmer et al [1]. From this dataset, we used both (a) the estimated number of anesthesiologists per country and (b) the total physician surgical workforce per country. A limitation of these data for this study is that there are some physician app users that are not anesthesiologists or part of the "surgical workforce" (e.g. users that are critical care physicians). For example, Holmer et al estimated that there was one physician anesthesiologist in Somalia. Our dataset contains 11 unique physician users in Somalia, three of whom self-identify as anesthesiologists, so no plausible app adoption rate estimate can be made. Such inconsistencies resulted in a reduction in the number of countries that can be used be used in the analysis.

The key independent variables examined in the study included healthcare provider role (e.g. physician, anesthetist), provider country, country income level (categorized using the World Bank database [6]), provider length of time in practice, anesthesia practice model (e.g. physician only, physician supervised), anesthesia practice environment (e.g. small clinic, university hospital), size of anesthesia group, and community served. Figure 2 provides an outline of how these dependent and independent variables were culled from the broad dataset and the N available in each category. It also indicates the N available after combining the indicated subsets. Tables presenting univariate regression models always include information about total N as well N per category.

The key statistical methods used in the analysis of the app data include chi-square contingency table analysis, binomial logistic regression, and negative binomial regression. Chi-square analysis was used in comparisons of the provider rating of importance and country income level against categorical variables such as provider type.

Binomial logistic regression was employed to examine the association between app importance rating and the following variables: provider role, country income level, length of time in practice, anesthesia practice model, anesthesia practice type, group size, and community served. App importance rating was collected on a 5-point Likert scale which suggests using ordinal logistic regression to analyze these results. However, due to imbalances in response across levels of the Likert-survey scale, as well as violation of the ordinal regression assumption of proportional odds, binary logistic regression was conservatively used with the categories of app importance combined as follows: (a) "Absolutely Essential"/"Very Important" and (b) "Of

Average Importance"/"Of Little Importance"/"Not Important At All." In the regression analyses, Wald-type statistics were reported to test the significance of each of the independent variable [7].

Negative binomial regression was used to examine the association between frequency of app use and the following independent variables: app importance rating, provider role, country income level, length of time in practice, anesthesia practice model, anesthesia practice type, group size, and community served. The negative binomial approach was chosen over Poisson regression due to right skewness of the count data and noted overdispersion in rates across levels of the independent variables. When overall significance was found in the negative binomial regressions (as determined by the Wald Type III p-values), Tukey's honestly significant difference (HSD) method was used to examine post-hoc differences between levels of the factors. Similarly, negative binomial regression was used to examine the association between rate of physician app adoption and the country income level. As with the individual user rates, both Wald-type tests [7] and likelihood ratio tests [8] were used to test the overall significance of each of the independent variables in the regression analyses.

Methodology for Calculation of App Use Frequency

Under circumstances with no "complications," the frequency of app use for a fixed time interval would be estimated in a straightforward and intuitive manner by counting the number of app uses in the time interval and dividing by the length of the interval. The situation encountered in estimating the app use frequency based on the data obtained from the Survalytics platform is more complicated. This is because the app can be unloaded or otherwise abandoned (e.g., lost phone), and the Android operating system does not allow app unload events to be detected and reported by in-app analytics.

Because of this, estimating the app use rate as the number of uses between the time of consent and the time of conclusion of the study divided by the length of that interval would underestimate, potentially by a large amount, the rate of app use (while the app was available) for any user that unloaded the app or otherwise abandoned it. Similarly, estimating the rate of app use based on a time interval determined by the last time the app was used causes over estimation of the usage rate because the time after the last use until the end of the study (or until the app is unloaded) is truncated from the interval used to calculate the rate.

The approach used here to estimate the usage rates is designed to help correct for these biases in a reasonable way. The method is based on the assumption that, for any user i, the use of the app while installed (or otherwise not abandoned) follows a Poisson distribution with a constant usage rate λ_i. In this case, it can be shown that the expected value of the latest usage time t_n in an interval $[0, \mathrm{T}]$ where there have been n uses in that interval is

$E(t_n) = T\, n/(n+1)$. This last equation is derived from the fact that, for a Poisson process with n events occurring in the time interval $[0, \mathrm{T}]$, the times of those events will have the same distribution as the order statistics of n uniform random variables on the same interval (see, for example, Doob, page. 400) [9]. The formula above for $E(t_n)$ can be used to estimate T, the end of the time interval. Specifically, the estimated unload time is $\hat{T} = t_n\,(n+1)/n$, where t_n is the latest usage time and n is the number of observed uses.

Using this idea, the usage rate λ_i for user i is estimated as follows. First the app unload time predicted from the time of the last use is estimated by

$$\hat{T}_{U,i} = \frac{n_i + 1}{n_i}(t_{n_i} - T_{C,i}) + T_{C,i}$$

where n_i is the number of app uses by user i, t_{n_i} is the time of the last use, and $T_{C,i}$ is the time of consent for user i.

The time which is then used as the end of the time interval in the estimation of the usage rate is the minimum of the estimated unloading time $\hat{T}_{U,i}$ and T_S, the time of the conclusion of the study. The estimate of the rate λ_i for user i is then given by:

$$\hat{\lambda}_i = \frac{n_i}{\min(\hat{T}_{U,i}, T_S) - T_{C,i}} \ .$$

These estimated usage rates will be smaller than ones based on using the last observed time of use, and larger than those based on the end time of the study (unless the estimated unload time is later than the end of the study).

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