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Does Perceived Exertion Influence Perceived Affect in Response to Music? Investigating the "FEELA" Hypothesis

Kirk N. Olsen and Roger T. Dean
Western Sydney University

Time-series modeling of perceived affect in response to a range of instrumental and sound-based music has shown that continuously perceived arousal, and to a lesser extent, perceived valence, are well modeled when predictors include listener engagement, perceptual loudness, and acoustic factors such as intensity and spectral flatness. A "FEELA" hypothesis has been proposed to explain processes underlying production and perception of affect in music: FEELA suggests a chain of contributing factors such as the Force and Effort (realized here throughout as physical exertion) required for a performer to produce a musical sound, the Energy of the resulting sound (realized as acoustic intensity), and the experience of the listener in the form of perceived Loudness and Arousal. The present study investigated the early portions of this process by asking whether listeners' continuous perception of physical exertion required to produce music from a range of genres contributes to and strengthens previous time-series models of perceived affect. An analysis of factors in the perception of exertion in the context of 8 excerpts of Classical and Electroacoustic music was first undertaken. Results showed that acoustic intensity, perceived source complexity, and event density contributed in varying degrees to the perception of exertion. When these 4 factors were included in time-series models of affect in response to 5 excerpts of music, results showed that when human agency is apparent in the production of classical or electroacoustic music, nonmusicians' perception of exertion required in producing the music is pertinent to the perception of arousal and to a lesser extent, valence. With the more abstract sound-sculpted electroacoustic pieces of music where human agency is not always apparent, listeners could identify exertion when required, but it was not influential in their perception of arousal.

Keywords: affect, exertion, FEELA, music perception, time-series analysis

The relationship between listeners' perception of affective elements in response to music and the key musical features that give rise to such perceptions has received ongoing empirical investigation in the fields of music and emotion (Juslin & Sloboda, 2010). For example, time-series modeling has shown that continuously perceived *arousal* (one dimension of the two-dimensional circumplex model of affect; Russell, 1980, 2003) in response to music from multiple genres can be well modeled when model predictors include cognitive factors such as listener engagement (Olsen, Dean, & Stevens, 2014), perceptual factors such as loudness (Olsen, Dean, Stevens, & Bailes, 2015; Schubert, 2004), and acoustic factors such as intensity, the primary physical counterpart to perceptual loudness (Dean & Bailes, 2010c; Dean, Bailes, & Dunsmuir, 2014a, 2014b; Dean, Bailes, & Schubert, 2011).[1] Time-series models of the second affective dimension of *valence* have been less successful when these predictors are investigated, although timbral perceptions of the acoustic parameters of spectral flatness, spectral centroid, and spectral entropy make some contribution (Bailes & Dean, 2012; Schubert, 2004).

To conceptualize the process between performers' real-time communication of affect from music and listeners' perception of affect in response to music, we proposed the "FEELA" hypothesis. In the context of performed instrumental music (e.g., classical and jazz genres), the FEELA hypothesis suggests a chain of contributing factors such as the Force and Effort (realized here throughout as physical exertion) required for a performer to produce a musical sound, the Energy of the resulting sound (realized as acoustic intensity), and the experience of the listener in the form of perceived Loudness and Arousal (Dean & Bailes, 2010a; Dean, Olsen, & Bailes, 2013). In addition, sound-based music such as that comprising electroacoustic genres contains recurrent patterns of acoustic intensity that directly correspond to those observed in classical and jazz genres (Dean & Bailes, 2010b). Consequently, FEELA predicts that the relationship between acoustic intensity profiles and continuously perceived loudness in electroacoustic music with varied degrees of human agency also significantly

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Kirk N. Olsen and Roger T. Dean, The MARCS Institute for Brain, Behaviour and Development, Western Sydney University.

Correspondence concerning this article should be addressed to Kirk N. Olsen, The MARCS Institute for Brain, Behaviour and Development, Western Sydney University, Locked Bag 1797, Penrith NSW 2751, Australia. E-mail: k.olsen@westernsydney.edu.au

[1] Although acoustic and perceptual factors such as intensity and loudness have a strong and intimate psychophysical relationship, there are some responses to acoustic intensity (such as the extreme case of the startle reflex) that do not depend on the perception of loudness. Similarly, subtle differences in predictive capacity have been observed in time-series models of perceived affect in response to Western orchestral and electroacoustic music (Olsen et al., 2015) between the acoustic feature, changing intensity, and the perceptual feature, changing loudness. Generally, the latter is the stronger predictor of perceived arousal, but intensity may yet have direct predictive roles in some situations.

influence perceived affective expression. There is now strong evidence of the latter portions of the FEELA hypothesis across all aforementioned genres.

