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Predicting Participation in Healthy Marriage and Responsible Fatherhood Programs

Consistent participation is an essential requirement for social services interventions. Intervention research suggests that programs are most effective when participants receive the intended dosage of programming—that is, when participants attend most of the planned programming (see, for example, Nation et al. 2003; Yalom and Leszcz 2005). But achieving high rates of attendance can be difficult, particularly when programs support underserved populations with low incomes, because of the many stresses and economic challenges these populations often face (Eisner and Meidert 2011; Fabiano 2007; Nock and Photos 2007).

Healthy Marriage and Responsible Fatherhood (HMRF) programs funded by the Office of Family Assistance (OFA) at the Administration for Children and Families (ACF), U.S. Department of Health and Human Services, are generally required to offer a primary workshop aimed at improving healthy relationship and parenting knowledge and skills. RF programs also offer employment and economic stability opportunities. A long-standing body of research demonstrates some positive effects of HMRF programs on certain outcomes (see, for example, Holcomb et al. 2019; Holmes et al. 2020; Markman et al. 2022; Patnaik et al. 2021; Wu et al. 2021). Similar to other social services programs, HMRF programs often face challenges with consistent participant attendance in their primary workshops (Baumgartner et al. 2022; Michalopoulos et al. 2022). Studies find that consistent participation is required for participants to achieve positive outcomes. For example, a few noncausal studies found that greater participation was associated with better outcomes for program participants (Arnold and Beelmann 2018; Bradford et al. 2017; Cobb and Sullivan 2015). Overall, preliminary evidence suggests that consistent participation and dosage are important for HMRF programs to achieve their intended goals (Markman et al. 2022; Wadsworth and Markman 2012).

To date, little published research has focused on understanding the factors that predict regular participation in HMRF programs. Three recent exceptions have addressed this gap by focusing on either participant or workshop characteristics as key predictors. One study examined characteristics of couples when they enrolled in an HMRF program (Bulling et al. 2020). The authors found that younger couples attended fewer sessions and that those more likely to drop out of the program included couples with higher relationship commitment, less engagement in the program from the female partner, and a weaker alliance between the couple and program staff. A second study found that couples' perceived intentions to attend predicted their participation in services within 30 days of program enrollment (Carlson et al. 2022). This study also found that attending services earlier (for example, attending the first two sessions of a workshop) was the strongest predictor of later attendance. The Fatherhood, Relationships, and Marriage– Illuminating the Next Generation of Research (FRAMING Research) project published a brief that examined HMRF workshop characteristics associated with participation (Avellar et al. 2021a). In general, this brief suggested that longer and more frequent workshop sessions were associated with greater attendance in a particular workshop series across populations served by HMRF programs. Further, the brief suggested that a single workshop structure likely would not work for all programs or participants. The analysis found that workshop characteristics were associated with participant attendance but did not account for all the differences in attendance; this suggests that other factors such as participant characteristics might also play a role.

ACF's Office of Planning, Research, and Evaluation (OPRE) oversaw a special topic report (STR) as part of the Building Usage, Improvement, and Learning with Data in HMRF Programs (BUILD HMRF) project. This STR uses innovative analytic methods to explore how both participant and workshop characteristics predict participation in HMRF programs' primary workshops. The STR team used comprehensive data on participants and workshops from the 2015 cohort of HMRF grantees (a group of 85 grantees who received funding from 2015 to 2020) and applied a series of restrictions to the data files to produce findings that are relevant for the 2020 cohort of HMRF grantees. We envision that findings from this STR can eventually be used to help HMRF practitioners better design and implement their programs to maximize participation in services.

The remainder of this brief describes findings from the STR and is structured as follows. First, we provide a short introduction to HMRF programs and highlight the methods used in the analysis, including some key equity considerations in the predictive modeling approach we adopted. We then discuss the findings from our analysis and demonstrate potential uses of the results through a series of simulations. We conclude with a discussion of potential next steps for this work and considerations for ensuring that results are used equitably to help all HMRF participants. A technical appendix provides a more detailed description of our methods.

