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Actively Participating in Live Events as an Avenue for Social Connection

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Abstract

While many studies highlight the benefits of social connection for psychological and physical health, less is known about cultivating connection in daily life. This study explored whether attending live events (e.g., concerts, fitness classes) promotes feelings of social connection. Machine learning analyses revealed that in-person (vs. virtual) events, involving active (vs. passive) participation, and attendance with others (vs. alone) reliably predicted connection, whereas linear regression analyses further identified recurring (vs. one-time) events as a significant predictor. Across 1,551 participants reporting pre- and post-event experiences, these predictors held beyond baseline socioemotional factors (e.g., loneliness) and individual differences (e.g., personality). However, feelings of social connection were not consistently sustained 24 hrs after events with these features. These results suggest that attending in-person, engaging, and recurring events with others is a promising pathway to fostering connection, although additional research is needed to explore how these feelings can be maintained over time.

Keywords

social connection, intervention, loneliness

Social connection is a powerful driver of psychological well-being (Diener & Seligman, 2002; Sun et al., 2020) and is recognized for its influence on physical health (Holt-Lunstad, 2021) and longevity (Holt-Lunstad et al., 2010). Humans—like other primate species—have an innate need to belong and connect with others (Baumeister & Leary, 1995), and lacking meaningful interaction can result in feelings of loneliness and social isolation. Indeed, the United States (U.S.) Surgeon General recently published an advisory on the detrimental effects of loneliness and the healing effects of social connection, noting their profound impacts on health and well-being (Office of the Surgeon General, 2023). Furthermore, loneliness has been described as a behavioral epidemic of the modern world (Jeste et al., 2020), with recent data showing that nearly 60% of U.S. adults report being lonely (The Cigna Group, 2021). Considering the detrimental effects of social isolation and loneliness, worldwide public health initiatives have emphasized the need to explore potential interventions to address this widespread issue (Holt-Lunstad et al., 2017).

A recent global event that highlighted the impacts of loneliness and connection on well-being was the COVID-19 pandemic. Mandated protocols (e.g., social distancing and quarantining) presented unique challenges to creating and maintaining connections with others. For example, research conducted during the pandemic reported an overall increase in loneliness from June 2019 (before the outbreak) to June 2020 (the midst of COVID-19) and a decrease in individuals' number of close friends (Kovacs et al., 2021). Thus, an important tradeoff of taking action to mitigate the spread of COVID-19 was the loss of opportunities for people to socialize with others.

Less talked about, but perhaps equally important, was the loss of opportunities to attend public events and local gatherings during the pandemic. People could not engage in many of their favorite activities—concerts, sporting events, fitness classes, movies, and so on—that form the fabric of daily life. Opportunities for interacting with the wider community (e.g., strangers and acquaintances), which can be beneficial for one's well-being (Epley & Schroeder, 2014; Sandstrom & Dunn, 2014), were also hindered. Many situations, like live events, allow people to

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engage close with others and strangers simultaneously, creating opportunities for social interaction and connection. Keyes and colleagues (2023) recently found that attending live sporting events was associated with increased life satisfaction and reduced loneliness, however, no research has comprehensively examined the potential link between live event attendance and social connection.

Many factors of event experiences might contribute to feeling connected, including whether they are in-person or virtual, active (e.g., interaction among attendees) or passive (e.g., listening or observing), attended with others or alone, and recurring (e.g., fitness classes) or one-time (e.g., concerts). Prior theory and research provide some indication of the nature of these links. For example, regular in-person contact is associated with lower loneliness and greater connection, whereas online and remote communication is often less satisfying and associated with poorer outcomes (Lee et al., 2011). In addition, actively engaging in activities with others is associated with greater connection (Aron et al., 1997, 2000). Furthermore, experiences with others are associated with greater enjoyment relative to individual experiences (Larson & Bradney, 1988). Finally, early work in social psychology showed that the more frequently people interact with each other, the closer they feel (Zajonc, 1968). This is reflected in findings that trust, intimacy, and a sense of community are built over time (Anderson & Weitz, 1989; Baumeister & Bratslavsky, 1999), and the benefits of social connection and risks of loneliness are typically the result of persistent exposure (Crowe et al., 2021; Stokes et al., 2021). This suggests that attending recurring (vs. one-time) events may provide greater opportunities for social connection. However, while prior work might indicate that in-person events, for example, would enhance connection (Lee et al., 2011), this may not always be the case. For instance, in-person events may provoke social anxiety, discouraging attendance or engagement for some individuals. This would align with findings that people often hesitate to interact with strangers despite the benefits of doing so (Sandstrom & Dunn, 2014). Such complexities highlight that even seemingly intuitive event characteristics might have nuanced effects on social connection. Exploring these links further could refine our understanding of what fosters meaningful social interactions in everyday life.