However, the earlier portions of the FEELA process are yet to be investigated in the context of real-time perceived affect in response to music. Specifically, little is known about the possible influence of listeners' perception of physical exertion required to produce the sonic signal in instrumental and sound-based music. This question is important when one considers that instrumental music comprises obvious human agency in sound production. For example, a violin, piano, or guitar timbre is perceived and more often than not, enculturated listeners will immediately associate human agency in the form of causal relationships between physical force/effort applied to an instrument and the corresponding sound, its intensity, and loudness. Electroacoustic music, on the other hand, is often characterized by abstract sound-based stimuli with often little-to-no obvious human agency. The causal correspondence between performer action and performed sound is obscure, and this may lead to differences in the relevant processes underlying the FEELA hypothesis. Therefore, the present study investigates listener's perception of exertion required to perform music, and asks whether such perceptions have a predictive role in time-series models of continuous affective response to pieces of music that involve varied degrees of human agency in their presentation.

Perceived exertion has been investigated commonly in the context of health and exercise sciences, with a person's own subjective experience the primary focus, rather than the perception of exertion expressed by another individual (Borg & Kaijser, 2006; Borg, 1982; Haile, Gallagher, & Robertson, 2015). The measurement of perceived exertion in the context of health and exercise science is a valid and useful research tool (Scherr et al., 2013). When investigating the concept of perceived exertion in the context of musical production, it is important first to consider key aspects of music that may elicit the perception of exertion. Three candidate features of music are applicable here: (a) acoustic intensity/loudness profiles; (b) source complexity (here defined as the number of sound sources or abundance of different sound "trajectories" at any given point in time); and (c) event density (the rate at which successive audible events occur throughout each piece of music).[2] First, changes of acoustic intensity and listeners' perception of loudness share an intimate (yet not straightforward) relationship (Canévet & Scharf, 1990; Fletcher & Munson, 1933; Florentine, Popper, & Fay, 2011; Olsen, 2014). The acoustic intensity profile of a piece of instrumental music is likely to be the primary cue to one's perception of exertion required to make the music; that is, fluctuations of intensity and thus perceived loudness are likely to correspond to listeners' ratings of perceived exertion because the louder and more intense the music, the more likely that a greater level of exertion was involved in performing the music. Second, the range (or numerosity) of perceived timbres associated with the complexity of sound sources is applicable to music comprising instrument-based or sound-based sources and may also influence perceived exertion. By means of additivity, the number of perceived sources may directly influence the total level of perceived exertion involved in producing the music. Finally, a listener may associate the rapidity of changing acoustic events with the magnitude of exertion required to create such events: the more events heard per unit time, the faster they are required to be performed and hence a greater level of exertion. In sum, the acoustic intensity profile, the abundance of "timbral trajectories" or complexity of sound sources, and the density of events perceived throughout a piece of music may influence listeners' perception of exertion required to create the music. All of these factors are investigated here in the present study.

The concept of dimensional integrality is applicable to a discussion of the role that perceived exertion may have in modulating additional perceptual factors (Garner & Felfoldy, 1970). In general, two auditory dimensions are said to be integral when variations in one unattended dimension (e.g., intensity/loudness) affect the outcome of a perceptual task focused on an additional primary dimension (e.g., frequency/pitch). In this case, the two "integral" dimensions are likely to be perceived holistically rather than separably (Melara & Marks, 1990a, 1990b). It may be that acoustic intensity, source complexity, event density, and perceived exertion are somewhat integral dimensions and not separable in their predictive roles for time-series models of continuously perceived affect. Before including a continuous measure of perceived exertion in time-series models of affect, our first aim was to investigate the factors that contribute to the perception of exertion by means of Vector AutoRegression with eXogenous predictors (VARX), a conservative approach that allows perceptual variables to be mutually influential in time-series modeling. This was first accomplished with a focus on three pieces chosen specifically to reflect musical genres containing varied levels of these features (e.g., orchestral music, hybrid instrumental/sound-based music, ambient music). Further analyses were then made on five core Classical and Electroacoustic pieces of music that represent a diversity of musical styles, ensembles, and sound sources (see Method for more detail on stimulus selection and description). Providing that perceived exertion is not solely a surrogate of one or more of the other predictors, the second aim was then to use a VARX approach to investigate whether perceived exertion contributes to models of perceived arousal and perceived valence. In these analyses, all perceptual (endogenous) and acoustic (exogenous) variables were considered as potential predictors in time-series models of perceived affect in response to the five core pieces.

Specifically, it was hypothesized that perceived event density, perceived source complexity, and acoustic intensity will significantly contribute to listeners' perception of exertion required to make instrumental and electroacoustic music. Furthermore, it was hypothesized that under conditions where human agency is apparent, perceived exertion makes a complementary significant contribution to time-series models of perceived affect that include additional acoustic (intensity) and perceptual (perceived event density, source complexity) factors.

