

# Community Stakeholder Preferences for Evidence-Based Practice Implementation Strategies in Behavioral Health: A Best-Worst Scaling Choice Experiment

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## Research article

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# Abstract

**Background:** Community behavioral health clinicians, supervisors, and administrators play an essential role in implementing new psychosocial evidence-based practices (EBP) for patients receiving psychiatric care; however, little is known about these stakeholders' values and preferences for implementation strategies that support EBP use, nor how best to elicit, quantify, or segment their preferences. This study sought to quantify clinician, supervisor, and administrator preferences for implementation strategies and to identify segments of these stakeholders with distinct preferences using a rigorous choice experiment method called best-worst scaling (BWS).

**Methods:** A total of 240 clinicians, 74 clinical supervisors, and 29 administrators delivering publicly funded behavioral health services in a large metropolitan behavioral health system participated in a best-worst scaling choice experiment. Participants evaluated 14 implementation strategies developed through extensive elicitation and pilot work within the target system. Preference weights were generated for each strategy using hierarchical Bayesian estimation. Latent class analysis identified segments of stakeholders with unique preference profiles.

**Results:** On average, clinicians, supervisors, and administrators preferred two strategies significantly more than all others—compensation for use of EBP per session and compensation for preparation time to use the EBP; two strategies were preferred significantly less than all others—performance feedback via email and performance feedback via leaderboard. However, latent class analysis identified four distinct segments of stakeholders with unique preferences: Segment 1 ( $n = 121$ , 35%) strongly preferred financial incentives over all other approaches; Segment 2 ( $n = 80$ , 23%) preferred technology-based strategies; Segment 3 ( $n = 52$ , 15%) preferred an improved waiting room to enhance client readiness and strongly disliked any type of clinical consultation; Segment 4 ( $n = 90$ , 26%) rejected financial incentives and strongly preferred strategies focused on clinical consultation.

**Conclusions:** The presence of four heterogeneous subpopulations within this large group of behavioral health administrators, supervisors, and clinicians suggests optimal implementation may be achieved through targeted strategies derived via elicitation of stakeholder preferences. Best-worst scaling is a feasible, systematic, and rigorous method for eliciting stakeholders' implementation preferences and identifying subpopulations with unique preferences in behavioral health settings.

## Background

The need to improve the quality and outcomes of health and behavioral health services has led to increased emphasis on the implementation of evidence-based practices (EBPs) in community settings (1–4). Effective implementation of EBPs requires the cooperation of clinicians, supervisors, and administrators who deliver clinical care. However, little is known about these stakeholders' values and preferences for specific types of implementation strategies, defined as the active approaches used to improve adoption, implementation, and sustainment of EBPs (5). It is also not clear how best to elicit,

quantify, and segment stakeholders' implementation preferences. Community stakeholder preferences should be considered when selecting implementation strategies for several reasons. First, the process of eliciting preferences is, in and of itself, a way to increase stakeholder engagement and buy-in, a key component of the implementation process (6–8). Second, there is evidence that tailored implementation strategies (i.e., those that address localized barriers) are more effective than non-tailored strategies (9, 10) and stakeholder preferences may provide insights regarding how to tailor to local contexts (9). Third, because stakeholder preferences may not align with evidence on what works, understanding their preferences is an essential first step in determining where implementation efforts should start in terms of targeted mechanisms of change.

To date, efforts to elicit stakeholder implementation preferences using both qualitative and quantitative approaches have had several limitations. Qualitative interviews are useful for generating deep understanding among a small group; however, they are resource intensive and may have limited generalizability. Recent advances in quantitative measurement include pragmatic Likert-type scales that allow stakeholders to rate the acceptability, feasibility, and appropriateness of implementation strategies (11). These approaches are relatively low-cost even for large samples; however, because they do not require respondents to consider trade-offs, they typically suffer from strong ceiling effects with many strategies ending up highly-ranked, thus undermining their utility.

Conjoint analysis is a promising set of methods for eliciting stakeholder preferences that may overcome these limitations by engaging stakeholders in an intuitive yet powerful set of choice tasks that closely mimic real-life decisions and that can be easily implemented in large samples (12). By requiring respondents to consider trade-offs across a set of choices, conjoint analysis generates highly-accurate estimates of implicit preferences for a targeted set of objects (e.g., implementation strategies) in a time-efficient, cost-effective, and generalizable manner (12–15). These methods are especially valuable when the set of objects are carefully derived through elicitation work within the target population and when information on actual behavior or decisions are unavailable (or unobtainable), as is typically the case in implementation (16).

