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A Bayesian Network Analysis of Exercise Experiences With Audio-Visual Stimuli

Jonathan M. Bird[1] | Costas I. Karageorghis[2] | Jasmin C. Hutchinson[3] | David J. Harris[4]

[1]Department of Targeted Intervention, University College London, London, UK | [2]Department of Sport, Health and Exercise Sciences, Brunel, University of London, London, UK | [3]Department of Exercise Science, Springfield College, Springfield, Massachusetts, USA | [4]Department of Public Health and Sport Sciences, University of Exeter, Exeter, UK

Correspondence: Jonathan M. Bird (j.m.bird@ucl.ac.uk)

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ABSTRACT

Audio-visual stimuli are widely used to enhance the exercise experience, yet the technological devices used to display these stimuli have received limited research attention. The aim of the present investigation was to apply a Bayesian Network (BN) to formally model and quantify the relationships between technological features of exercise-related audio-visual interventions and aspects of the exercise experience, offering a novel approach to understanding these complex interactions. A dataset compiled from the extant literature ($k = 6$) was used to construct the BN, specifying the network structure and learning the conditional probability distributions of the model. Through this framework, we examined how technological features—viewed through the lens of the Embodiment–Presence–Interactivity Cube—and music influence the exercise experience. The findings indicated that the pairwise combination of high interactivity and presence increased the probability of more positive affective valence. The three-way effect of high embodiment, presence and music increased the probability of high arousal as well as a more external focus of attention. The combination of high affective valence and high arousal was the strongest indicator of exercise enjoyment. Collectively, the findings offer new insights into how technological features of audio-visual interventions can shape the exercise experience, providing guidance for the optimal design of such interventions. These results have important implications for both research and practice, suggesting that practitioners should prioritise interactive audio-visual interventions with music to promote positive exercise experiences.

1 | Introduction

Sustained engagement in physical activity can help reduce the risk of noncommunicable diseases, mobility difficulties, cognitive dysfunction and mental ill-health [1, 2]. The benefits of physical activity are so well documented that the World Health Assembly (WHA) set a goal of a 15% relative reduction in physical inactivity by 2030 [3]. Unfortunately, recent estimates have suggested that nearly a third of adults globally (1.8 billion) were insufficiently active in 2022 and that if current trends continue, the WHA's physical inactivity target will not be met [2]. Hence, evidence-based interventions to promote engagement in regular physical activity among the general population are a pressing imperative [4].

1.1 | Affective Responses to Exercise

Traditional physical activity interventions have targeted cognitive constructs (e.g., self-efficacy), in accord with social-cognitive theories that have dominated the exercise psychology literature for the past 40 years [5]. However, such interventions have only yielded small benefits for physical activity behaviour [6], leading many scholars to question the suitability of social-cognitive theories in these contexts [7]. Contrastingly, dual-process models support the notion that behavioural decision-making is governed by two types of processes [8]. *Controlled processes* are slow and deliberate and rely on higher brain functions. *Automatic processes* are intuitive and rely on heuristic cues. One such cue concerns the *affect heuristic,* which holds that individuals tend to engage in behaviours that feel good and avoid behaviours that feel bad [9]. Accordingly, affective responses (i.e., feeling states) have become integral to dual-process models of physical activity behaviour [8, 10] and feature prominently in taxonomies of behaviour change [11].

1.2 | Audio-Visual Technology

There are many strategies to facilitate pleasant exercise experiences, and these can be categorised as either intrinsic or extrinsic in nature [12]. Intrinsic strategies are those that target the main principles of exercise prescription (i.e., frequency, intensity, time and type), whereas extrinsic strategies are employed to manipulate the exercise environment (e.g., the landscape or soundscape). A frequently employed extrinsic strategy concerns the use of technology to deliver audio-visual stimuli, such as music, videos and interactive simulations.

A large corpus of work has demonstrated the efficacy of audio-visual stimuli on affective responses to exercise [13, 14]. This has enabled researchers to develop evidence-based recommendations to facilitate the selection of audio-visual stimuli that are likely to enhance exercise-related affect [15, 16]. However, there is a paucity of research attention afforded to technological devices that are used to display such stimuli. This is somewhat surprising given that modern technologies such as augmented and virtual reality offer substantially different user experiences to those associated with traditional screen displays. For example, Bird et al. [17] reported that a 10-min bout of cycle ergometry at the ventilatory threshold was rated as more enjoyable when accompanied by a 360° video when compared to the same video viewed via a standard laptop screen.

The Embodiment–Presence–Interactivity Cube [18] is a useful framework in furthering understanding of how various technologies are related to one another (see Figure 1). The Cube incorporates three dimensions: *Embodiment* refers to the degree of integration between the technological device and the human body. External devices (e.g., television screens, portable speakers) can be considered to offer low embodiment, whereas internal devices (e.g., head-mounted displays, over-ear headphones) can offer high embodiment, as they are more fully integrated with the human body. *Presence* refers to the sense of being transported to another environment [19], and it was theorised that internal devices can prompt greater perceptions of presence than external devices [18]. Finally, *interactivity* is a behavioural factor pertaining to the extent to which users can manipulate the environment in which the experience is taking place.

Bird et al. [20] sought to understand how technologies depicted on the EPI Cube might influence the exercise experience. They administered four conditions, each of which was related to a distinct vertex of the cube (i.e., television, augmented reality, 360° video and virtual reality) and accompanied by music. The registered report indicated that technologies with greater affordances on the EPI Cube, such as 360° video and virtual reality, were associated with more positive affective valence scores, as well as higher ratings of exercise enjoyment. In empirical terms, the Bird et al. [20] study represents a useful point of origin with a view to elucidating the effects of different technologies on the exercise experience. However, there remains a need for a fuller and more nuanced understanding of the concepts that are integral to the EPI Cube. This would lead to the development of theoretical models that seek to underscore causal relationships. It is envisioned that such work will contribute to the development of evidence-based audio-visual interventions in an exercise context, with the long-term goal of promoting sustained engagement in physical activity (cf. [21]).

1.3 | Bayesian Networks (BNs)

In the present study, BNs [22] serve as a methodological tool to illuminate the relationships between audio-visual features of technologies and exercise phenomenology through formalising their probabilistic relationships. A BN is a probabilistic graphical model that represents a joint probability distribution over a set of variables using a directed acyclic graph (DAG [23]). The *nodes* in the graph correspond to the variables of interest, and the directed *edges* between nodes encode conditional dependencies between the variables of interest [24]. Each node in the network encapsulates a probability distribution that quantifies the likelihood of the variable it represents (or particular values of that variable) given its 'parents' (direct causes) in the graph. By computing this joint probability distribution, we can analyse the relationships among variables and estimate unobserved instances through probabilistic inference. This process effectively simulates potential outcomes of a specific exercise intervention, facilitating an assessment of its likely success [25].

