Review of iLO Micro-Learning Aims & Measures

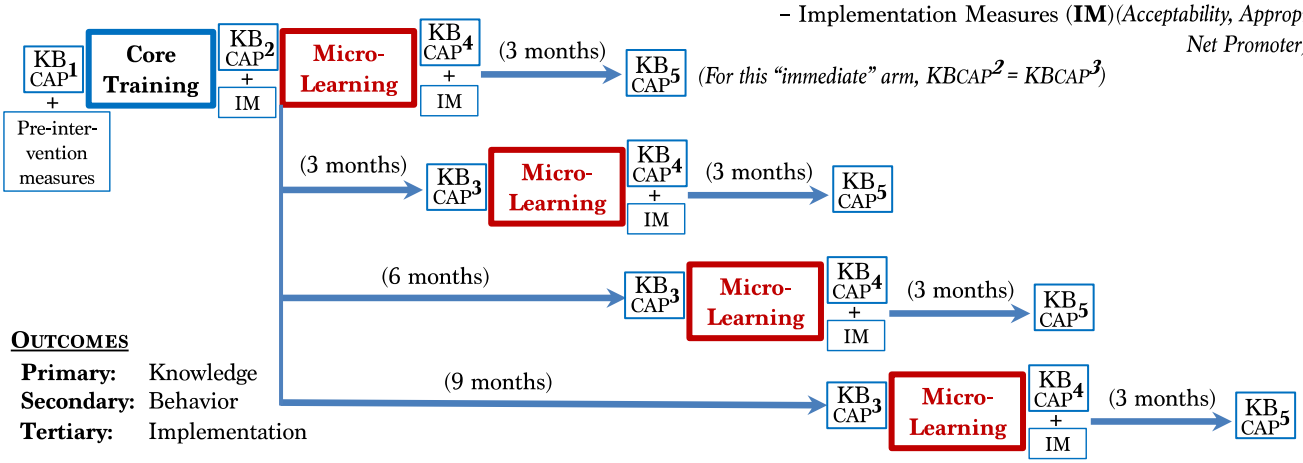
Overall Study Design

FIG. 6. iLOOKOUT MICRO-LEARNING STUDY DESIGN

SUMMARY: Early childhood professionals (ECPs) in PA complete measures on **K**nowledge, **B**ehavior, **C**onfidence, **A**ttitudes, and **P**reparedness before (**KBCAP[1]**) and after (KBCAP[2]) *iLookOut*'s Core training. After being randomized to receive Micro-Learning –either immediately, or after a delay (3, 6, or 12 months, respectively)– ECPs then complete the measures before (KBCAP[3]) and immediately after (KBCAP[4]) the Micro-Learning course, and again 3 months after (KBCAP[5]) completing the Micro-Learning course.

INTERVENTION = iLookOut's **Core** training (3 hr) + follow-up gamified **Micro-Learning** (3 hours total, delivered over a 3-month period in 5-10 minute units to ECPs' mobile devices)

MEASURES
- Knowledge re. child abuse & reporting (**K**)
- Behavior re. at-risk children (**B**)
- Confidence, Attitudes, Preparedness (**CAP**)
- Implementation Measures (**IM**)*(Acceptability, Appropriateness, Net Promoter)*



OUTCOMES

Primary: Knowledge
Secondary: Behavior
Tertiary: Implementation

Specific Aims

AIM 1: *To establish that iLookOut's Micro-Learning promotes long-term learning regarding child abuse and its reporting* –as measured by change in KNOWLEDGE at 5 time-points.

HYPOTHESIS I: Knowledge scores will decay over time.

HYPOTHESIS II: Micro-learning will remediate those decays and result in greater knowledge retention.

AIM 2: *To evaluate whether iLookOut's Micro-Learning is associated with changes in BEHAVIOR regarding child abuse and its reporting* –as measured by both self-report and data from the State (viz, Pennsylvania).

HYPOTHESIS III: Micro-Learning will be associated with changes in ECP behavior with regard to 1) increased identification of at-risk children, 2) more actions taken to help support the families of these at-risk children, and 3) increased reports to Pennsylvania child protective services when abuse is suspected.

AIM 3: *To establish that a multi-faceted implementation strategy that includes micro-learning is feasible.* We will judge *iLookOut*'s Micro-Learning to be feasible if:

1) >50% of ECPs who complete *iLookOut*'s Core training also complete *iLookOut*'s Micro-Learning program;
2) >75% of participants endorse *iLookOut*'s Micro-Learning, as measured by the Net Promoter Score; and
3) >75% of participants report that *iLookOut*'s Micro-Learning is acceptable and appropriate.