Best-worst scaling (BWS) choice experiments (16, 17) are a type of conjoint analysis uniquely suited to the task of eliciting implementation preferences. This is because BWS is flexible enough to identify either (a) the most preferred strategy(s) from a list of irreducible and dissimilar strategies, or (b) the most preferred level (e.g., dollar amount) of an attribute (e.g., compensation) that multiple strategies have in common (17). This is important because there are 73 discrete implementation strategies which can be combined in many permutations (18). Second, respondents' BWS choices can be segmented using model-based clustering procedures such as latent class analysis to identify subpopulations that share similar preferences (19, 20). Segmentation allows planners to optimally target implementation strategies to subpopulations based on their preferences and therefore potentially optimizes their impact.

The goals of this study were to apply BWS to (1) characterize and quantify the preferences of clinicians, supervisors, and administrators who deliver publicly-funded behavioral health services for a set of 14

implementation strategies, (2) empirically identify segments of stakeholders that exhibit distinct preferences, and (3) examine differences across segments in professional characteristics (e.g., age, education, primary role in organization).

## Methods

### Setting

Philadelphia, a city of over 1.5 million residents, is the poorest of the United States' 10 largest cities (26% of residents live below the poverty level) (21, 22). The city's population is 41% African-American, 35% Non-Hispanic White, 15% Hispanic, 8% Asian, and 2% other race (22, 23). Public behavioral health services (i.e., mental health and substance use treatment) in Philadelphia are financially supported by Medicaid and managed by Community Behavioral Health (CBH), a non-profit managed care organization (i.e., "carve-out") established by the City that functions as a component of the Department of Behavioral Health and Intellectual disAbility Services (DBHIDS). In 2018, DBHIDS included 175 in-network provider organizations serving 118,011 unique members (24).

Since 2007, DBHIDS has supported EBP delivery in Philadelphia through a series of "EBP initiatives" that include training, expert consultation, and implementation supports (e.g., booster trainings, implementation meetings) for participating clinicians (25). These initiatives supported implementation of several cognitive behavioral therapy models addressing a range of psychiatric disorders. In 2013, DBHIDS created a centralized infrastructure called the Evidence-based Practice and Innovation Center (EPIC) to oversee EBP implementation efforts. EPIC supports EBP implementation by coordinating and consulting EBP efforts across CBH (the managed care organization), contracting with treatment experts to deliver EBP training, contracting with treatment providers to deliver EBP, providing EBP consultation and implementation support, hosting events to publicize EBP delivery, maintaining web-based resources (e.g., webinars), designating EBP programs within provider agencies, and providing financial incentives (e.g., enhanced rates) for delivery of EBPs.

### Participants

The target population for this study included clinicians and administrators delivering publicly-funded behavioral health services in the City of Philadelphia. Because DBHIDS does not maintain a roster of email addresses to directly contact active clinicians, we used a two-pronged recruitment and sampling approach. We sent invitation emails to leaders of behavioral health organizations ( $n = 210$ ), clinicians ( $n = 527$ ), and other community stakeholders (e.g., directors of a clinician training organization;  $n = 6$ ) in Philadelphia. We also e-mailed the invitation to four local electronic mailing lists known to reach large swaths of the CBH network (e.g., managed care organization listserv) and asked organization and network leaders to forward the email. From these contacts, the survey link was opened 654 times and 343 respondents completed the BWS choice experiment.

### Study Design and Procedure

The BWS choice experiment was designed to quantify stakeholders' preferences for 14 implementation strategies developed through iterative elicitation, pilot, and pre-testing work completed with members of each stakeholder group in the target population (17, 26). Elicitation of strategies was completed via a system-wide innovation tournament, described elsewhere (27), through which clinicians submitted ideas for strategies to support EBP implementation in Philadelphia. Following the tournament, submitted ideas ( $N = 65$ ) were analyzed and refined by a team of implementation scientists, behavioral scientists, and clinicians, in order to develop a set of distinct, clearly operationalized implementation strategies with ecological validity for the target system. This process resulted in a set of 14 implementation strategies (see Table 1: *List of Implementation Strategies Included in the BWS Experiment*), which were subsequently evaluated in pre-testing interviews with clinicians, supervisors, and administrators ( $n = 9$ ) within the system to ensure that the strategies, as described, spanned the full range of approaches viewed as relevant by stakeholders and were clearly described. The 14 strategies fell into six categories: (1) financial incentives, (2) clinical consultation, (3) clinical support tools, (4) clinician social support and networking, (5) clinician performance feedback/social comparison, and (6) client supports (27).