BNs are potentially powerful tools in furthering understanding of numerous aspects of human experience [26]. By leveraging BNs, we can describe the dependencies and conditional independencies in empirical data [27, 28], offering insights into the complex interplay of psychological factors that influence an individual's exercise experiences. A strength of BNs lies in their ability to capture and represent complex dependencies in a structured and interpretable manner. They enable the integration of prior knowledge, expert opinions and/or observational data to estimate the conditional probabilities associated with each variable given the states of its parents [29]. In the present context, they enable us to better understand the complex causal relationships between audio-visual stimuli and exercise experiences. An illustrative example of a simple BN, as well as additional explanation of this technique, is provided in Supporting Information 1.

1.4 | Aims

The aims of the present investigation were to: (a) use a BN as a way to formalise the relationships between the technological features[1] of exercise-related audio-visual interventions and aspects of the exercise experience as a step towards building a conceptual model and (b) use the BN as an inference engine to answer questions about the influence of technological features—through the lens of the EPI Cube—and music on the exercise experience. To do so, we constructed a large dataset from

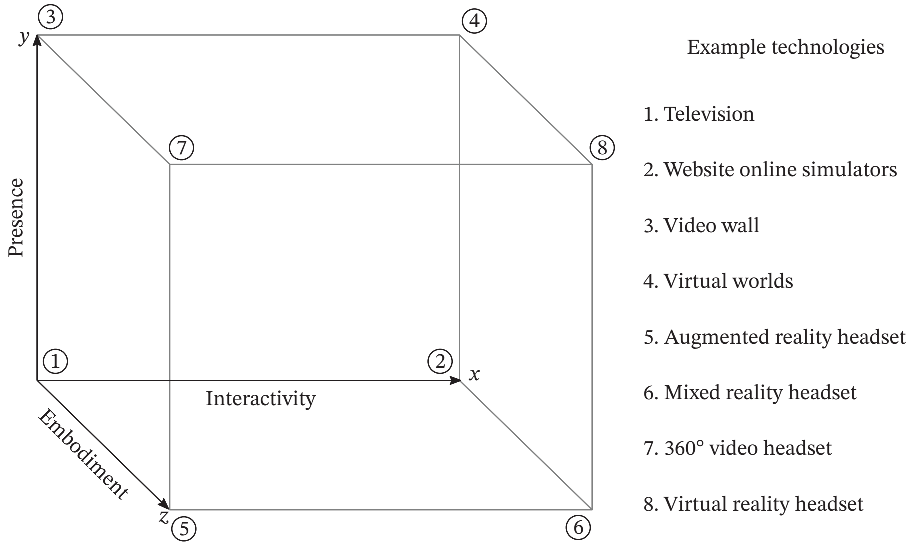

FIGURE 1 | The Embodiment–Presence–Interactivity (EPI) Cube. *Note:* The EPI Cube depicts a range of technologies according to three dimensions: embodiment (z-axis), presence (y-axis) and interactivity (x-axis). Adapted from Flavián et al. [18].

a collection of published studies in the exercise domain, which we used to train a BN model of exercise phenomenology.

2 | Methods

2.1 | Data Identification and Extraction

Initially, we sought to identify studies that employed audio-visual stimuli as an extrinsic strategy during exercise. We endeavoured to select studies that were relatively homogeneous in relation to the exercise modality and intensity, as well as methods of data collection. Specifically, we searched for studies involving cycle ergometer exercise performed at, or proximal to, the ventilatory threshold. To have comparable variables, studies were considered eligible if they used (most of) the following affective and perceptual measures: Feeling Scale (FS [30]), Felt Arousal Scale (FAS [31]), Borg CR10 Scale [32], Attentional Scale (AS [33]) and Physical Activity Enjoyment Scale (PACES [34]). Details of each of these measures are located in Supporting Information 2. Six studies were identified that fitted these criteria [17, 20, 35–38]. Table 1 provides a summary of study characteristics, and Supporting Information 3 provides an overview of each of the technologies employed across studies. It is noteworthy that not all studies employed every measure described above. However, a strength of BNs is that they are adept at dealing with missing data.

The present authors were associated with four of the six studies deemed eligible for inclusion, and hence, the related data were immediately accessible. For the remaining two studies, we contacted the corresponding author to request the data. Affective and perceptual responses to exercise are typically measured repeatedly throughout an exercise bout [39]. However, for modelling purposes, we extracted data from the final timepoint only. This decision was predicated on the rationale that the largest effects of extrinsic strategies, such as audio-visual stimuli, are likely to emerge towards the end of each exercise bout when conducted at a set intensity such as ventilatory threshold (see e.g., [35]). Moreover, the final timepoint of exercise performed at the ventilatory threshold often coincides with an affective low peak [40], which serves as a useful indicator of exercise enjoyment, in accord with the peak–end rule [41]. Hence, these data were considered to be the most informative for the BN.

After obtaining affective and perceptual data pertaining to the exercise experience, we extracted scores for the technologies used in each study in accordance with the EPI Cube [18]. JMB and DJH served as the primary and secondary raters, respectively, and there were no disagreements in scoring. Technologies could either be low or high on the dimensions of embodiment, presence and interactivity, creating a binary scoring system (1 or 2). It is noteworthy that some of the eligible studies [17, 35, 36] incorporated music-only conditions, and these were excluded from the present analysis, given the focus on audio-visual interventions. Nonetheless, given music's strong influence on affective and perceptual experiences during exercise, we scored it as being either *absent* (1) or *present* (2) in the context of each audio-visual intervention.

As is common in BN construction, variables were discretised, a method that has been shown to improve the performance of several BN and logistic regression techniques [42]. We used median splits for the affective and perceptual variables (see Supporting Information 4 for distribution plots) to account for the actual distribution of values during exercise, rather than using the scale midpoint or other anchors. Scores for the technological features were already binary. We did not intend to predict specific values on the affective and perceptual self-report measures; rather whether technological features increased/decreased the probability of higher or lower values in relation to the values that are typical during moderate-intensity exercise.