AIM 1 involves assessing knowledge decay (following Core training) regarding child abuse and its reporting, and the impact of Micro-Learning on knowledge remediation. Analyses will be based on a 4-arm design, in which (*immediately after completing Core training)* ECPs are randomized to start Micro-Learning right away, or after a delay of 3, 6, or 9 months, respectively (see C.1). Knowledge assessments (see C4.1) will occur at 5 time points (**K^1-K^5**, **see Fig. 6**, where *knowledge* is notated as the "**K**" in the Knowledge-Behavior-Confidence-Attitudes-Preparedness [**KBCAP**] measurement). To test **Hypothesis 1**, the change in score from K^2 to K^3 will be used to calculate mean knowledge decay for each of the arms in which there is a delay between the Core and Micro-Learning programs. Based on work by Ebbinghaus[101] and more recent research on learning and forgetting,[15, 102-104] we expect that (relative to mean knowledge scores immediately following the Core training, ie, K^2) knowledge loss will be greater the longer the interval between completing Core training and beginning Micro-Learning.

For **Hypothesis 2**, we expect that completing Micro-Learning exercises will result in improved knowledge scores (K^4>K^3). This hypothesis is based on broad evidence on the efficacy of post-intervention "booster" sessions.[105-107] We also plan to investigate whether Micro-Learning related improvement in knowledge scores (K^4 vs K^3) and their sustainability (K^5 vs K^4) vary based on the timing of Micro-Learning. Here, our hypothesis is that longer delays between the Core training and Micro-Learning will be associated with greater recovery (ie, greater increases from K^3 to K^4, given the greater initial knowledge loss from K^2 to K^3), but that the longer the delay, the lower the subsequent knowledge (K^4). We then expect to see roughly equal rates of knowledge loss in the 3 months after completion of Micro-Learning (K^5 vs K^4). This hypothesis is based on observations that specialized knowledge requires more immediate practice following initial information acquisition.[108] This design enables examination of behavioral drift, that is, how long knowledge (and skill, for AIM 2) regarding child abuse and its reporting will be sustained after reinforcement is removed.

AIM 2 focuses on behavior change consequent to Micro-Learning, in terms of 1) ECPs' reporting of suspected abuse, and 2) behaviors ECPs take to support at-risk children and their families. We will measure **reporting practices** in two ways. **First**, as part of the KBCAP, we will survey ECPs about the number of children they have reported over the preceding 3 months. ECPs' responses after completing Micro-Learning (ie, B^4 and B^5) will be compared to reporting practices both before (B^1) and after (B^2) the Core training, as well as prior to starting Micro-Learning (B^3). Second, in collaboration with Pennsylvania's child protection services (see LOS from CYS), we will assess whether reports of suspected abuse were more likely to be substantiated if the person who made the report had completed *iLookOut*'s Micro-Learning. To accomplish this, a child protection service administrator will cross-check the names of ECPs who completed Micro-Learning (which we will share) with the names of ECPs who reported suspected child abuse, and then will compare substantiation rates for those reports vs reports from ECPs who did *not* engage in Micro-Learning.

The **second** type of behavior change we will evaluate is actions ECPs take to protect and/or support at-risk children and their families. These data will be collected as part of the KBCAP measures at the time points indicated above for reporting practices. The actions we will measure include: *identifying resources to help children/families in need* (eg, making referrals to social

services, creating handouts with contact information for resources); *promoting protective factors for children and their families* (eg, participation in activities that build parental resilience, social connections, social/emotional competence); and *formal documentation of concerns related to a child being at-risk* (eg, inadequate resources, family stress, intimate partner violence, substance use disorders). In addition, given the likely link between an individual's knowledge and their subsequent behavior, we will explore whether increased knowledge mediates changes in reporting behavior.

AIM 3 is to establish the feasibility of a multi-faceted strategy (Core+Micro-learning), as defined by all the following criteria being met: **1)** ≥ 50% of ECPs who complete Core training also complete the 3-hour Micro-Learning course; **2)** >75% of ECPs who complete Micro-Learning endorse the multi-faceted strategy, as defined by a positive (>0) Net Promoter Score (see C.4.2) **3)** >75% of ECPs rate the multi-faceted strategy as acceptable, defined as a mean score >30 on the (8-48) Abbreviated Acceptability Rating Profile;[109] and **4)** >75% of ECPs rate the multi-faceted strategy as *appropriate* using the *Assessment Follow-Up* scale adapted from Bartholomew[110] (where appropriateness is the perceived fit, relevance, or compatibility for addressing a particular issue or problem[111]). Additionally, we will compare the magnitude of parameter estimates between Core→implementation vs Core+Micro-Learning→implementation (see Fig. 5).