Table 1

*List of Implementation Strategies Included in the BWS Choice Experiment*

<b>Strategy Name</b>	<b>Definition</b>
EBP certification bonus	Receipt of a 1-time bonus for verified completion of a certification process over a 1-year period, in which clinicians: attend four, 1-day booster training sessions; pass a multiple-choice knowledge test; and submit one tape of a session with a client where they use the EBP.
Compensation for use of EBP per session	Receipt of additional compensation (in addition to regular paycheck) upon verification of using the EBP in sessions with clients for whom it is appropriate (i.e., per session), up to a specified amount per year.
Compensated time for preparation	Ability to bill for any verified time clinicians spend preparing to use the EBP (e.g., reviewing the protocol, preparing materials for session, reviewing client homework, etc.), up to a specified amount per year.
Client mobile app/ texting service	Provides clients with reminders to attend sessions, prompts to complete homework assignments, and clinician-tailored messages about practicing EBP skills.
Improved waiting room	Create a relaxing waiting room (e.g., physical appearance, sensory experience) that helps prepare the client to enter the session ready to work on EBP content.
EBP-focused online forum	Confidential site available only to registered clinicians who use the EBP, where clinicians can login and post questions and answers about using the EBP, share tips, and identify resources for using the EBP.
Community-based EBP mentoring program	One-on-one mentoring program, where clinicians are matched with a local peer clinician who works with the same population to support each other in implementing the EBP.
Web-based resource center/ mobile app	Includes: (a) video examples of how to use specific techniques for the EBP, (b) "session checklists" with steps outlined for using the EBP techniques in session, and (c) downloadable worksheets and measures needed to use the EBP.
Electronic evidence-based screening instrument inventory	Evidence-based screening instruments included in an electronic medical record, completed electronically by clients in the waiting room (e.g., tablet); results are automatically scored and immediately available so clinicians can assess treatment needs and track client progress.
Expert in your back pocket (on call)	Network of EBP trainers on call via phone or web chat for same-day, 15-minute consultations to problem-solve issues with implementing the EBP.
Expert-led EBP consultation	1-hour, monthly, web- or phone-based consultation, with up to 5 other clinicians, for one year led by an expert EBP trainer.
Peer-led EBP consultation	1-hour, monthly web- or phone-based conference, with up to 5 other clinicians, for one year led by a clinician with experience implementing the EBP in Philadelphia.

Strategy Name	Definition
EBP Performance benchmark leaderboard	Posted where only agency staff can view it, recognizing clinicians in the agency who met a benchmark for EBP implementation each month (based on 3 randomly selected sessions).
EBP Performance benchmark email	Available only to the clinician and his/her supervisor, reporting whether s/he met a benchmark for EBP implementation each month (based on 3 randomly selected sessions).

Because each of the 14 strategies represented a qualitatively unique strategy, we used object case BWS (as opposed to profile case or multi-profile case BWS) (28). The BWS experimental design was generated using the Sawtooth Discover algorithm which produces randomized choice sets with optimal frequency balance, orthogonality, positional balance, and connectivity for a given sample size (29–33). Within the design, each participant was shown 11 sets of four randomly selected and randomly ordered strategies and, within each set, asked to choose which strategy was “Most useful” (i.e., best) for supporting clinicians’ implementation of psychosocial EBPs and which strategy was “Least useful” (i.e., worst). The Discover algorithm optimizes 1-way, 2-way, and positional balance within the randomization sequence such (a) that each strategy is presented an equal number of times, (b) each pair of strategies appears in a set an equal number of times, and (c) each strategy is shown in each position an equal number of times. For this study, each strategy was included in at least three sets. Participants were instructed to imagine that their organization had decided to adopt a new psychosocial EBP that exhibited excellent outcomes for their specific client population, and that this treatment was new to the respondent (or to clinicians working in the respondent’s setting). The prompt explained that initial training in the EBP would be provided and would include active learning approaches, and their input was sought regarding the best implementation strategies that could be used to support clinicians’ implementation of the new practice following training. Additional file 1 shows the BWS prompt and an example set of strategies.

Sample size calculations assumed an alpha level of .05, margin of error of 0.1, and 14 implementation strategies to be rated with each strategy appearing in a minimum of 3 sets. Based on these assumptions, the required sample size was N = 244 participants rating 11 sets of 4 strategies each (28, 34).

The BWS experiment was implemented via a web-based computerized survey emailed to clinicians, supervisors, and administrators from March 2019 to April 2019. Consistent with best practices in survey administration, we utilized a process (35) in which participants received a pre-survey priming email, survey invitation email, and three follow-up reminders, delivered approximately one week apart. Surveys took approximately 30 minutes and participants received a \$25 gift card.