2.2 | BN Creation

A BN for a given set of random variables $X = \{X_1, ..., X_n\}$ is made up of: (a) a network structure S, a DAG that encodes the conditional independencies about the variables in X and (b) a set p of local probability distributions associated with each variable (X_1, ..., $X_{n)}$. These two elements define the joint probability

TABLE 1 | Study characteristics.

Study	Sample			Exercise protocol		Measures				
	N	M_{age} (SD)	% women	Intensity	Duration (min)[a]	FS	FAS	BS	AS	PACES
Bird et al. [17]	18	24.1 (4.2)	50.0	VT	10	Y	Y	Y	Y	Y
Bird et al. [35]	24	26.7 (4.1)	41.6	10% < VT	6	Y	Y	Y	Y	Y
Bird et al. [20]	24	26.2 (3.1)	54.1	VT	15	Y	Y	Y	Y	Y
Jones et al. [36]	38	21.1 (1.9)	50.0	10% < VT	10	Y	Y	N	Y	Y
Jones and Ekkekakis [37]	21	34.6 (9.6)	76.2	VT	15	Y	Y	N	Y	Y
Jones and Wheat [38]	12	26.2 (7.7)	33.3	VT[b]	20	Y	Y	N	Y	Y

Note: All studies employed a crossover design and examined the effects of audio-visual stimuli during cycle ergometry.
Abbreviations: AS, Attentional Scale; BS, Borg Scale; FAS, Felt Arousal Scale; FS, Feeling Scale; N, No; PACES, Physical Activity Enjoyment Scale; VT, Ventilatory threshold; Y, Yes.
[a]Duration refers to the main exercise phases only and is not inclusive of any time spent during warm-up/downs.
[b]Participants in the Jones and Wheat study [38] were asked to 'maintain an intensity that you can sustain for 20 min' during the virtual reality condition only.

distribution for X. The structure, S, is made up of nodes that have a one-to-one correspondence with the random variables in X and edges representing dependencies between nodes. The absence of an edge between two nodes implies conditional independence (i.e., given certain other variables in the graph, these values become independent). Provided the structure S, the joint probability distribution for X is then:

$$p(\boldsymbol{x}) = \prod_{i=1}^{n} p(x_i|pa_i). \quad (1)$$

This denotes that the joint probability distribution over X is a product of the probability distributions over the variables x, conditional on their parent nodes (pa).

BN creation consists of three broad steps. First, domain variables are identified (i.e., $X \in F$). Here, F represents the relevant exercise-related affective and perceptual variables, as well as the technological features of each audio-visual intervention. BN construction aims for causal sufficiency, meaning all direct causal influences between the variables are captured [22]. However, in practice, this assumption cannot be guaranteed due to the inherent incompleteness of knowledge and measurement error. Therefore, the variable set F was chosen based on current domain knowledge and the measurements taken in the extant literature. Second, the BN's structure is chosen by identifying the conditional independencies among these random variables. Third, once the BN structure is defined, the associated joint probability density function (PDF) can be learned from the training data. Once the PDF is learned, the researcher is able to perform probabilistic inference, using the BN as the computational engine to examine the influence of technological features on the exercise experience.

2.3 | BN Structure Learning

Two approaches are used to construct BNs. *Knowledge-based approaches* rely on the knowledge of domain experts and logical reasoning to construct the network [43, 44]. *Data-based approaches* rely entirely on conditional independencies in the data to estimate the structure and parameters of the network [45]. We adopted a hybrid approach, relying primarily on expert knowledge but also using data to confirm and refine the model structure, which could be considered *computer-assisted model refinement,* as opposed to *de novo* learning.

Determining the structure was relatively straightforward, and we identified a likely DAG from domain knowledge alone. As the technological features of the audio-visual interventions were experimentally controlled, these variables could not have any parent nodes, and therefore connections to other nodes could only take on one causal direction. Additionally, four of the experiential variables (i.e., affective valence, arousal, rating of perceived exertion [RPE] and state attention) were measured during exercise, while enjoyment was measured post-exercise. Hence, the temporal ordering was known, which circumvents problems around Markov equivalence, where the direction of certain edges can be reversed without altering the conditional independence relationships in the DAG [27]. As variables measured during exercise were recorded simultaneously, we precluded connections between their associated nodes. It is likely that these variables exhibit complex and potentially cyclical interrelationships over time. However, we adopted a simplification for the purposes of modelling the overall pattern of relationships between the technological features of the audio-visual interventions and the experiential outcomes. When constructing the DAG, we reasoned that all the technological features could influence all of the experiential variables. Moreover, we reasoned that affective valence, arousal, RPE and state attention could all potentially influence cognitive evaluations of exercise enjoyment that were measured post-exercise (see Figure 2).

We then examined whether the removal of any of these hypothesised edges improved the fit of the model to the data. Specifically, we specified a matrix of the *neighbouring* DAGs—all variants of the hypothesised model, but with a single edge removed—and computed the Bayesian information criterion (BIC) as a measure of goodness of fit. The BIC was calculated as $\ln\,(p(D|\theta)) - 0.5 * d * \ln\,(N)$, where D is the data, θ is the maximum likelihood estimation of the parameters, d is the number of parameters, and N is the number of data cases. BIC values indicated that the removal of the edge from RPE to enjoyment substantially improved the model fit (> 10 ΔBIC; [46]), and hence this arc was removed (see Figure 2). Subsequently, we fitted the observed data to this structure to populate the joint distribution and complete the BN.

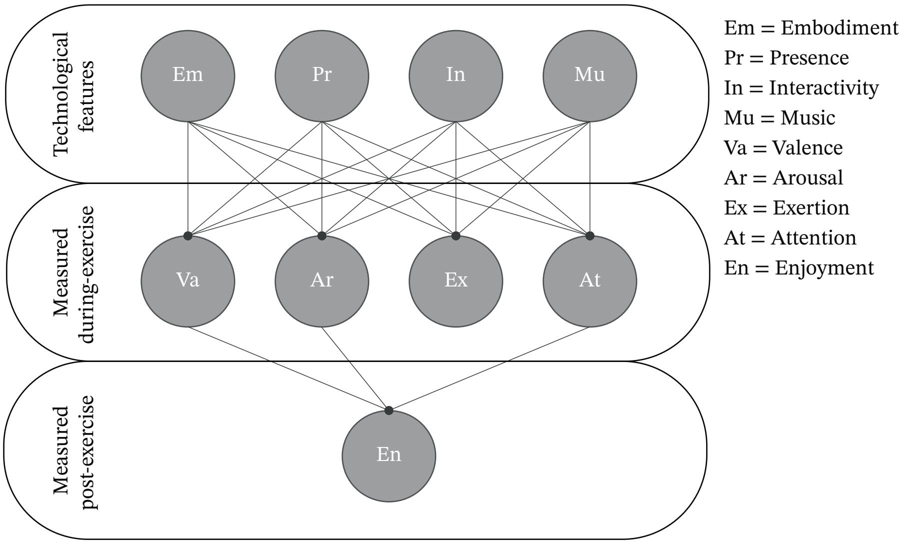

FIGURE 2 | Directed acyclic graph for final BN structure. *Note:* Circles represent the random variables ($X \in F$) and arrows the causal dependencies between them. For ease of interpretation, we have grouped the variables into three levels according to their connections, but these levels are a conceptual segmentation and thus do not represent any additional features of the model. Enjoyment is typically measured post-exercise as a cognitive evaluation of the exercise bout.