The current study aims to fill a gap in the social connection literature by assessing peoples' socioemotional traits (e.g., loneliness), event experiences (e.g., feelings of connection), and post-event socioemotional states (e.g., daily loneliness, daily connection). Longitudinal data was collected from 1,551 users of Eventbrite, a widely-used event management and ticketing platform, before and after attending events with various characteristics. Machine learning and linear regression models were utilized to analyze the data, allowing us to leverage numerous predictor variables and accurately assess model performance.

Based on previous research examining the social benefits of in-person interactions (Lee et al., 2011), mutual engagement (Aron et al., 2000), shared experiences (Larson & Bradney, 1988), and repeated exposure (Zajonc, 1968), it was hypothesized that attending events (1) in-person rather than virtually; (2) with active rather than passive participation; (3) with others rather than alone; and (4) repeatedly rather than only once is associated with feeling more socially connected. Additional characteristics were explored, such as whether the event was held indoors or outdoors and was free or required payment, to gain a stronger understanding of specific aspects that might be associated with event experiences. Feature importance scores were obtained for each predictor variable from machine learning analyses to assess how strongly they contributed to accurate model predictions; tests of statistical significance and effect size estimates were obtained from linear regression analyses.

Method

Transparency and Openness

To facilitate transparency, the preregistered hypotheses and analytical approach were shared on the Open Science Framework (OSF) (https://osf.io/wt47e) before data examination. Data were analyzed using R Software; the dataset and script are publicly available on the study's OSF page (https://osf.io/93jfy/?view_only=35e028b6ade147a0b8f6bac40d2f3d24). Additional detailed information about analytic steps and how the variables were measured are shared in the Online Supplemental Materials.

Participants

Participants were recruited via the Eventbrite website and email newsletter. The initial sample size of 200 participants was estimated based on expected recruitment rates by February 2023 due to potential attrition and exclusions; however, substantially more data were collected than anticipated. Of 38,470 Eventbrite users who visited the study's landing page, 1,667 consented and attended an event. After removing participants who failed attention checks ($n = 57$) and duplicate entries ($n = 59$), the final sample included 1,551 participants. The sample was comparable to the U.S. population in terms of ethnicity (58% White, 13% Black/African American, 12% Asian, 7% Hispanic, 4% Native American, First Nation, Alaska Native, Native Hawaiian or Pacific Islander, 2% Middle Eastern/North African, 4% another ethnicity), gender (61% women, 37% men, 2% self-identified gender), age ($M = 45$ years old; $SD = 16.45$ years), sexual orientation (82% heterosexual), and relationship status (38% married). All participants were entered into a drawing for a chance to win $500. To increase response rates, later participants were compensated with a $25 Amazon gift card once they completed all questionnaires.

Procedure

Prospective participants navigated from the Eventbrite website to a study introduction landing page. This page included

Table 1. *Frequency of Events by Event Type (In-Person vs. Virtual)*

	Event characteristic	Frequency	
		In-Person	Virtual
Active vs Passive	Active	440 (56.48%)	273 (38.78%)
	Passive	297 (38.13%)	380 (53.98%)
	Missing Data	42 (5.39%)	51 (7.24%)
With Others vs Alone	With Others	447 (57.38%)	128 (18.18%)
	Alone	332 (42.62%)	576 (81.82%)
	Missing Data	0	0
Indoors vs Outdoors	Indoors	593 (76.12%)	621 (88.21%)
	Outdoors	101 (12.97%)	38 (5.40%)
	Missing Data	85 (10.91%)	45 (6.39%)
Recurring vs One-Time	Recurring	214 (27.47%)	185 (26.28%)
	One-Time	563 (72.27%)	519 (73.72%)
	Missing Data	2 (.26%)	0
Paid vs Free	Paid	261 (33.50%)	73 (10.37%)
	Free	518 (66.50%)	631 (89.63%)
	Missing Data	0	0

Note. Frequencies are reported with percentages (reflecting the in-person [n = 779] vs. virtual [n = 704] subsamples) in parentheses. These categories are listed separately as the other predictors may co-occur with in-person or virtual events. Visualizations of these co-occurrences and descriptive statistics of frequencies not split between in-person and virtual events can be found in the Online Supplemental Materials.

participant eligibility criteria and a link to the pre-event survey. Measures within this survey included socioemotional traits, demographics, the date of the anticipated event, and the participant's email address. This made it possible to (1) control for participants' individual traits and characteristics in analyses and (2) program the survey software to email the post-event survey to participants 24 hrs after their event. Reminders were also pre-programmed to alert participants who had not finished the post-event survey to complete it up to 7 days after the event, after which participants could no longer complete the survey. This procedure was approved by the university institutional review board.