Data Analysis

Separate mixed-effects linear regression model[131] will be applied to assess (1) the *knowledge decay* effect based on the data collected at KBCAP[2] and KBCAP[3], (2) the *knowledge remediation* effect of Micro-Learning based on change from KBCAP[3] to KBCAP[4], (3) the knowledge retention effect using data at KBCAP[4] and KBCAP[5], and (4) the behavior change between any time points and how it is correlated to the knowledge score for Aims 1 & 2, after controlling for participants' baseline characteristics and work setting. In addition, the regression model will adjust effects for allocation blocks and the factors for stratification in the analysis to reduce group variability.

Given the nested structure of the data (e.g., multiple reports from ECPs nested within a child care program, and multiple child care programs within each program type), the random-effects in the model are designed to be multilevel to account for shared variance explained by child care program. It is a useful approach in such contexts (ie, non-independent data structure) that models both within-program and between-program changes in knowledge and behavior (measured via KBCAP^t) over time. Demographic and site characteristics will also be included in subsequent models to examine potential conditional effects (ie, **moderation**) on intervention. The multilevel model will be fit in R using the *nlme* package[132] with restricted maximum likelihood. If singular fit error occurs, Bayesian multilevel modeling will be applied instead using *JAGS*.[133]

Figure 8 illustrates a typical multilevel model example that we will apply for data analysis. For these equations, Y_{ijk} is an outcome variable representing the change of knowledge or behaviors (ie, ΔKBCAP^t) for individual k in intervention arm i and randomization block j; A_i is the effect for being in arm i; and B_j is the random effect for being in block j, respectively. $f(P_{ijk}, \mathbf{X}_{ijk})$ is the moderator

FIG. 8. MULTI-LEVEL MODEL EQUATION

$$Y_{ijk} = \mu + A_i + B_j + f(P_{ijk}, \mathbf{X}_{ijk}) + \varepsilon_{ijk}$$

$$f(P_{ijk}, \mathbf{X}_{ijk}) = \sum_p \theta_p * I(P_{ijk} = p) + \mathbf{X}_{ijk}\boldsymbol{\beta}$$

$$\theta_p = \sum_t \eta_c * I(T_p = c) + \mathbf{Z}_p\boldsymbol{\gamma} + u_p$$

effect from factors P and **X**, where P denotes the child care program, and **X** is a multivariate vector of baseline characteristics such as age and gender that are all program-unrelated. θ_p is the effect for program p, which consists of η_c, the effect of the program type T_p=c, and the effect of other program-related factors **Z** such as size, QRIS rating, and rurality level. ε_{ijk} and u_p are the random effects of ECP intercept and program intercept, respectively.

The binomial test will be applied for outcomes in Aim 3. Mixed-effects logistic regression will assess the heterogeneity in child care programs and the effect of the time-delay on Micro-Learning following the Core training after controlling demographic and site characteristics. P-values and 95% confidence intervals (CIs) for comparison between arms. For behaviors listed as the second type in **C.3.** p-values and 95% CIs will be adjusted for multiple comparison using Bonferroni correction. Because we will track when ECPs receive their first Micro-Learning activity, and when they complete Micro-Learning, we will also explore the impact of any lag time prior to engaging in Micro-Learning, and how long it actually takes ECPs to complete the full course of Micro-Learning.

Plan for the Handling of Missing Data

We will handle missing data by taking advantage of all observed information while not exaggerating precision of findings based on incomplete data. *Full information maximum likelihood* will be employed as a data estimation method to account for missing variables in the data, and can produce unbiased parameter estimates and standard errors under the assumption data are missing completely at random (**MCAR**) or missing at random (**MAR**). The MCAR assumption will be tested using the single global test proposed by Little & Rubin.[134] If an MCAR or MAR assumption seems tenuous, we will explore the use of modern missing data methods (eg, maximum likelihood or Bayesian multiple imputation)[135] that address uncertainty when participants are lost-to-follow-up.[136-139] To minimize risk of selective enrollment and differential attrition, we will use logistic regression to compare participants with national data on ECPs, and conduct post-hoc analyses[140] to correct for any differences.