2.4 | Parameter Learning and Model Validation

We set uninformative Dirichlet priors on the tabular conditional probability distributions at each node before performing parameter learning using Leray and Francois's [47] implementation of the Expectation–Maximisation (EM) algorithm for BNs with missing data. The algorithm iterated until parameter estimates stabilised, ensuring convergence by monitoring log-likelihood changes across iterations. We then identified the optimal structure within the space of plausible candidates. However, there is still a need to demonstrate empirically that our BN topology corresponds to a model of exercise phenomenology that would hold ecological validity. Accordingly, we tested the predictive power of the model using cross-fold validation ($k = 10$) before averaging the results to minimise bias and variance [48]. At each fold, we performed probabilistic inference on the BN from the training set to predict the main outcome variable (i.e., exercise enjoyment), computing the predicted outcome as the highest estimated marginal probability. Subsequently, we computed a confusion matrix to evaluate the accuracy (i.e., proportion of true results, both true positives [TP] and true negatives [TN], among the total number of cases) and precision (i.e., proportion of TP results among all positive results predicted by the classifier, reflecting the accuracy of positive predictions) of the trained models as performance indicators:

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total cases}}, \tag{2}$$

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{false positive}}. \tag{3}$$

The BN model demonstrated strong performance in predicting exercise enjoyment, with a precision of 84% and an accuracy of 71%. The log-likelihood values ranged from −3.62 to −5.71, with low variance, indicating model stability and minimal risk of overfitting.

2.5 | Probabilistic Inference

Probabilistic inference involves using the trained BN to derive marginal and conditional probabilities of specified nodes given certain evidence. We inputted observed values for nodes (and combinations of nodes) of interest and then computed the posterior probabilities of unobserved nodes using the junction tree engine. This enabled us to ask questions about the effect of particular combinations of conditions (e.g., the probability of attaining a high exercise enjoyment score when an audio-visual intervention is characterised by high embodiment coupled with high presence). We sought to understand (a) the potential effects of combinations of technological features on the experiential variables during exercise; (b) the potential effects of the technology on exercise enjoyment; and (c) the potential effects of combinations of experiential variables during-exercise on exercise enjoyment. The interested reader can perform additional inference operations on the network using the MATLAB code that is provided online (https://osf.io/82eyp/).

3 | Results

3.1 | Influence of Technological Features on Experiential Variables During Exercise

First, we examined whether singular and pairwise combinations of technological features of audio-visual interventions altered the probabilities of the experiential variables during exercise taking on high or low states. We performed probabilistic inference on the network, specifying the values of parameters of interest and marginalising over other nodes, to compute an estimated probability that the variable of interest would be 'high' or 'low'. We then plotted the *difference* in probability between high or low (or present/absent) using heatmaps (see Figure 3). Consequently, values further from zero indicate a larger effect of that parent node or pairwise combinations of nodes.

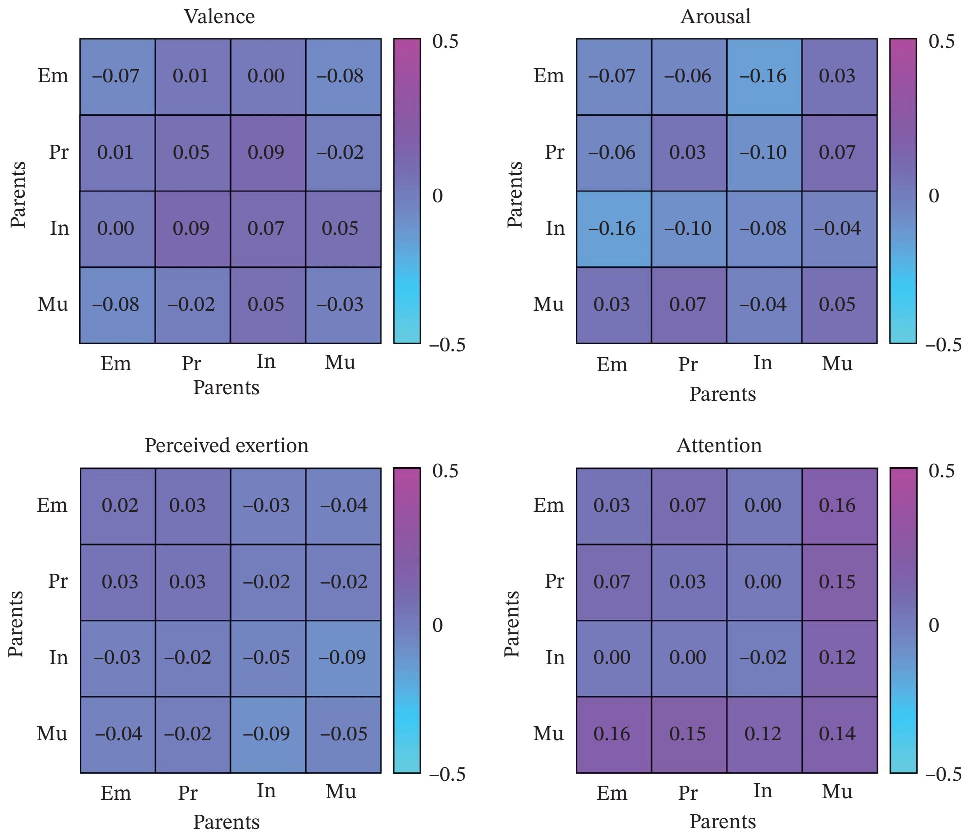

FIGURE 3 | Effects of technological features on affective and perceptual responses during exercise. *Note:* Diagonal squares represent the difference in probability of attaining a high value on the target variable for the parent (Pa) variable when its value is high compared to low (marginalising over the other parents); that is, *p* (outcome = high | Pa = 'high')—*p* (outcome = high | Pa = 'low'). Other squares, therefore, indicate the effects of both parents taking the 'high' value. Abbreviations: Em, embodiment; In, interactivity; Mu, music; Pr, presence.