Measures

Predictors. Two categories of pre-event predictors were included in all baseline models: socioemotional traits and demographics. The former category included measures assessing subjective happiness (Lyubomirsky & Lepper, 2020), life satisfaction (Diener et al., 1985), quality of social networks (Berkman & Syme, 1979), Big-5 personality traits (Soto & John, 2017), trust (OECD, 2017), social anxiety (Connor et al., 2001), depression (Kroenke et al., 2001), loneliness (Mary et al., 2004), and quality of life (Hyde et al., 2003), whereas the latter category included measures such as age, race/ethnicity, and gender.

Models incorporating baseline variables and event characteristic variables were built and tested against (i.e., compared with) baseline models to evaluate the unique predictive power of event characteristics. Standardized root-mean-square-error (RMSE) was used to assess how well event characteristic variables uniquely predicted the outcome variables of interest, beyond the socioemotional trait and demographic predictors included in baseline models. Event characteristic variables included: "Virtual vs. In-Person," "Active vs. Passive," "Attended Alone vs. With Others," "One-time vs. Recurring," "Indoors vs. Outdoors," and "Paid vs. Free."

Independence of Predictors. Assuming many event characteristics may overlap with being in-person or virtual (e.g., in-person events often involve others, whereas virtual events may be less likely outdoors), Table 1 presents the diversity of predictor occurrence by event type.

Outcomes. Outcome variables were divided into two categories: event experiences and post-event socioemotional states (i.e., daily moods). The former category included measures of enjoyment/fun and social connection. These variables sought to capture how much enjoyment, fun, and connection participants experienced at the events. The latter category included measures assessing daily levels of loneliness (Buecker et al., 2020), daily social connection (Inagaki & Human, 2020), depression (Dejonckheere et al., 2017), social anxiety (Kashdan & Steger, 2006), and general anxiety (Flanders, 2015). These variables sought to capture participants' socioemotional *state* the day they completed the post-event survey (at least 24 hrs after the event; M = 1.05 days, SD = 3.09).

Statistical Analyses

Overview. A machine learning approach, specifically random forest modeling, was integrated with classic linear regression models. Machine learning, a sub-field of artificial intelligence (AI), constitutes a wide-ranging field that is overarchingly concerned with creating computers that can behave intelligently (Winston, 1992). In this context, machine learning is a method of making inferences and predictions and drawing conclusions from large datasets. The widespread adoption of machine learning can be attributed to its capacity to handle a high number of predictor variables and ability to apply intensive resampling techniques (e.g., cross-validation and bootstrapping; (Mitchell, 1997)) on training datasets to estimate out-of-sample parameters in test datasets (Jiang et al., 2020; Urban & Gates, 2021; Yarkoni & Westfall, 2017). Said differently, machine learning models return final parameter estimates closer to what would be expected if the model were introduced to new data.

Random Forest Modeling. Two machine learning models were created for analyses: (1) a baseline model consisting of only pre-event socioemotional trait and demographic variables and (2) an event characteristics model that added the event characteristic variables to assess how well event characteristics uniquely predicted the outcome variables. The baseline model was created to be consistent with the linear regression models.

Pre-Processing. Before building the machine learning models, the data were pre-processed to ensure valid results. Since they are flexible, the tree-based machine learning models did not require any pre-processing outside of imputing missing data, which was done using k-Nearest Neighbors (KNN) imputation (Zhang, 2012). This approach identifies the k (in this case, 5) most similar rows and then imputes the missing value with the mean of the values collected from the nearest neighbors for numeric variables, or the most common class of the nearest neighbors for categorical variables. Crucially, these pre-processing steps were performed separately for each fold of the cross-validation (see below) as well as separately for each model. This prevents data leakage, in which information about a test set "leaks" into training data models (Papadimitriou & Garcia-Molina, 2010), which can lead to incorrect model evaluations.

Training and Test Sets. For each model set, the data were initially split into training and test sets. The training set consisted of a random 80% of the original dataset, while the test set consisted of the remaining 20%. Cross-validation and model comparisons were completed using the training set only. The final model was fitted using the full training dataset, and its performance was evaluated on the test dataset to obtain the final test set RMSE estimate.