## Measures

In addition to completing the BWS questions, respondents reported on professional and workplace characteristics: primary role (administrator, supervisor, clinician), education level, type of clinic in which they were employed (mental health, substance use, dual diagnosis), salary versus fee-for-service

employment, tenure in current agency, years of experience as a clinician, extent to which their graduate training emphasized EBP (ranging from 1 = *Never* to 7 = *Always*), average hours worked per week, number of City-sponsored EBP training initiatives in which the respondent had participated (ranging from 0 to 6), number of BWS strategies currently in use by their employing agency (ranging from 0 to 14), age, sex, race, and ethnicity.

## Data Analysis

Best and worst choice frequencies for each strategy were summarized at the sample level using count analysis which represents the proportion of times a strategy was chosen as most or least useful relative to the number of times it was displayed (17). Preference weights for each strategy were calculated at the individual level using hierarchical Bayes estimation with a multinomial logit model implemented using CBC/HB software from Sawtooth (version 5) (36–40). Latent class analysis (LCA) (19, 20, 41) was used to identify segments of the population with different preferences and to estimate preference weights for each class using Sawtooth Software's LCA program (version 4.7), which generated solutions from 1 through 5 classes. Differences across segments on professional characteristics were tested using analyses of variance and chi-square tests (SPSS, Version 25). Participants with missing data on professional and sociodemographic variables were excluded from these analyses on a pairwise basis.

## Results

Table 2 shows the best and worst choice frequencies for each strategy. Figure 1 shows the mean preference weights for each strategy with 95% confidence intervals. The two strategies viewed as most useful were both within the financial incentives category and included (1) compensation for EBP use per session and (2) compensation for EBP preparation time. Both of these were preferred significantly more than all other strategies (see Fig. 1). Conversely, both performance feedback/social comparison strategies were viewed as significantly less useful than all others (see Fig. 1): (1) performance feedback via leaderboard was the least preferred, followed by (2) performance feedback via email. On average, financial incentive strategies were preferred 9.2 times more than performance feedback/social comparison strategies (Mean Best = .46 vs. .05) and performance feedback/social comparison strategies were disliked 5.1 times more than financial incentive strategies (Mean Worst = .56 vs. .11).

Table 2  
*Sample Best and Worst Choice Frequencies*

<b>Implementation Strategy</b>	<b>B</b>	<b>W</b>	<b>B - W</b>	<b># of times displayed</b>
Compensated per session	0.46	0.10	0.36	1,079
Compensated prep time	0.45	0.11	0.35	1,079
Web-based resource center	0.36	0.12	0.24	1,084
Expert monthly supervision	0.32	0.15	0.18	1,094
Certification bonus	0.34	0.17	0.17	1,074
Electronic screening inventory	0.31	0.18	0.13	1,075
Community clinician mentor	0.27	0.20	0.08	1,079
Client mobile app/ texting	0.22	0.24	-0.02	1,076
Peer monthly supervision	0.18	0.23	-0.05	1,080
Expert on call	0.19	0.24	-0.05	1,080
Online therapist forum	0.18	0.26	-0.08	1,081
Improved waiting room	0.12	0.41	-0.29	1,070
Performance email	0.05	0.52	-0.47	1,076
Performance leaderboard	0.04	0.59	-0.55	1,065

*Note:* N= 343. B = sample-level best choice frequency calculated as the proportion of times the strategy was selected as “Most Useful” relative to the number of times it was displayed; W = sample-level worst choice frequency calculated as the proportion of times it was selected as “Least Useful” relative to the number of times displayed. B – W = best minus worst scores calculated as proportion best less proportion worst.

Figure 2 shows the preference weights and 95% confidence intervals for each strategy for each of the four segments identified in the optimally-fitting four-class LCA model. Table 3 shows the distribution of professional and sociodemographic characteristics by segment and for the full sample. Segment 1, labeled *Support Therapists through Financial Incentives*, included 35% of the sample ( $n = 121$ ) and exhibited significantly higher preferences for compensation per session, compensation for preparation time, and compensation for certification compared to all other segments. Segment 1 had the highest proportion of administrators (17%,  $n = 20$ ) relative to the other groups (3–5%,  $p = .006$ ) (see Table 3 included as an additional file [see Additional file 2]).