For affective valence, combinations of high interactivity and presence increased the probability of more positive experiences, albeit that these were relatively weak in magnitude (+0.09). The heat map for arousal indicated that no single feature had a strong impact on whether scores were likely to be high or low (values close to zero). The combination of high embodiment and interactivity did, however, reduce the probability of high arousal (−0.16). Effects on RPE were relatively small, but the combination of high interactivity and music was found to reduce the probability of high RPE (−0.09). Stronger effects were evident for state attention, where music increased the likelihood of greater dissociation (i.e., higher state attention scores; +0.14). Combinations of music with any of the remaining three technological features (i.e., embodiment, presence and interactivity) also increased the likelihood of greater dissociation (+0.12–0.16; see Figure 3).

We also explored the three-way effects of the technological features on the experiential variables measured during exercise. The findings revealed much stronger effects, and illustrative examples are depicted in Figure 4. High embodiment, presence and interactivity had a strong likelihood of decreasing the probability of high arousal (−0.30; see Figure 4a). Contrastingly, when substituting interactivity for music, the three-way effect increased the probability of high arousal (+0.17; see Figure 4b). The three-way combination of high embodiment, interactivity and music increased the probability of dissociation (+0.16; see Figure 4c). Substituting interactivity for presence revealed an even stronger three-way effect on dissociation (+0.33; see Figure 4d).

Next, we examined the isolated effect of each technological feature on enjoyment by marginalising over all other technological features (see Figure 5). This indicated that when considered alone, none of the technological features strongly shifted the probability of high enjoyment far from its baseline (dashed black line). High interactivity appeared to provide a small increase, as did presence, but the probabilities did not shift substantially.

We also considered the effects of each of the vertices of the EPI Cube [18] on affective valence and exercise enjoyment. We calculated the probability of more positive valence and higher enjoyment based on each of the combinations of embodiment, presence and interactivity. These are depicted in Figure 6 as probability values at each vertex of the cube. It is noteworthy that we did not have data for some combinations of embodiment, presence and interactivity (EPI Cube vertices 2, 3, 4 and 6). Accordingly, these points were very similar and did not change much from their prior values.

We examined pairwise combinations of the technological features to determine whether the interactions were determinants of exercise enjoyment (see Figure 7). We computed the marginal probabilities of high and low enjoyment given pairs of parents being both high or both low. The values in the probability matrix represent the increase in *p* (Enjoyment = High) when both parents were 'high' compared to 'low'. This indicated that even pairwise combinations of

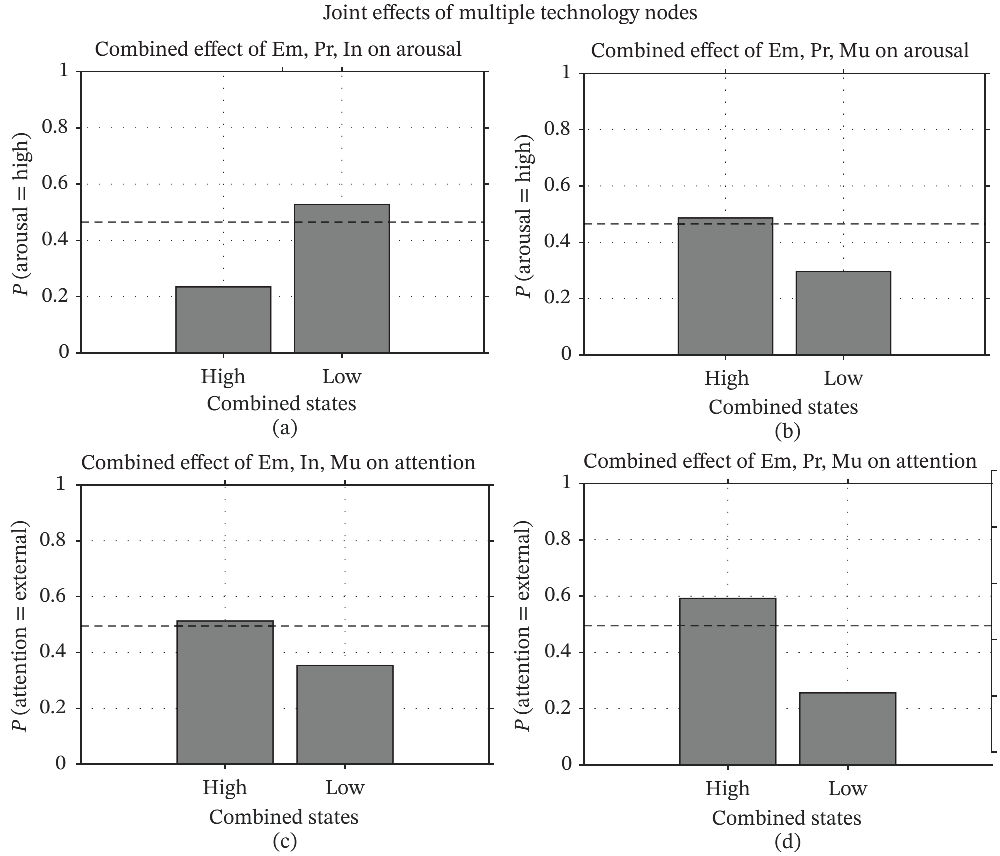

FIGURE 4 | Three-way effects of technological features on arousal (a and b) and state attention (c and d). Abbreviations: Em, embodiment; In, interactivity; Mu, music; Pr, presence.

technological features did not have strong influences on the probability of deriving high enjoyment. Figure 7 shows that all values are close to zero. Hence, the model illustrates that given the intervening complexity of affective and perceptual responses to exercise (e.g., affective valence and state attention), the technological impacts of an audio-visual intervention are uncertain.