Important terms and acronyms

- **HMRF:** Healthy marriage and responsible fatherhood
- **HM:** Healthy marriage
- **RF:** Responsible fatherhood
- **STR:** Special topic report
- **TBPAs:** Tree-based predictive algorithms
- **Workshop:** The umbrella term for the curriculum or group service being provided, such as Within My Reach or 24/7 Dad®
- **Workshop series:** Each offering of the workshop, such as nine weeks of Within My Reach offered every Thursday
- **Workshop session:** The individual class or occurrence in a series. In the example above, the Thursday series would have nine individual sessions

About HMRF programs

Since 2005, Congress has funded $150 million each year in HMRF grants. OFA has awarded and overseen four cohorts of these grants, with each cohort operating for four to five years. OFA designed the grants to promote economically secure households and communities to support the well-being and long-term success of children and families (OFA 2020a). OFA works with OPRE to research how to best serve families through these grants. Currently, OFA funds 111 HMRF grantees in the 2020 cohort that use a shared management information system (called Information, Family Outcomes, Reporting, and Management, or nFORM) to enter data on participants and their level of participation in HMRF services (Box 1).

Box 1. Overview of nFORM

Under ACF's direction, Mathematica developed and maintains the nFORM system for HMRF grantees to collect, analyze, and report performance measure data. For example, grantees use nFORM to document services, report on program operations (such as outreach, recruitment, and implementation challenges), track participation in services, and administer surveys to participants about their characteristics and outcomes. Participants complete web-based surveys directly in nFORM. nFORM supports ACF's and grantees' data analysis through automated calculations for required reports, data visualizations, a data export function, and other analytic tools.

To support healthy families and children, HM and RF programs offer a variety of activities depending on their grant type, such as marriage and relationship education skills or divorce reduction for HM grantees, and responsible parenting and economic stability for RF grantees. The primary service provided by HM and RF grantees is group-based workshops led by trained facilitators, which typically last a few days to a few months. Depending on their grant type, programs are required or encouraged to offer case management. Case management provides clients with individualized attention and referrals to other services as appropriate. HM grantees can serve adult individuals, adult couples, or youth, and RF grantees can serve community fathers, community couples, or reentering fathers.

Compared with the 2015 cohort, ACF created more specific standards for workshop formats and participation benchmarks for the 2020 cohort. For example, HM grantees now must offer at least 12 hours of primary workshop programming to participants, and RF grantees must offer at least 24 hours of primary workshop programming. This programming must be offered across more than two sessions and have two weeks between the first and last workshop sessions (OFA 2020b, 2020c). In addition, ACF and grantees closely monitor how many participants receive 90 percent of the intended primary workshop hours, which is a key performance measure for the grantees.[1] The requirements for the 2020 cohort informed our analytic methods, which are discussed in the following section.

[1] Participation benchmarks for the 2020 cohort are defined in the following ways: initial attendee is a participant who has attended at least one primary workshop session; halfway attendee is a participant who has received at least 50 percent of the total hours of primary workshop programming; completed is a participant who has received at least 90 percent of the total hours of primary workshop programming; and fully finished is a participant who has received at least 100 percent of the total hours of primary workshop programming.

Analytic methods

Data source and analytic sample

For this analysis, we used performance data from the 2015 cohort of HMRF grantees that was entered into nFORM. This analysis drew on data from grantees' primary workshops, participant surveys, and participant attendance records. We analyzed all data at the participant level; that is, we looked at individual participant (or couple) attendance in the first primary workshop series they attended, the characteristics of the first primary workshop that participants attended, and demographic characteristics for each participant. Box 2 summarizes the variables used in the analysis.[2] Section A of the technical appendix includes more detail on each of these data sources.

Box 2. Key variables included in analysis

- **Outcome variable.** This indicates whether a participant attended at least 90 percent, or less than 90 percent, of the hours offered in the first primary workshop series they attended.
- **Workshop characteristics.** These are the primary workshop variables that grantees enter in nFORM for each workshop series (such as day of the week a workshop is delivered, frequency of workshop sessions, and length of each session). We included 44 variables for the HM populations and 39 for the RF population.
- **Participant characteristics.** These are the participant-focused variables that document a participant's baseline demographics and attitudes (such as age, educational attainment, and relationship quality). We analyzed 89 variables for the HM populations and 90 for the RF population.

We selected grantees to include in the analysis that served the following three populations: (1) HM adult couples, or adults participating with their romantic partner; (2) HM adult individuals, or adults participating without a partner regardless of their romantic relationship status; and (3) RF community individuals, or adult fathers participating without a partner regardless of their romantic or co-parenting relationship status. Because factors associated with attendance might differ by population, and because participants in each of these populations completed different surveys, we analyzed results for these three populations separately. We focused on these populations because they likely face different barriers to program participation than participants of programs for youth or reentering fathers, which often offer services where participants are already located (such as in schools or prisons, respectively).