Segment 2, labeled *Support Therapists through Technology*, included 23% of the sample ( $n = 80$ ) and exhibited significantly higher preferences for the client mobile app/texting service and the web-based clinician resource center/mobile app compared to the other segments. This segment exhibited significantly less favorable preferences for the performance feedback email and performance

leaderboard relative to other groups. Segment 2 tended to have fewer years of experience in their current agency ( $p = .061$ ) and to be younger on average ( $p = .065$ ).

Segment 3, labeled *Support Therapists through Autonomy*, included 15% of the sample ( $n = 52$ ). This segment exhibited the only positive rating of the improved waiting room strategy and these ratings were significantly higher than those of the other segments. This segment also exhibited significantly less preference for EBP consultation led by either experts or peers. Members of this segment exhibited lower than average participation in the EBP initiatives provided by the City ( $p = .021$ ) and the fewest average hours worked per week ( $p = .009$ ).

Segment 4, labeled *Support Therapists through Consultation*, included 26% of the sample ( $n = 90$ ) and exhibited significantly higher preferences for expert-led monthly consultation, peer-led monthly consultation, and a community-based EBP mentoring program. This segment also exhibited significantly lower preferences than the other groups for compensation per session and compensation for preparation time. This segment had the highest proportion of clinicians (38%) who worked in clinics focused on the treatment of substance use disorders ( $p = .020$ ), although similar to other segments, most in this group worked in clinics focused on the treatment of mental health disorders (62%).

## Discussion

This study provides valuable insights on clinician, supervisor, and administrator preferences for implementation planning in large public behavioral health systems and highlights important directions for future research. Results also illustrate the utility of BWS as a methodology for rigorously and efficiently eliciting stakeholder preferences for implementation strategies in large-scale behavioral health and health systems.

By identifying four distinct subpopulations of clinicians, supervisors, and administrators whose preferences reflected distinct foci for implementation strategies, these findings highlight the heterogeneity of stakeholder preferences and point to the need for a new research agenda that unpacks the relationships between preference, implementation effectiveness, and tailoring of implementation strategies. Even as Segment 1 (35% of the sample) strongly preferred all financial incentive strategies above any other strategy, another group, Segment 4 (26% of the sample), showed no interest in financial incentives, preferring instead consultation with EBP experts, and yet another group, Segment 2 (23% of the sample) exhibited strong preferences for technology-based strategies. These groups were all distinct from Segment 3 (15% of the sample) which preferred an improved waiting room (to help relax patients and prepare them to engage in an EBP-focused session) and viewed any type of clinical consultation as unhelpful. These distinct segments suggest that a one-size-fits-all implementation strategy may not be successful, and certainly will not be preferred, by the majority of stakeholders. Different implementation strategies may need to be matched with these distinct subpopulations. There is growing consensus in implementation science that strategies should be selected and tailored based on contextual factors with regard to the EBP, setting, and individual characteristics (48, 49). Our results highlight stakeholder

preference as a potentially important dimension for tailoring implementation strategies and point to the need for research to better understand how preferences influence EBP implementation.

Targeting implementation strategies based on stakeholders' preferences may result in more successful EBP implementation in at least three ways. First, *if* implementation strategies are differentially effective for different individuals and contexts, stakeholder preferences may signal which strategy will be most effective for a given situation. This is similar to the idea of precision medicine in which the most effective intervention (i.e., implementation strategy) depends on the characteristics of the specific individual in context. Second, targeting strategies to stakeholders' preferences may have a general *accelerator effect* that increases the effectiveness of any strategy compared to its baseline effectiveness due to engagement or buy-in. For example, if participants are more engaged or invested in a strategy and willing to exert more effort to ensure its success because they chose it, this may increase the strategy's effectiveness. Ideally, research could quantify the magnitude of this 'preference effect' to determine how much increase in effectiveness could be expected for any strategy simply by allowing stakeholders to choose it. Third, assuming that some strategies are universally more effective than others, it may be beneficial to understand stakeholders' preferences so that policymakers and other leaders can identify stakeholders who do not prefer effective strategies and use supplemental interventions (e.g., a readiness strategy) with these individuals prior to or concurrent with the launch of the effective strategy. Finally, it may be that preference has no effect on the outcome of implementation strategies. The identification of four distinct preference subpopulations in this study points to the need for research to determine how preferences relate to implementation effectiveness so that resources devoted to implementing EBPs can be optimized.

Across the full sample, one consistent finding was the overall rejection of performance feedback/social comparison strategies, which were rated lower than all other strategies on average for the full sample and were the lowest rated strategies for 3 out of 4 subpopulations. These findings suggest stakeholders overwhelmingly viewed performance feedback/social comparison strategies as unhelpful for supporting EBP implementation. This is consistent with findings from primary care practices, in which primary care clinicians also disliked strategies using social comparison (42). Future qualitative inquiry could provide valuable insights into why stakeholders view feedback/social comparison strategies as unhelpful. Potential mechanisms include discomfort with receiving information that is misaligned with one's perception of one's performance or feeling as though there will be negative consequences for poor performance.