3.2 | Effects of Experiential Variables During Exercise on Enjoyment

Finally, we examined which intervening exercise variables were stronger determinants of enjoyment, which is typically assessed post-exercise. Unsurprisingly, affective valence *during* exercise was a substantial determinant of enjoyment, with high valence scores shifting the probability of high enjoyment by +0.42, compared to low valence scores (see Figure 8). Additionally, the combination of high valence and arousal was the most beneficial for high enjoyment (+0.60). As a singular entity, arousal had a smaller but still important impact on exercise enjoyment (+0.15). However, state attention did not (−0.01), suggesting that (in the presence of the other variables) a more external focus of attention was not contributing to a more enjoyable experience.

4 | Discussion

We sought to develop a BN as a novel approach to systematically formalise the complex relationships between technological features of exercise-related audio-visual interventions and key aspects of the exercise experience. Drawing from a comprehensive dataset compiled from a curated selection of published studies, we constructed a DAG to map out the hypothesised interactions before refining the model through parameter learning. The refinement process indicated that all hypothesised edges were critical to the model, with the exception of the arc from RPE to enjoyment. Removing this arc improved the fit of the model without reducing its predictive accuracy. This underscores the intricate and multifaceted interplay between technological features and salient experiential factors. Leveraging the BN as a powerful inference engine, we were able to advance our understanding of how technological features influence the exercise experience, offering new insights that have the potential to shape future research and applied interventions in the exercise domain.

4.1 | Experiential Variables During Exercise

Regarding the affective variables that are typically examined during an exercise bout, the findings indicated that the pairwise combination of interactivity and presence had a small but positive effect on the probability of prompting more positive affective valence. This is important when considered in light of empirical work demonstrating how pleasurable exercise experiences can be indicative of future exercise behaviour [49]. For example, Williams et al. [50] reported that a one-unit improvement in affective valence during exercise (derived via the FS) was associated with 27–29 additional min of physical activity per week cross-sectionally and an increase of 15 min of physical activity per week, 6 months later. Similarly, an instructional intervention designed to enhance affective valence during exercise prompted

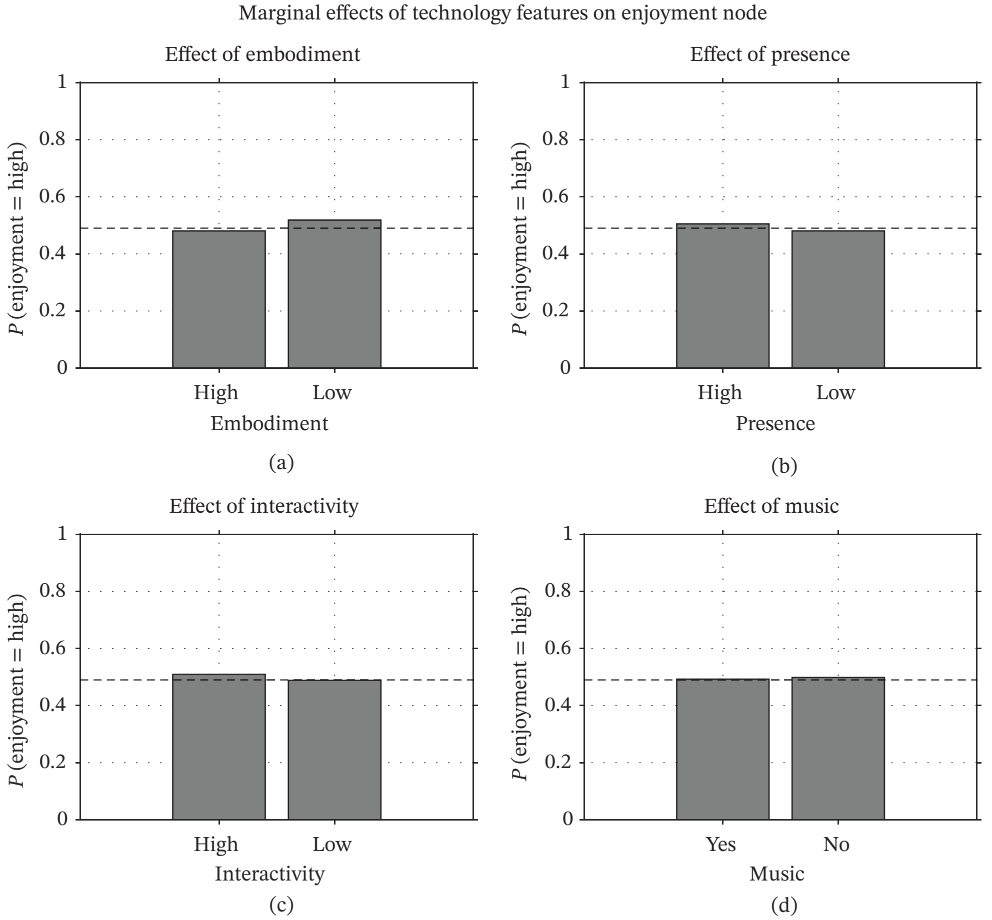

FIGURE 5 | Effects of embodiment (a), presence (b), interactivity (c) and music (d) on enjoyment. *Note:* Bar plots show the marginal probability of high enjoyment (dashed line) and the probability of high enjoyment when each technological feature is low or high, or when music is absent or present.

a 77% increase in attendance at a fitness facility over an 8-week period when compared to the control [49].

No single technological feature had a strong impact on arousal. The pairwise combination of embodiment and interactivity did reduce the probability of high arousal (−0.16), while the three-way combination of embodiment, presence and interactivity decreased the probability of high arousal to a greater extent (−0.30). However, substituting interactivity for music appeared to increase the probability of high arousal (+0.17; Figure 4b). It is noteworthy that researchers typically administer measures of