Cross-Validation. Resampling methods are an essential part of machine learning model building (Gareth et al., 2013). This involves repeatedly drawing samples from a training set, fitting a model on each sample, and aggregating the model fit estimates. K-folds cross-validation was used as the resampling method (Fushiki, 2011) for this study. In k-folds cross-validation, the training set of observations is divided into equally large k folds or groups. The first fold serves as the initial test set (i.e., validation set), while the remaining folds make up the training set. The model is fit on the training set and then assessed on the validation/test set. This process is repeated with each remaining fold acting as the validation/test set. Once all the k validation/test set error estimates have been made, the average validation/test set error is computed as an estimate of model performance. The k-fold cross-validation approach is a commonly used resampling technique as it combines computational efficiency with accurate test set error estimates. Based on common practice and empirical assessments, a k value of 10 was used as this parameter choice is a good balance between mitigating against excessive bias and high variance (Gareth et al., 2013).

Model Assessment. Model performance for the random forest models was assessed with the standardized RMSE, which is calculated as the square root of the average of the squared difference between the actual value and the value predicted by the model across all k-folds. This metric is valued for its interpretability as it returns values in the same units as the response variable. For each model set comparison, the model with the lowest train RMSE was selected as the final model and the test set RMSE was subsequently calculated. Overall, the RMSE differences between baseline and event characteristic models were examined to assess whether event characteristics uniquely predicted outcomes. A substantively lower (i.e., better) test RMSE in the event characteristics model, compared with the test RMSE for the baseline model, indicated that event characteristics uniquely predicted the outcome variable.

Feature Importance. Feature importance was assessed using Gini impurity gain, which measures how well observations are separated at each decision tree node (Nembrini et al., 2018). This is estimated by the amount of Gini impurity eliminated at each branch of the decision tree due to the presence of a particular predictor variable. Essentially, features were deemed more important the more often they were present at nodes, enhancing estimation accuracy when splitting the data.

Linear Regression

Pre-Processing. Missing data were imputed using KNN imputation, and two additional pre-processing steps were performed: polynomial transformations and normalization. The former produces synthetic features (i.e., newly created variables) that are the polynomial squares of the initial predictor variables, which accounts for any potential quadratic relationships between the predictors and the outcome variables. The latter step consisted of centering and scaling the variables to ensure the predictors in the models could be meaningfully compared.

Model Assessment. Model performance for the linear regression models was assessed the same way as the random forest model assessment, as it is appropriate to use for linear and non-linear models (Chai & Draxler, 2014).

Regression Parameters. Effect size and directionality were assessed with standardized beta coefficients.

Integration of Random Forest With Linear Regression Models. The study's pre-registration stipulated that machine learning methods would only be used in an exploratory manner; however, we opted to more fully integrate this method, along with classical linear regression, for several reasons. Integrating both approaches allowed the utilization and comparison of linear and non-linear models to analyze the data. Therefore, we were able to gain additional insight into the underlying relationships between predictor and outcome variables. Moreover, machine learning allows the

Table 2. *Test Set of Self-Reported Feelings and Experiences at the Event*

Model	Random forests
Enjoyment/Fun Baseline	1.29
Enjoyment/Fun Event Characteristics	1.25
Enjoyment/Fun Difference	**0.04 (3.2%)**
Social Connection Baseline	1.26
Social Connection Event Characteristics	1.12
Social Connection Difference	**0.14 (11.1%)**

Note. RMSE values are standardized based on a scale of *1 = lower bound estimate* to *7 = higher bound estimate*. RMSE differences (and percent improvement in RMSE scores) between baseline and event characteristics models are bolded.

incorporation of a large number of predictor variables without risking overfit models (Mitchell, 1997). As data were collected on various traits, demographics, and event characteristics, we wanted to leverage all these variables to gain as much insight into the links among events, social connection, and emotions as possible.

In addition, while feature importance scores indicate the relative magnitude of a predictor variable's effect on the outcome variable, they do not specify directionality (i.e., positive or negative relationships). Thus, linear regression adds insights into the direction of these links. Together, random forest and linear regression models provide a thorough perspective of the phenomena of interest.

Results

Overview

For each outcome variable, two types of baseline models were created—linear regression and random forests—that only included socioemotional trait and demographic variables. Then, two types of corresponding event characteristic models were created which added event characteristic variables to the predictor set. To determine whether the event characteristic variables uniquely predicted a particular outcome variable (over and above individual differences), the final event characteristic model RMSE was subtracted from the final baseline model RMSE. If this result was positive, it was concluded that event characteristic variables uniquely predicted the outcome variable. Furthermore, these results suggest that the nature of the relationships between the predictor and outcome variables were at least partly non-linear.