Across the data sources, we implemented several selection criteria to define an analytic sample that could achieve the goals of this STR. For example, to align with ACF's current workshop requirements for the 2020 cohort, we restricted the analysis to workshop series that had more than two sessions and offered 12 or more primary workshop hours for HM and 24 or more primary workshop hours for RF. In addition, we examined a participant's attendance for a single workshop series. Specifically, for each participant, we selected the first primary workshop series they attended (if they attended more than one series). Participants were then classified as completed if they had attended 90 percent or more of the intended hours for that primary workshop series.[3] Section B of the technical appendix includes more information on how we defined the

[2] Many of the variables are the same across the three populations, but minor differences exist. Other differences involve the structure of the data. Specifically, HM couples programs constitute dyadic data that include information for both members of the couple.

[3] While some grantees may offer their programming over two or more primary workshops, our approach facilitated analysis of a participant's ability to complete the minimum number of primary workshop hours required by ACF for the 2020 cohort, in their first workshop for that given workshop structure.

analytic sample. Figure 1 provides a snapshot of the number of grantees, participants, and workshop series included in the analysis for each population, as well as the percentage of participants who completed (attended at least 90 percent of) their workshop series.

Analytic approach

Our analysis used a particular type of tree-based predictive algorithm (TBPA) named *random forest* (Breiman 2001; Liaw and Wiener 2022). In their most basic form, TBPAs are data driven and make predictions by using a decision rule in the form of a series of yes-or-no questions that are applied to the predictor variables. Visually, the sequence of these yes-or-no questions forms a decision tree that shows how different splits in yes/no variables (branches) produce predictions. Because TBPAs are primarily data driven, the predictions are based on which variable splits produce the most information gain compared with other potential splits. A basic TBPA starts with a split of a single variable and then makes further splits based on which variables improve prediction.

Figure 2 depicts a very basic example of a decision tree produced by a TBPA. In the example shown in Figure 2, the tree starts with a split related to a participant's age—those older than 30 or 30 and younger. Following the branch on the left, the next split involves a participant older than 30 being currently involved in a romantic relationship. If they are and participated in a workshop that offered more than 20 hours of content, they were likely to complete. If they were not in a romantic relationship, and took a workshop offered on the weekends they were also likely to complete. The trees in our analysis are more complex than the Figure 2 example, with over 1,000 branches for each model, and cannot be easily visualized.

Figure 1. Grantees by population included in analysis

HM adult couples

Grantees: **21**
Participants: **10,182 (5,091 couples)**
Workshop series: **724**
39% of participants completed