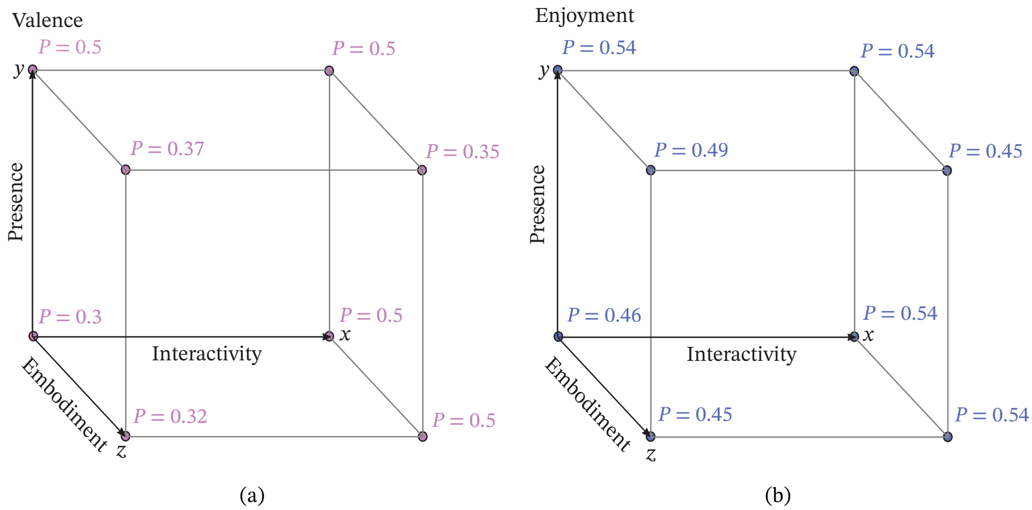

FIGURE 6 | Singular effects of the EPI Cube vertices on affective valence and enjoyment. *Note:* Probabilities (p) shown at each vertex represent the probability of more positive affective valence (a) or high exercise enjoyment (b) for each vertex of the EPI Cube.

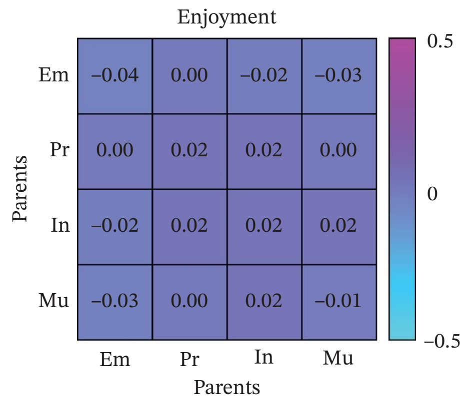

FIGURE 7 | Probability matrix heatmap showing the effects of technological features on exercise enjoyment. *Note.* Diagonal squares represent the difference in probability of attaining high enjoyment for the single variable when its value is high, compared to low. Nondiagonal squares, therefore, indicate the impact of both variables being high on the probability of high enjoyment. Abbreviations: Em, embodiment; In, interactivity; Mu, music; Pr, presence.

arousal during exercise protocols to ensure theoretical coherence [49, 51], given that affective arousal represents one-half of core affect (alongside affective valence) when conceptualised using dimensional approaches, such as Russell's [52] Circumplex Model of Affect. Accordingly, arousal responses are typically reported for descriptive purposes and are rarely germane to the efficacy of exercise-related interventions (see e.g., [49, 51]). It is also important to note that self-selected measures of arousal are particularly challenging. This is because respondents are required to extract the arousal component from what they are feeling, quantify it, and report it, without influence from the pleasure–displeasure dimension of core affect [53].

Regarding the perceptual variables that are typically measured during an exercise bout, the findings indicated that interactivity, and the combination of interactivity and music, appeared to mildly reduce the probability of high RPE (−0.09). There are several examples in the literature wherein interactive music interventions have lowered RPE during exercise. For example, Fritz et al. [54] adapted three fitness machines so that participants either created musical sounds while exercising or passively listened to similar music produced by other individuals. The researchers reported that the experimental condition elicited lower RPE when compared to the passive music condition. More recent interventions can ingest data from a variety of sources captured in real-time during exercise (e.g., heart rate and cadence) to produce personalised music tracks [55].

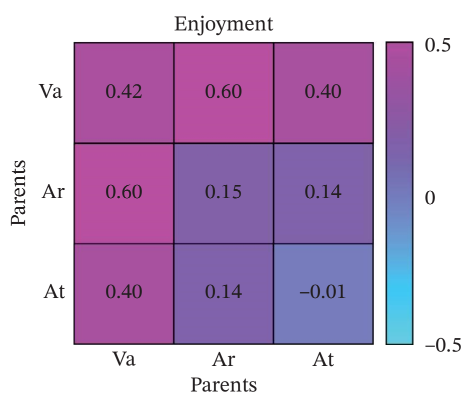

FIGURE 8 | Probability matrix heatmap showing the effects of experiential variables during exercise on enjoyment. Notes. Diagonal squares represent the difference in probability of attaining high enjoyment when the parent variable (Pa) assumed the value high, compared to low, that is, p (enjoyment = high | Pa = 'high')—p (enjoyment = high | Pa = 'low'). Other squares, therefore, indicate the impact of both variables being high. Abbreviations: Ar, arousal; At, attention; Va, valence.

The strongest direct effects of technological features were on state attention. Singularly, music increased the likelihood of dissociation, while the other technological features had minimal effects. However, the three-way combination of presence, embodiment and music greatly increased the probability of dissociation (+0.33), as did the three-way combination of embodiment, interactivity and music (+0.16). Attentional dissociation helps individuals divert their focus away from exercise-related interoceptive cues (e.g., elevated heart rate), thus rendering the exercise experience more pleasurable [35]. Pragmatically, technologies that combine high levels of embodiment, presence and interactivity, such as virtual reality, can be used to good effect in promoting attentional dissociation during exercise, a finding that aligns with the extant literature [20, 56]. Music appears to heighten this effect, ostensibly by occupying greater attentional resources, in accordance with parallel processing models of attention (cf. [57]).

4.2 | Exercise Enjoyment

The modelling process indicated that simple changes in the technological features of an exercise-related audio-visual intervention were unlikely to increase the probability of exercise enjoyment to any meaningful degree when considered in singularity or in paired combinations. However, it is important to note that the technological features did influence the experiential outcomes measured during exercise. The experiences during exercise, in turn, influenced enjoyment, which was assessed following the cessation of exercise. This finding emphasises the complexity of these relationships and the value of BN models, in which researchers are required to formalise such relationships [26].

It is plausible that experiential variables act as mediators between technological features and exercise enjoyment. However, enjoyment has been theorised to reflect a combination of affective experiences and cognitive appraisals when assessed post-exercise [58]. These appraisals are shaped not only by the affective experience of exercise but also by feeling states experienced immediately afterwards. It is noteworthy that rapid rebounds towards pleasure generally occur following the cessation of strenuous exercise that prompts decreases in affective valence [53]. Hence, such rebounds could, conceivably, have coloured individuals' appraisals of exercise enjoyment. The relationship between affective rebound slopes and exercise enjoyment is therefore a topic that warrants further investigation.