Event Experience Outcomes

The two event experience outcome variables examined were how much enjoyment/fun was had at the event and how much social connection was felt. The training set RMSE values for each model can be found in the Online Supplemental Material in Table S4, and the final test set RMSE values of the baseline models and the event characteristics models can be found in Table 2.

Overall, event characteristic variables uniquely predicted both event experience outcome variables. Specifically, when event characteristics were included in the models, the test RMSE improved by 3.2% for reports of enjoyment/fun, and the RMSE improved by 11.1% for reported social connection. Feature importance measurements for the final enjoyment/fun event characteristics model can be found in Figure 1, whereas measurements for social connection can be found in Figure 2. To aid interpretability, these measurements are normed to be on a scale of 0–100, where the most important feature is given a score of 100, and the remaining features are scored relatively. For example, if Feature A had a score of 100 and Feature B had a score of 50, one would conclude that Feature A was the most important and Feature B was half as important.

While less impactful in predicting enjoyment/fun, "Active vs. Passive" was notably the strongest event characteristic predictor of both event experience outcome variables. Remarkably, it was the single strongest predictor of social connection felt at the event, substantially more than any baseline socioemotional or demographic variables. Other important event characteristic features included "Virtual vs. In-Person" and "Attending Alone vs. With Others."

These measurements indicate that features such as personality, social networks, and happiness strongly influence the models' predictions of enjoyment and connection at events as well. This aligns with prior research on these features' broader links to overall life enjoyment (Bergland et al., 2015; DeNeve & Cooper, 1998; Veenhoven, 2012). However, linear regression analyses confirm that the hypothesized event characteristics independently predict event outcomes, even when controlling for socioemotional and demographic variables.

Linear Regression

For the first linear regression analysis predicting enjoyment/fun at the event, results revealed that active participation (vs. passive; $\beta = -0.896$, $t = -6.057$, $p < .001$), attending events with others (vs. alone; $\beta = -0.478$, $t = -2.897$, $p < .01$), recurring events (vs. one-time; $\beta = 0.561$, $t = 3.404$, $p < .001$), and paid events (vs. free; $\beta = -0.677$, $t = -3.695$, $p < .001$), were significant predictors of enjoyment/fun. In-person versus virtual ($p = .11$) and indoors versus outdoors ($p = .08$) were not significant predictors. These results suggest that actively participating in paid, recurring events that were attended with others were reported to be more enjoyable/fun than passive, free, and one-time events attended alone.

For the second linear regression analysis predicting social connection at the event, results revealed that active participation (vs. passive; $\beta = -3.743$, $t = -14.283$, $p < .001$), attending events with others (vs. alone; $\beta = -1.173$,