HM adult individuals

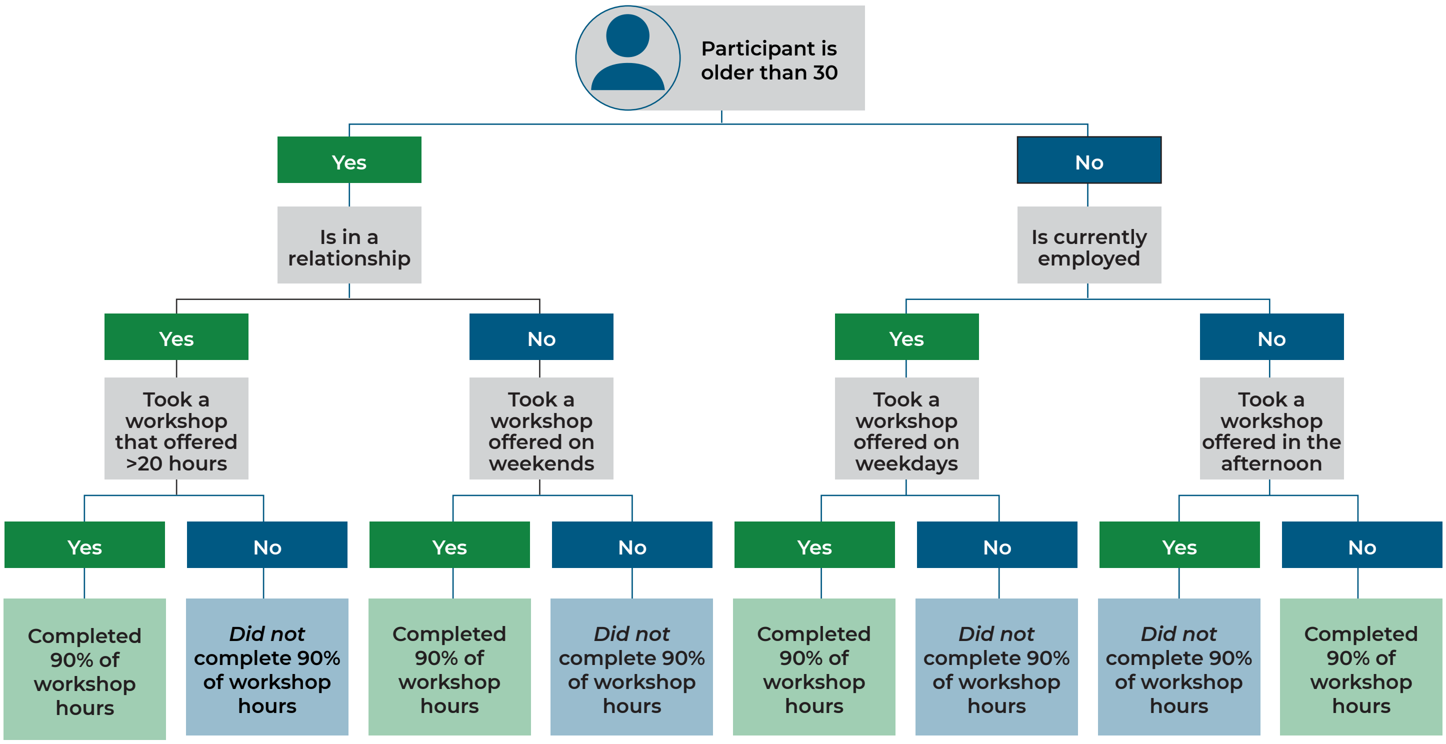
Grantees: **22**
Participants: **7,909**
Workshop series: **847**
44% of participants completed

RF community fathers

Grantees: **17**
Participants: **5,742**
Workshop series: **825**
34% of participants completed

Note: HM = healthy marriage; RF= responsible fatherhood

Figure 2. Example of a tree-based predictive algorithm (TBPA) decision tree



A random forest makes predictions by growing many decision trees simultaneously and randomly selecting a subset of predictor variables to use for splitting within each tree. After the trees have been created, the random forest algorithm averages all the individual tree predictions to produce a final prediction. Growing multiple trees simultaneously increases the robustness of the final predictions because the model compares and integrates the performance of multiple trees using different splits of the predictor variables. This flexible modeling approach enables random forests to capture complex relationships between participant and workshop predictors and completion status.

Box 3 lists a few key advantages of TBPAs. For more information on TBPAs and how we fit them to our data, see Section E of the technical appendix.

Box 3. Advantages to tree-based predictive algorithms (TBPAs)

1. Given the limited research on factors that predict participation in HMRF workshops, we needed a flexible and data-driven approach. The TBPA framework provides a flexible approach that is data-driven while still useful for theory building and more formative work.
2. TBPA methods enable teams to efficiently handle large data sets and explore the predictive value of the variables and their potential interactions without the need to prespecify any interactions in advance.
3. TBPA methods offer several options to increase predictive stability (for example, use of random forest).

Source: James et al. 2013; McAlexander and Mentsch 2020; Schonlau and Zou 2020.

We developed a series of random forest models for each population. After fitting the models for each of the three populations (HM adult couples, HM adult individuals, and RF community individuals), we examined several metrics to extract key insights from these models and determine if they produced reliable and accurate estimates (see Section E of the technical appendix for more information on these metrics).

The analytic approach we used, although rigorous, does not produce causal estimates. Therefore, these results cannot determine that the characteristics studied are directly responsible for consistent participation, but rather suggest the potential likelihood or probability of workshop participation. Further testing of these predictions through causal methods—such as random assignment—is needed.

Considerations when employing predictive modeling

Many fields use predictive models. However, they are susceptible to misuse and misapplication (Cuccaro-Alamin et al. 2017; de Haan and Connolly 2014; Kazem 2017; Rudin et al. 2020; Vannier Ducasse 2021). Fields adjacent to HMRF programs, such as child welfare and criminal justice, have used models to predict the risk of child abuse and neglect or re-offending that are similar to the models used in this study. These models have drawn criticism, with experts urging caution because predictive algorithms might profile certain groups and exacerbate disparities (Drake et al. 2020; Eckhouse et al. 2019; Mayson 2018; McSilver Institute 2021; Pika 2018).