The large preference gap between feedback/social comparison and other strategies, such as financial incentives, which emerged as the most preferred strategy on average in the full sample and the first or second choice strategy for 3 out of 4 subpopulations, raises an important question about the relative effectiveness of high cost financial incentives compared to lower cost performance feedback strategies, both of which have some evidence of effectiveness (43, 44). Comparative effectiveness trials that include cost-effectiveness analyses would aid policymakers in selecting among strategies when there is a mismatch between stakeholders' preferences versus what is known to be effective (45). The generally

favorable view of financial incentives in this sample is not surprising against the backdrop of a publicly-funded behavioral health workforce that is poorly compensated and financially stressed, often employed as independent contractors, and are working within organizations that are also struggling financially (46, 47).

Another issue highlighted by these findings is the question of which stakeholder group's preferences have the strongest implications for successful implementation. Many systems, such as Philadelphia, focus implementation policies primarily at the program level by designating EBP programs and providing financial incentives to agencies (versus clinicians). This raises the question of to what extent policymakers should focus their attention on the preferences of executives and administrators, who make agency-level decisions about EBP (e.g., whether to respond to agency incentives by implementing an EBP program), versus attending to the preferences of clinicians, who ultimately are responsible for implementing EBPs in direct care. Preliminary evidence regarding pay-for-performance in behavioral healthcare suggests organization-focused financial incentives have minimal impact on practice whereas individual clinician-focused incentives can change provider behavior (44).

Our results are subject to limitations and qualifications. Stated preferences were elicited from a controlled experiment on hypothetical implementation options. Real-world implementation behaviors are complicated by numerous factors not accounted for in our controlled experiment; thus, actual implementation behavior could be different from that predicted by our data. However, several features of the study design were implemented following best practice methods and consequently limit the potential for bias. For example, the scenario and implementation strategies were presented as realistically as possible and the number of questions each respondent answered was limited considering the cognitive burden of choice questions. The specific implementation preferences described by this sample of clinicians and administrators in this large public behavioral health system may not generalize to clinicians in more rural areas or in cities or states that have not exhibited similar support for EBP. Further, the particular set of strategies is likely tied to the structure of the US behavioral healthcare system and likely would not generalize to other countries with different healthcare systems. The use of a motivated volunteer sample of stakeholders, while preserving internal validity, may also limit generalizability and affect the relative proportions in the latent class analysis. Finally, clinician preferences are but one factor in many that should guide the selection of implementation strategies to support EBP in a specific setting.

## Conclusions

Effective implementation of EBP in health and behavioral health systems must include the active participation of stakeholders who receive, deliver, and/or oversee the delivery of clinical care. Numerous groups, including service participants, family members, clinicians, supervisors, administrators, funders, and policymakers, have a stake in implementation decisions and understanding their values and preferences for implementation strategies may be one way to increase stakeholder engagement and implementation effectiveness. Results from this study demonstrate the presence of four distinct subpopulations of clinicians, supervisors, and administrators whose implementation preferences differ

and who may not all respond positively to a one-size-fits all implementation strategy. As such, these findings highlight the need for research on how stakeholder preferences intersect with implementation effectiveness and the tailoring of implementation strategies.. Furthermore, this study demonstrates that BWS choice experiments are a highly feasible and rigorous method for eliciting stakeholders' preferences regarding how to support their implementation of EBP.

## Abbreviations

BWS

Best-Worst Scaling

CBH

Community Behavioral Health

DBHIDS

Philadelphia Department of Behavioral Health and Intellectual Disability Services

EBP

Evidence-Based Practice

EPIC

Philadelphia Evidence Based Practice and Innovation Center

LCA

Latent Class Analysis

## Declarations

**Ethics Approval and Consent to Participate:** Ethics approval for this research was provided by the City of Philadelphia (2017-51) and University of Pennsylvania IRBs (827425). Since the research presented no more than minimal risk of harm to subjects and involved no procedures for which written consent is normally required outside of the research context, we were granted waiver of documentation of consent. The required elements of informed consent were described on the first page of the electronic survey and, if they agreed to participate, participants consented by proceeding to the second page of the electronic survey.