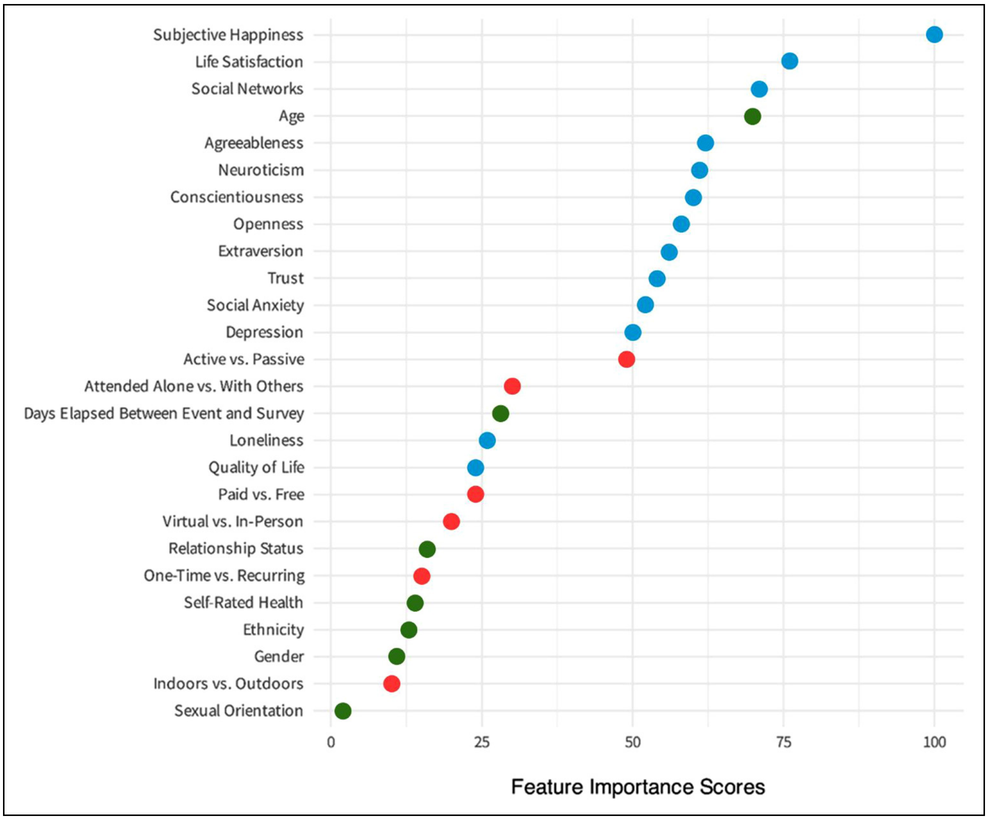

Figure 1. *Dot Plot for Final Random Forests Model Predicting Enjoyment/Fun at the Event*
Note. Feature importance scores are standardized such that the most important feature is assigned a score of 100 and other features are scored relatively. These scores do not indicate significance. Red dots indicate event characteristic variables assessed after the event; Blue dots indicate socioemotional trait variables (i.e., covariates) assessed before the event; Green dots indicate demographic variables.

$t = -4.015$, $p < .001$), recurring events (vs. one-time; $\beta = 0.689$, $t = 2.362$, $p < .05$), and in-person events (vs. virtual; $\beta = -1.71$, $t = -5.885$, $p < .001$) were significant predictors of social connection. Paid versus free ($p = .08$) and indoors versus outdoors ($p = .36$) were not significant predictors. These results suggest that actively participating in recurring events that were attended in person and with others were more socially connecting than passive, one-time, virtual events attended alone, thus supporting our hypotheses.

Post-Event Socioemotional State Outcomes

On an exploratory basis, machine learning was utilized to examine five post-event socioemotional state outcome variables, including daily levels of: loneliness, social connection, depression, social anxiety, and general anxiety to capture participants' moods one day, on average, after the event. The training set RMSE values of each model for these variables can be found in the Online Supplemental Material in Table S5, and the final test set RMSE values of the baseline and event characteristics model sets can be found in Table 3.

Overall, when examining event characteristic variables altogether with machine learning analyses, they did not uniquely predict any post-event socioemotional state variables (i.e., RMSE values did not improve). Surprisingly, four of the five test RMSE values for the models were worse than their baseline counterparts, whereas the test RMSE value for daily social connection was only negligibly better. However, linear regression analyses revealed that event locations did predict socioemotional states 24 hrs later. Specifically, outdoor events and virtual attendance were linked to greater daily social connection (outdoor: $\beta = 1.03$, $p < .001$; virtual: $\beta = 0.40$, $p < .001$). However, this finding should be interpreted with caution as these factors also predicted greater daily depression (outdoor: $\beta = 2.02$, $p < .001$; virtual: $\beta = 0.88$, $p < .001$), loneliness (outdoor: $\beta = 2.73$, $p < .001$; virtual: $\beta = 0.98$, $p < .001$), social anxiety (outdoor: $\beta = 3.69$, $p < .001$; virtual: $\beta = 1.74$, $p < .001$), and general anxiety (outdoor: $\beta = 0.34$, $p = .003$; virtual: $\beta = 0.16$, $p = .044$). Other predictors were not significant. These findings shed light on the nuanced effects of event characteristics on socioemotional states; however, future work is needed to explore the mechanisms