The models discussed in this brief have the same potential for misuse. For example, if the models predict that an existing workshop structure is not optimal for a certain group within a community, it might be tempting to focus services and workshop structures toward prospective participants with characteristics more highly associated with completion. This can have a detrimental effect on equity. ACF and HMRF practitioners believe that communities are best served when everyone has a chance to have a strong, healthy family. When applying the findings of predictive models, HMRF and similar programs are encouraged to work with their communities to understand the needs and disparities that exist and to identify and understand more thoroughly the barriers to participation. Then, programs can aim to offer multiple workshops with varying structures that are predicted to best serve community members—particularly those most in need.

Findings

The constructed models predicted the likelihood of participant attendance in the primary workshop series with a high level of accuracy. To determine whether our models produced reliable and accurate results for each of the three populations, we compared the performance of three separate models that predicted participation. The first model included only participant characteristics, a second model included only workshop characteristics, and a third model included participant and workshop characteristics.

We found that using a combination of workshop and participant characteristics produced the best performing model with accuracy ranging from 0.78 to 0.84 across the populations (see Table 1). In social sciences research, estimates above 0.70 are generally considered to reflect models that are at least moderately predictive of the outcome, with higher values indicating stronger predictive accuracy (Rice and Harris 2005). Models that used both types of characteristics boosted accuracy for HM adult couples and had a very small effect for HM adult individuals (positive) and RF community fathers (negative). Despite this uneven effect on model accuracy, both workshop- and participant-level characteristics are important for predicting completion. First, using both sets of characteristics is important for other

Table 1. Model accuracy estimates for each population

	HM adult couples	HM adult individuals	RF community fathers
Participant characteristics only	0.70	0.62	0.65
Workshop characteristics only	0.73	0.81	0.85
Full model	0.78	0.82	0.84

Note: Numbers represent the area under the receiver operator characteristic curve (AUC-ROC) that summarizes the overall predictive performance of the model. The AUC is the probability that a randomly selected true completer has a higher predicted probability of being a completer based on the model than a randomly selected true noncompleter.

HM = healthy marriage; RF = responsible fatherhood.

model performance statistics noted in the technical appendix. In particular, the ability of the model to predict true completers was highest across all three populations when both participant and workshop characteristics were included. Second, as discussed further below, the interactions between these two sets of variables are important to consider when applying and interpreting the model. Third, including a full range of predictors in the model allows for more comprehensive analyses that would not be possible if participant characteristics were excluded.

After establishing the overall predictive strength of the model, we then examined which variables and variable combinations were most important for predicting completion. To that end, we examined various statistics to identify key variables and interactions that were important for prediction. Specifically, we examined three metrics: variable importance scores, partial dependence, and variable interaction strength (see Section E of the technical appendix for more details on these metrics and results). Importance scores and partial dependence plots showed that many variables made small contributions to the accuracy of the overall model. However, assessing each variable's importance to the model separately might not reveal all influential factors, as some variables might only influence the outcome in combination with other variables. Furthermore, the relationship between a characteristic and the outcome might vary based on the values of another characteristic, which limits our interpretation (Goldstein et al. 2015).

To better contextualize these results, we examined the variable interaction strength metrics. These measures enable us to describe the magnitude and direction of two-way interactions between the variables in our model. We found that many small interactions contributed to prediction. It is important to note that higher-order interactions (three-, four-, or five-way) are also highly likely to contribute to the predictive power of the model, but they are much harder to interpret (Breiman 2001). Our simulation analyses in the next section show how these high-order interactions are important.

Overall, these results highlight the importance of context when determining how to structure a workshop series. We found that there are numerous ways participant and workshop characteristics interact to predict the likelihood that a participant will complete a workshop series. No single variable or set of variables appears to be the most important in predicting participant attendance. Instead, participant and workshop characteristics should be considered holistically when considering ways to improve participation in HMRF programs.

The models show that many variables and interactions matter in terms of prediction. In short, context and specific characteristics of the participant and workshop affect participation in HMRF programs.