**Consent for Publication:** Not applicable.

**Availability of Data and Materials:** Data will be made available upon request. Requests for access to the data can be sent to the Penn ALACRITY Data Sharing Committee. This Committee is comprised of the following individuals: Rinad Beidas, PhD, David Mandell, ScD, Kevin Volpp, MD, PhD, Alison Buttenheim, PhD, MBA, Steven Marcus, PhD, and Nathaniel Williams, PhD. Requests can be sent to the Committee's coordinator, Kelly Zentgraf at zentgraf@upenn.edu, 3535 Market Street, 3<sup>rd</sup> Floor, Philadelphia, PA 19107, 215-746-6038.

**Competing Interests:** Dr. Beidas receives royalties from Oxford University Press and has consulted for the Camden Coalition of Healthcare Providers. All other authors declare that they have no competing interests to report.

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**Authors' Contributions:** This paper has been developed with contributions from all authors. RB developed the study concept. All authors contributed to the study design. Testing and data collection were performed by YVB and KZ. Data analysis and interpretation were performed by NJW, MC, RES, MB, AMB, and RB. NJW drafted the manuscript, and RB provided critical revisions. The second draft was circulated to all authors for comment and endorsement of the consensus. Following further amendments, all authors approved the final manuscript.

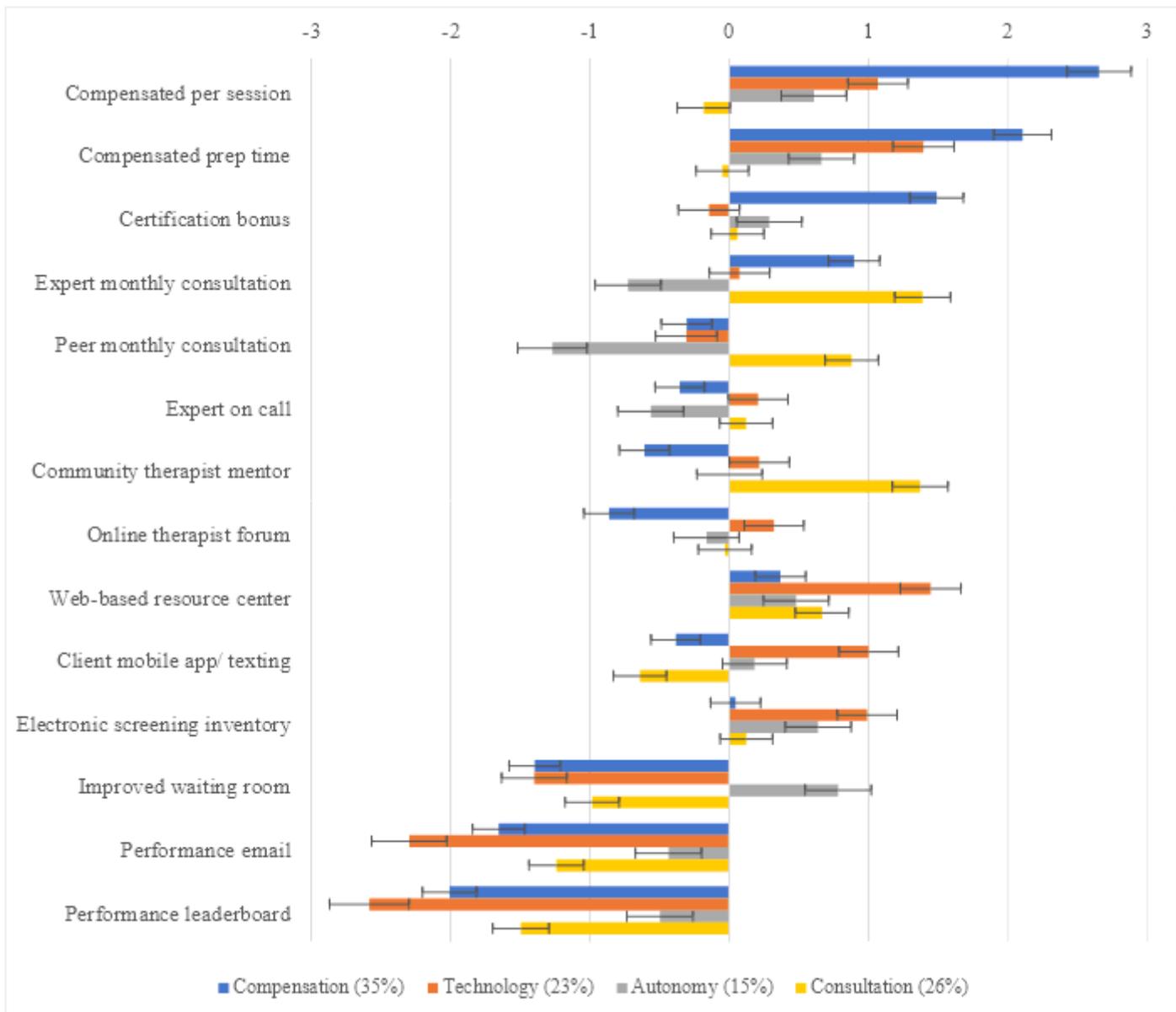
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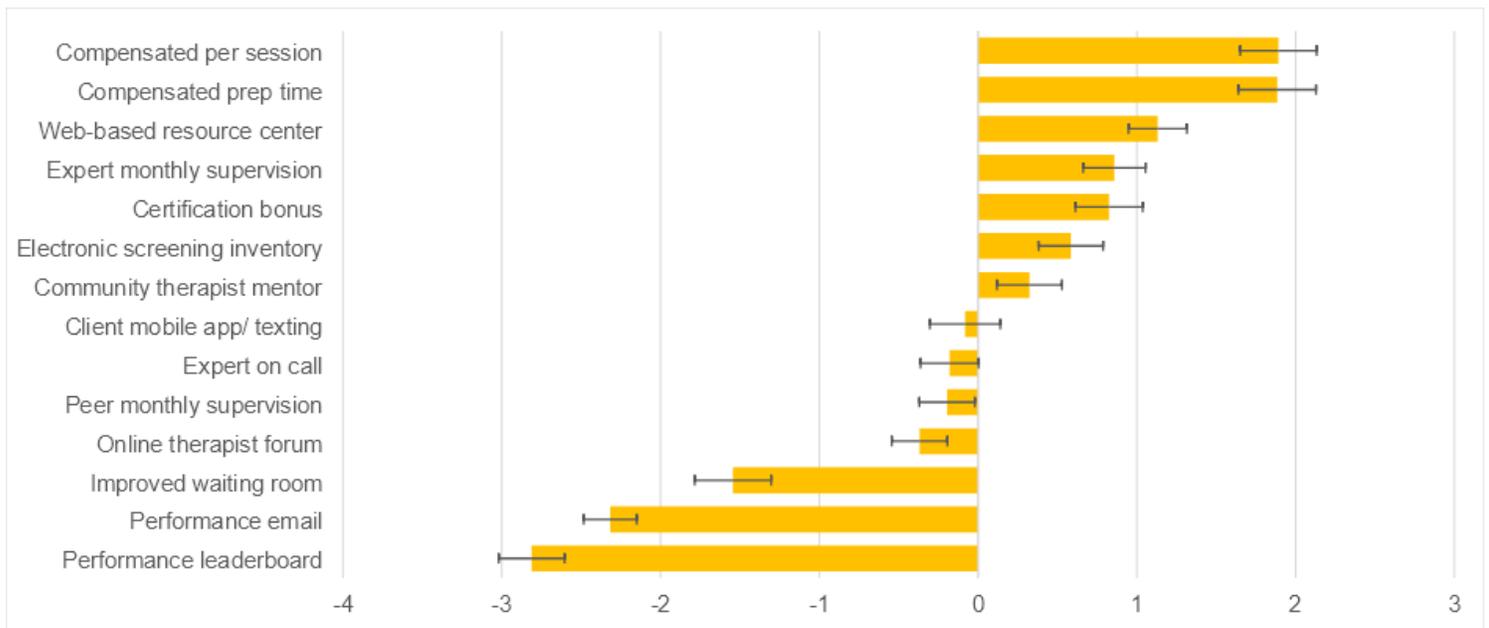
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## Figures



**Figure 1**

Mean Individual-Level Preference Weights by Strategy (N = 343) Note: Individual-level preference weights were estimated via hierarchical Bayes incorporating a multinomial logit model. Error bars indicate 95% confidence intervals. Positive and negative weights indicate the direction of preference for each strategy (i.e., preferred vs. not preferred, respectively).



**Figure 2**

Preference Weights by Latent Class Segment Note: N = 343. Segments and preference weights derived via latent class analysis. Error bars indicate 95% confidence intervals. Positive and negative weights indicate the direction of preference for each strategy (i.e., preferred vs. not preferred). Segment labels reflect the type of implementation support prioritized by the segment relative to others. Segment 1, Support me through Financial Incentives (Compensation), included n = 121 participants; segment 2, Support me through Technology, included n = 80 participants; segment 3, Support me through Autonomy, included n = 52 participants; and segment 4, Support me through Consultation, included n = 90 participants.

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