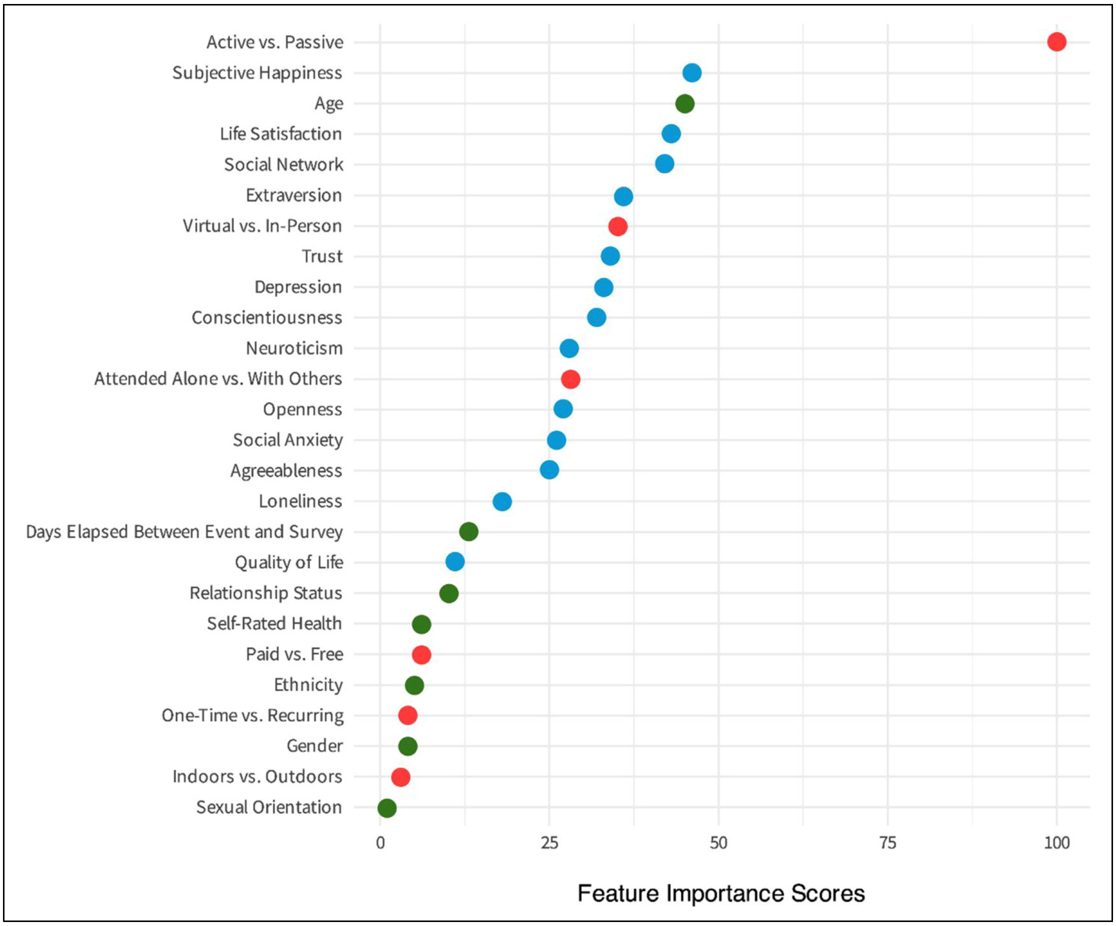

Figure 2. *Dot Plot for Final Random Forests Model Predicting Social Connection at the Event*
Note. Feature importance scores are standardized such that the most important feature is assigned a score of 100 and other features are scored relatively. These scores do not indicate significance. Red dots indicate event characteristic variables assessed after the event; Blue dots indicate socioemotional trait variables (i.e., covariates) assessed before the event; Green dots indicate demographic variables.

behind the impacts of outdoor and virtual events on these emotions.

Discussion

This research applied a dual approach of machine learning and linear regression techniques to analyze longitudinal data collected from 1,551 Eventbrite (an event management and ticketing platform) users to explore how live event attendance is associated with feelings of social connection. Importantly, this study focused on identifying event characteristics rather than differences between event attendees and non-attendees. Supporting the hypotheses, results revealed that in-person (vs. virtual) attendance, active (vs. passive) participation, attendance with others (vs. alone), and recurring (vs. one-time) events predicted feelings of social connection. These findings align with established theories and research. For example, the cues-filtered-out theory (Culnan & Markus, 1987) suggests a lack of nonverbal cues and reduced interactivity via online interactions as reasons for a potential lack of connection during virtual events. In addition, as social beings, humans have an adaptive need to belong (Baumeister & Leary, 1995) and a desire/motivation to share experiences (Jolly et al., 2019), suggesting that attending events with others may be a stronger path to feeling connected relative to attending alone. Furthermore, theoretical support for the benefits of active participation points to the concept of actively engaging in novel and exciting activities; activities of this nature are linked to stronger connections with both close others and strangers (Aron et al., 1997, 2000). Finally, research shows that repeated exposure to stimuli enhances one's attitudes and feelings around it (Zajonc, 1968). In this context, these findings suggest that attending an event multiple times may lead to stronger positive associations (e.g., increased feelings of connection) relative to attending only once.