The performance and predictive power of our models suggest that they can be useful to HMRF practitioners and staff involved in program design and improvement. However, TBPAs can be hard to interpret (Palczewska et al. 2014). To aid in interpretation, we conducted simulations to show how grantees might use the results of the model to design an optimal workshop structure—that is, one designed to maximize participants' likelihood of attending—given various participant and workshop characteristics. For every grantee included in our analysis, we identified the most common characteristics of the participants served by that grantee. We then used the predictive model to simulate the most optimal workshop structure for typical participants.

Across the grantees, the model predicted that workshops with fewer, longer sessions would improve completion rates for their typical participants. The data shown in Table 2 show how frequently a workshop characteristic was indicated as optimal for the typical participants of the grantees in our analysis. Optimal workshop characteristics varied by population, but across populations, workshop sessions of at least two hours held more often than weekly were strong predictors of completion. We found the following results in our analysis:

- For **HM couples,** there was little variation in the optimal predicted workshop structure. Workshops predicted as optimal 100 percent of the time were provided by the grantee, as opposed to a partner organization, held on both weekdays and weekends, met two to four times per week, and had three to five sessions lasting four or more hours. In addition, the model predicted afternoon sessions (from 12:00 to 5:00 p.m.) as optimal for 95 percent of grantees' typical participants.
- For **HM adult individuals,** workshops led by the grantee with three to five sessions were frequently predicted as optimal. However, there was more variation in whether other workshop characteristics were optimal for predicting completion among typical HM individuals. For example, sessions lasting four or more hours were optimal for just over half (54 percent) of grantees' typical participants, but sessions lasting two to four hours were also frequently identified as optimal (38 percent). Sessions offered on *both* weekdays *and* weekends were optimal for predicting completion for almost two-thirds (62 percent) of grantees' typical participants, with weekday sessions optimal for the remainder (38 percent).
- For **RF community individuals,** workshops offered on weekdays were always optimal for predicting completion (100 percent of grantees' typical participants). Daily workshop sessions were almost always optimal (94 percent), as were sessions lasting two to four hours (88 percent). There was more variation in whether other workshop characteristics were optimal for predicting completion among typical RF community individuals. For example, the model commonly identified afternoon sessions as optimal at predicting completion for 59 percent and mornings as optimal for 41 percent. The predicted optimal number of workshop sessions varied, with about one-third of grantees' typical participants having a predicted optimal structure of three to five sessions (30 percent), six to nine sessions (35 percent), or 10 or more sessions (35 percent).

Table 2. How often workshop characteristics were predicted as optimal for grantees' typical participants, by population

Workshop characteristic		HM couples (21 grantees)	HM individuals (22 grantees)	RF community individuals (17 grantees)	Total
Day of the week	Weekdays and weekends	100%	62%	0%	57%
	Weekdays	0%	38%	100%	43%
	Weekends	0%	0%	0%	0%
Time of day	Morning	5%	38%	41%	28%
	Afternoon	95%	52%	59%	69%
	Evening	0%	10%	0%	3%
Number of facilitators	One	45%	52%	41%	47%
	Multiple	55%	48%	59%	53%
Session duration	1 hour	0%	0%	0%	0%
	1–2 hours	0%	10%	6%	5%
	2–4 hours	0%	38%	88%	40%
	4 or more hours	100%	52%	6%	55%
Frequency of sessions	Daily	0%	29%	94%	38%
	2–4 times per week	100%	52%	6%	55%
	Weekly or once per week	0%	19%	0%	7%
Provider	Grantee provided	100%	90%	41%	79%
	Partner provided	0%	10%	59%	21%
Number of sessions	3–5	100%	90%	30%	76%
	6–9	0%	5%	35%	12%
	10 or more	0%	5%	35%	12%

Note: HM = healthy marriage; RF = responsible fatherhood

A note on shorter, more intensive session series

More intensive interventions (sometimes referred to as "brief" interventions in the literature) have been shown to be effective for a variety of behaviors, such as parenting (Cartwright et al. 2018; Chavis et al. 2013; Grolnick et al. 2021), health behaviors (Aveyard et al. 2016; Catanzano et al. 2020; Li et al. 2017; Wray et al. 2018), and overcoming addiction (Bray et al. 2017; Nilsen et al. 2008; Tanner-Smith et al. 2022). Several studies have also analyzed how more intensive interventions can promote uptake in other interventions or services (Batterham et al. 2021; Christiansen et al. 2015; Murphy et al. 2009).