An unexpected finding was that, when considered in isolation, an external focus of attention did not appear to contribute towards a more enjoyable experience. However, it should be acknowledged that this is not necessarily a reflection of the efficacy of audio-visual interventions. This is because an external focus of attention, as measured by the AS [33], can plausibly be orientated towards several targets (e.g., daydreaming, the external environment). Accordingly, it is difficult to ascertain whether an audio-visual intervention prompted attentional dissociation or whether participants were simply disengaging from the related exercise protocol. That said, there is a greater chance that dissociative thoughts were orientated towards audio-visual interventions when they were delivered via technologies that combine high levels of embodiment and presence (e.g., 360° video and virtual reality), owing to the capacity of such technologies to occlude individuals from their physical realities [35]. Another potential confounder is that an individual's dominant attentional style (i.e., associator, dissociator or switcher) is likely to influence the attention–exercise enjoyment relationship (see [59]).

4.3 | Implications for Theory

The EPI Cube [18] is a useful tool that delineates the key qualities of a range of technologies and how they are related to one another. Nonetheless, the framework was not designed for exercise contexts and cannot be used to predict how these technologies might influence affective and perceptual responses. The BN approach employed herein has helped in elucidating the relationships between the technological features of audio-visual interventions and exercise-related experiential outcomes. This is an important initial step in the development of a *mid-range theory,* which lies between highly abstract grand theories and specific empirical observations [60]. Mid-range theories focus on a limited aspect of a phenomenon, providing detailed explanations and predictions within a narrow scope. Moreover, they are designed to be more testable and practical than grand theories, addressing specific issues and bridging the gap between general theoretical frameworks and empirical data. It is hoped that the BN presented herein can provide a foundation for further context-specific theory development in relation to audio-visual interventions.

4.4 | Implications for Practice and Future Research

Collectively, the findings support the notion that technological features of audio-visual interventions can significantly alter the exercise experience, supporting the decision to employ the EPI Cube [18] as a guiding framework. Specifically, practitioners might seek to employ interactive audio-visual interventions and couple such stimuli with music. There has been a recent shift towards interactive audio-visual interventions in recent years, as increasingly sophisticated forms of technology continue to grow in popularity [13]. Accordingly, practitioners might explore the application of immersive technology, such as virtual reality, to help individuals who typically refrain from exercise regimens. An advantage of immersive technology is the potential to develop virtual scenarios that would otherwise be impossible to recreate in physical reality [61]. It is plausible that developing new and exciting virtual exercise scenarios would facilitate higher ratings of affective valence and arousal, which, collectively, were found to be the strongest indicators of exercise enjoyment. We can easily foresee a future in which artificial intelligence facilitates the personalisation of exercise experiences that adapt in real time according to a user's affective state.

Our primary outcome of interest was exercise enjoyment, given that researchers are increasingly recognising that affective phenomena are powerful drivers of human behaviour [49]. However, a logical extension to the present investigation would be to extend the BN to accommodate exercise adherence, albeit that longitudinal data concerning the effects of audio-visual stimuli are sparse. We incorporated music as a 'technological factor' in the interests of expediency, and music was scored as either absent or present in each audio-visual intervention. A useful direction for future research would be to classify the mode of music delivery in relation to each of the EPI Cube dimensions (e.g., portable speaker = *low embodiment*, over-ear headphones = *high embodiment*). Relatedly, the BN could be further developed to accommodate the type of auditory (e.g., motivational vs. neutral) and visual (exercise congruent vs. exercise incongruent) stimuli used in exercise-related interventions. Finally, there is a pressing need for work that examines the extent to which technological features are related to underlying neurophysiological processes. The last decade has seen an emergence of such work with musical stimuli [62], but technologies that comprise high presence and interactivity remain under-examined.

4.5 | Strengths and Limitations

A strength of the present work is that it shone a light on the underlying technological features of devices employed to deliver exercise-related audio-visual interventions, using an established conceptual framework [18]. This allowed us to examine how embodiment, presence and interactivity served to influence the exercise experience singularly and in combination. Another strength is that our model predicted exercise enjoyment relatively successfully, with 84% precision and 71% accuracy. Accordingly, we have demonstrated that this network, or similar ones, can be used to predict the effects of audio-visual interventions in an exercise context. Finally, we have adhered to several principles of open science (e.g., data availability), and we encourage other researchers to further develop the BN as and when new data become available.

A limitation of the study is that we dichotomised devices based on their potential to elicit perceptions of presence, but ratings of presence were not incorporated into the modelling process, as they were not consistently available across studies. Additionally, other experiential variables, such as cognitive load or engagement, may have been relevant but were not included due to data limitations. Methodologically, BN construction assumes causal sufficiency, meaning all direct causal influences between included variables are captured without unmeasured confounders [22]. In practice, this assumption is rarely fully met, but BN models can still provide valuable insights into the probabilistic relationships among observed variables, even in the presence of potential latent influences.

In some parts of the BN, certain combinations of parent node states—and therefore certain vertices of the EPI Cube—were not directly observed in the dataset, meaning the model had to generalise beyond the available data. While this introduces some uncertainty, BNs are well suited to navigating such cases by leveraging probabilistic inference to estimate relationships even in sparsely populated regions of the model [27]. A strength of BN approaches is that the existing model can be updated as more data becomes available.

5 | Conclusions

Audio-visual stimuli are often presented to make the exercise experience more appealing [13, 14]. A plethora of technologies has been employed to deliver such stimuli, such as television screens, video projectors and virtual reality devices. Importantly, each mode of delivery comprises a set of technological features (i.e., embodiment, presence and interactivity [18]), but these have rarely been taken into consideration when exploring the efficacy of audio-visual stimuli in the exercise domain. In the present investigation, we used a BN as a methodological tool to examine the relationships between technological features of audio-visual interventions and exercise-related experiential outcomes. We found that interventions combining high embodiment, presence, interactivity and music could prompt more positive affective valence, moderate arousal and cue greater attentional dissociation during exercise. Such interventions are typically administered via immersive technology, such as virtual reality. Researchers are increasingly acknowledging that how one feels *during* exercise influences future exercise behaviour [49]. Accordingly, virtual reality technology might be considered a useful tool to encourage the third of adults globally (1.8 billion [2]) who currently do not meet physical activity recommendations for enhanced health.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available via the Open Science Framework (https://osf.io/82eyp).

Endnotes

[1]Herein, we use the term *technological features* to refer to embodiment, presence, interactivity and music.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Supporting Information 1. Bayesian Network Example.
Supporting Information 2. Further Details of Measures.
Supporting Information 3. Technologies Used Across Studies.
Supporting Information 4. Distribution Plots.