Among these factors, active participation (i.e., attendees were encouraged to interact with others vs. simply listening or observing) stood out as the strongest predictor of feeling

Table 3. *Test Set of Self-Reported Post-Event Socioemotional States (24 Hrs After Event)*

Model	Random forests
Depression Baseline	1.21
Depression Event Characteristics	1.23
Depression Difference	**−0.02 (−1.7%)**
Daily Social Connection Baseline	0.75
Daily Social Connection Event Characteristics	0.74
Daily Social Connection Difference	**0.01 (1.3%)**
Loneliness Baseline	1.67
Loneliness Event Characteristics	1.68
Loneliness Difference	**−0.01 (0.1%)**
Social Anxiety Baseline	1.00
Social Anxiety Event Characteristics	1.01
Social Anxiety Difference	**−0.01 (1.0%)**
General Anxiety Baseline	1.28
General Anxiety Event Characteristics	1.29
General Anxiety Difference	**−0.01 (−0.8%)**

Note. RMSE values are standardized based on a scale of *1 = lower bound estimate* to *7 = higher bound estimate*. RMSE differences (and percent improvement in RMSE scores) between baseline and event characteristics models are bolded.

connected at an event, above and beyond baseline reports of socioemotional traits and demographics (see Figure 2). While event characteristics influenced feelings of connection during attendance, they did not predict sustained socioemotional states (e.g., daily moods) after events when examined collectively using machine learning. However, linear regression analyses revealed that events held outdoors and/or virtually predicted greater social connection, but also increased feelings of depression, loneliness, social anxiety, and general anxiety 24 hrs later. This suggests that while outdoor and virtual events might promote lasting feelings of connection, they may also evoke stress-related feelings such as loneliness and anxiety a day later. This dual effect could reflect the temporary nature of connection during these events, followed by unmet social needs afterward. These results highlight the importance of considering event characteristics' immediate and lasting effects on emotional well-being.

Benefits and Limitations of Machine Learning

This project utilized a machine learning approach, in addition to linear regression. We believe this approach is a useful methodological advance over previous research and lends confidence to these findings. For example, it allowed controlling for multiple pre-event socioemotional trait and demographic variables, ensuring the findings were not driven by underlying individual differences. In addition, using cross-validation resampling methods allowed for accurate out-of-sample parameter estimates (Gareth et al., 2013), providing greater certainty that the models are not overfit and would perform similarly on new data. This contrasts with classical statistical methods that tend to produce overfit models. However, as more research applies a machine learning approach to either supplement or complement more traditional analytical approaches, there should be more focus on best practices for assessing model fit and effect sizes across methods. For example, RMSEA is an appropriate fit metric that can be used across methods, but there are current limitations for clearly measuring statistical differences between them.

Implications

While scholars and public policy experts alike often point to the importance of social connection, researchers know little about what boosts social connection in everyday life. These findings document a positive link between live events with certain characteristics and feelings of connection while in attendance. Studying live events provides novel insight into ways people can find social connections beyond their long-term close relationships and social networks. Consequently, live event attendance offers a potential avenue for promoting feelings of connection. These findings can be easily and practically applied. Event creators can implement these findings to create active, in-person, recurring events while also encouraging them to be attended with others (e.g., friends, partners, family) to help attendees feel more connected while in attendance.

Although this research provides initial evidence of characteristics closely associated with feeling socially connected, it is still unknown whether simply attending an event leads to greater social connection compared with not attending an event at all. A real-world experiment randomly assigning participants to different event types or a control group (no event) could clarify whether the benefits of attending an event with active (vs. passive) participation, for example, are solely driven by active events promoting connection, by passive events hindering it, or a combination of both. An experimental design would also mitigate the potential for sample bias, where presumably individuals who are more inclined to attend in-person events may already possess specific characteristics or predispositions; however, our design did allow us to control for a host of individual socioemotional traits and demographics, thereby reducing possible selection effects.

In addition, while the hypothesized event characteristics uniquely predicted in-the-moment feelings and experiences, regression analyses revealed that only outdoor and virtual events predicted socioemotional feelings the days following attendance. However, there could be potential for benefits from attending multiple events over time. In the present study, a single event experience might not have been powerful enough to influence longer-term feelings of social connection, but continued attendance might gradually build lasting effects. For example, positive experiences at engaging events might spillover into one's general experiences if attended regularly. Thus, further research is needed to investigate how these feelings might be sustained in daily life.

Conclusion

Loneliness has been described as a modern epidemic, but fostering a sense of social connection can offset the experience and negative impacts of loneliness. As the U.S. Surgeon General recently stated in an advisory on social connection, "Loneliness and isolation represent profound threats to our health and well-being. But we have the power to respond. By taking small steps every day to strengthen our relationships. . .we can rise to meet this moment together. We can build lives and communities that are healthier and happier" (Office of the Surgeon General, 2023). Our findings suggest that regularly attending in-person, engaging events with others may be an effective and accessible way to enhance social connection. Research should continue to explore how people can sustain these positive feelings beyond the event to create a lasting sense of connectedness.

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Supplemental Material

Supplemental material is available in the online version of the article.

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