Similarly, it might be easier for HMRF participants—particularly those who face barriers to attending consistently, such as limited child care or long commutes—to arrange to participate in fewer, more intensive sessions. Experts in neuroscience and human behavior have found that humans are prone to choose options with the fewest barriers or the "path of least resistance" (for example, Hagura et al. 2017; Shenhav et al. 2016). However, while the models in this study identified fewer, more intensive workshop sessions as optimal for predicting completion, there is no research to suggest that this workshop structure results in better knowledge, skills retention, or outcomes for HMRF participants.

Future research could explore for whom this type of HMRF workshop structure works best and under what contexts. HMRF programs can further add to the field by using their local evaluations to examine differences in outcomes based on workshop structure. In addition, there could be research into why participants prefer certain workshop structures over others, to better tailor programs to the communities served.

Sample scenarios

To help contextualize the findings in Table 2 in specific contexts, we created sample visual scenarios for three illustrative grantees for each population (HM adult couples, HM adult individuals, and RF community individuals).[4] Each sample grantee, its typical service population, and the number of hours offered in its primary workshop are described in Appendix A for each of nine scenarios. The visuals in Appendix A present for each sample scenario (1) the set of optimal workshop characteristics that are predicted to promote the highest probability that the typical client will complete at least 90 percent of the workshop series' intended hours (displayed in green); and (2) the set of less-than-optimal workshop characteristics that are predicted to promote the lowest probability of the typical client completing at least 90 percent of the intended hours (displayed in peach).

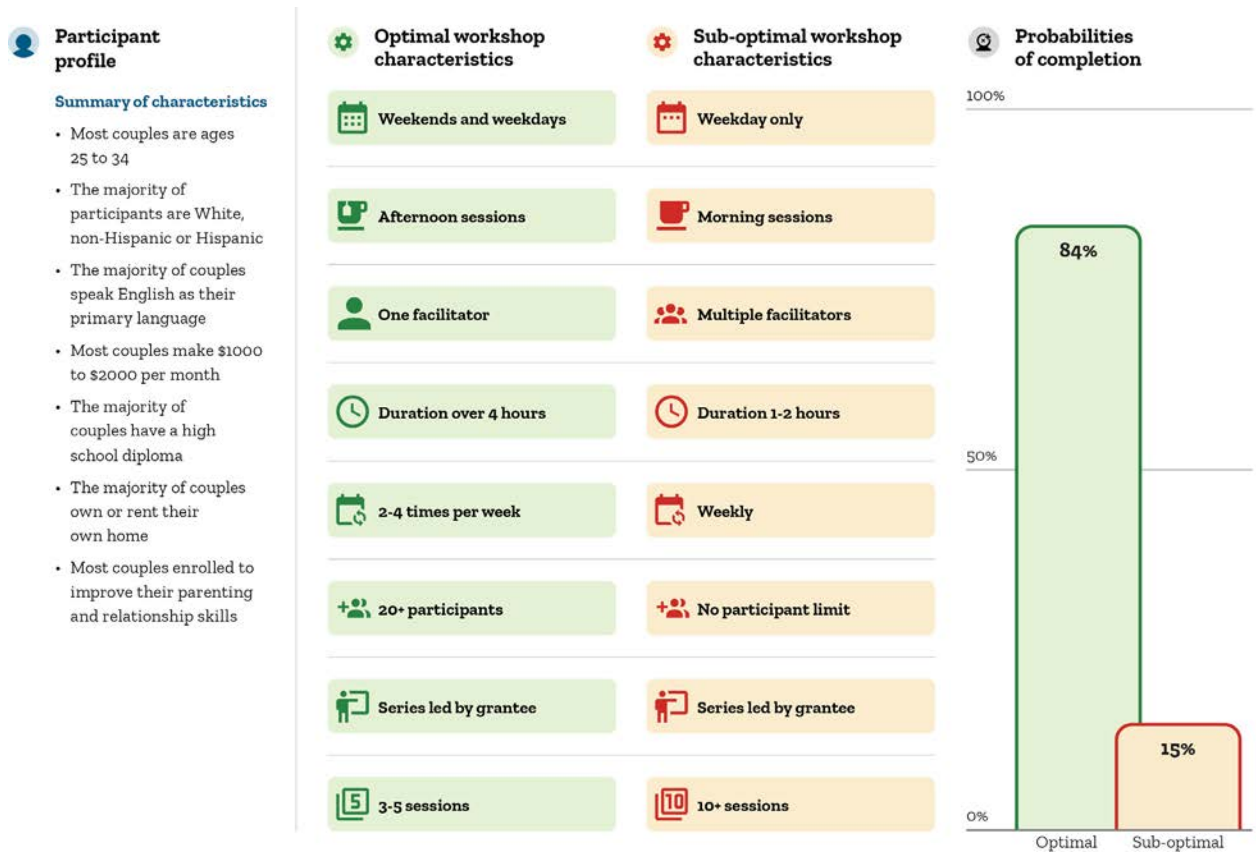
Some workshop characteristics are present in both optimal and suboptimal workshop structures. This is because a single feature does not independently determine a high or low probability of completion but rather works in combination with other workshop characteristics to predict attendance.

[4] We randomly selected unnamed grantees from each of the three populations. We compared the common participant profiles developed for these grantees to the aggregate population characteristics for the 2015 HMRF cohort to determine their representativeness (Avellar et al. 2021b, 2021c). If a profile was not representative of the population overall, we identified a new grantee for which the typical participant was a better match. We used the predictive results for the sampled grantees as the basis for the visualizations shown in Appendix A.

Figure 3 below presents an example scenario for a grantee that serves HM couples in a large metropolitan area. Its typical service population includes Hispanic and White, non-Hispanic couples who are pregnant with a subsequent child and are in a steady romantic relationship. The grantee's primary workshop curriculum provides more than 20 hours of content. The grantee is curious how to best structure its workshops to serve this population.

Figure 3 shows that the optimal workshop structure for participants who are married with children would be delivered on both weekend and weekday afternoons, two to four times per week. The workshop would have three to five sessions that are more than four hours each. The model also suggests that the grantee should lead the series, allow 20 or more participants per series, and deliver the workshop using one facilitator.

Figure 3. Sample scenario for HM grantee serving married couples with children



The scenarios in Figure 3 and Appendix A are illustrative—they are meant to show the promise of predictive models in specific contexts, and they do not provide specific recommendations. In addition, the optimal and suboptimal workshop structures only represent likely attendance. It is important to underscore that simply changing a workshop's structure does not guarantee improved participation and the model predictions are not causal. Any changes need to be made carefully within the context of the HMRF program and the population being served and should undergo thoughtful continuous quality improvement processes or causal research to determine success.

Next steps

The STR team developed well-performing models that are accurate for predicting workshop participation and help address current gaps in research on HMRF programs. These models show promise as powerful technical assistance tools to help HMRF grantees design programs and conduct improvement activities to promote and bolster participation. As our simulations show, workshops with fewer, more intensive sessions were predicted to result in higher participation for typical clients across the three HMRF populations we analyzed.

Looking closely at the grantee level, the simulations showed that different combinations of workshop characteristics predict higher participation. However, as noted in prior sections, rigorous causal research is necessary to test whether the optimal workshop structures result in better attendance or improved participant outcomes.

Because the simulations were based on typical clients served in the 2015 HMRF cohort, further work could explore less frequently served populations and the workshop structures that might be optimal for them. In addition, the optimal workshop structures presented in this brief do not take into account implementation restrictions that grantees might face. For example, a grantee might only employ contracted facilitators that work full-time jobs elsewhere. In this instance, offering workshops at the predicted optimal time might not be feasible. Technical assistance using the models could focus on identifying optimal workshop structures that account for grantee requirements (for example, sessions lasting two to three hours that are held weekly in the evenings) and potential limitations (such as facilitation quality, staff and participant relationships, and perceptions of the program).

Several next steps could maximize the usefulness of these promising models for HMRF programs and promote equitable use. We envision these next steps to include expanding and validating the models with new data and identifying how ACF and practitioners can best use the models for program improvement.

In addition, discussions with experts, decision makers, and those with lived experience would help ACF and practitioners consider how to use predictive models in ways that promote equity. There have been several recent advancements in how to incorporate equity methods into predictive modeling (for example, Mhasawade et al. 2021; Rojas et al. 2022), and future work should build on these efforts.

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For more information about the Building Usage, Improvement, and Learning with Data in Healthy Marriage and Responsible Fatherhood Programs (BUILD HMRF) project, please visit the project web page.

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