Method

Participants

The group that completed the perceived exertion task consisted of 35 adult psychology students recruited from the University of

[2] The features of acoustic intensity/loudness profiles, source complexity, and event density were three main themes observed from a pilot study asking seven nonmusicians who did not participate in the main experiment to describe strategies used for rating perceived physical exertion (effort) required to create classical and electroacoustic musical exemplars. Qualitative results of the pilot study are presented in Appendix A.

Western Sydney (28 females and 7 males; M = 19.84 years, SD = 3.17, range = 18–35 years; three participants did not provide age data). This group of participants had a mean Ollen Musical Sophistication Index (OMSI; Ollen, 2006) of 120.91 (SD = 90.10). The OMSI ranges from 0 to 1,000 and a score less than 500 means the individual is "not musically sophisticated." An additional group of five adult musicians from the MARCS Institute (1 female and 4 males; M = 39.60 years, SD = 17.20, Range = 23–65 years) completed the "event density" and "source complexity" tasks. This group reported a mean of 20.20 years of sustained musical activity (SD = 17.02) with a mean OMSI score of 736 (SD = 180.02). All reported normal hearing.

Stimuli

Stimuli comprised eight prerecorded excerpts of music. The rationale for the choice of stimuli was to contrast three types of music in which (Type I) the physical initiation of sounds by playing instruments was apparent; (Type II) the sounds derived both from the playing of instruments and from electro-acoustic (nonperformed) origins; and (Type 3) all sounds were electro-acoustic and not the result of a human applying physical energy to a sound-generating object. We argue that this range of musical "types" allows us to discern the perception of differing degrees of exertion by our listeners. Overall, the stimulus set can be divided into four categories that represent diversity of instrumentation, sound sources, and human agency:

1. **No obvious instrumentation.** The excerpts from this category comprise sonic material that have no obvious musical instrumentation or sound source origin. The first stimulus in this category was Roger Dean's (2003) "*soundAFFECTS*" (3'01"). The excerpt from this composition featured filtered noise and is part of an audiovisual work for performance and for the web (Brewster, Smith, & Dean, 2004). Only the audio portion was presented in this experiment. The second stimulus in this category was an excerpt from Brian Eno's "*Francisco*" (3'00"). The first three minutes of the piece was used here and is primarily ambient in its composition.

2. **Hybrid combination of sound sources.** The excerpts from this category comprised a hybrid set of sounds combining nonobvious and obvious sound source origins. The latter included naturally occurring and human-made sounds. The first stimulus in this category was Trevor Wishart's (1977) "*Red Bird, a political prisoner's dream*" (3'16"). This excerpt was taken from a recording on UbuWeb of the complete 45-min piece for tape and includes a strong narrative of obvious human and animate sounds. The second stimulus in this category was Iannis Xenakis's (1962) "*Bohor*" (3'15"), a four-track work for tape, from which a stereo recording was excerpted from EMF CD 003.

3. **Single instrument pieces.** The third category comprised excerpts characterized by a single musical instrument with apparent human agency. The first stimulus in this category was an excerpt from Johann Sebastian Bach's "*Violin Partita No. 3 in E major: Gavotte en Rondeau*" (3'12"). The second was a piano excerpt from Ludwig van Beethoven's "*Sonata No. 21 in C major, Op. 53 Waldstein*" (2'47").

4. **Multi-Instrument orchestral pieces.** The fourth and final category comprised orchestral music with multiple instruments and apparent human agency. The first stimulus in this category was excerpted from Iannis Xenakis's (1955) "*Metastaseis*" (1'59"). The second stimulus in this category was excerpted from Wolfgang Amadeus Mozart's "*Piano Concerto 21, K467*" (2'19").

Tables in the Results section present data sequentially in terms of these categories of excerpts and the pieces composed by Dean, Eno, Mozart, Wishart, and Xenakis (both cases) have been studied in our previous work on time-series modeling of affect (see below for more detail). In addition to these eight excerpts, two practice trials were presented: excerpts of the first movement from Mozart's "*Symphony No. 40*" (1'18") and of Xenakis's "*Orient-Occident*" (1'29"). Each stimulus excerpt in the experiment was presented as an .aiff stereo 16 bit audio file with a 44.1kHz sampling rate.

Procedure

For the perceived exertion task, nonmusician participants first read an experiment information sheet, gave written informed consent, and received standardized instructions regarding the task. Specifically, participants were instructed to continuously rate their perception of the level of physical exertion (effort) required to create the music they were listening to on a horizontal scale ranging from "No Exertion" on the far left to "Maximal Exertion" on the far right, with "Moderate" serving as the midpoint of the scale. These scale anchoring labels were adapted from the perceived exertion scales published in E. Borg and Kaijser (2006) and were assigned values from 0 – 100. The experiment comprised one block of eight stimuli and was preceded by two practice trials for participants to become accustomed to the task. After the experiment, participants completed the OMSI and were debriefed on the purpose of the experiment.

For the perceived event density task, each individual from the group of five musicians was asked to continuously track the rate at which successive audible events occur throughout each piece of music, on a vertical scale ranging from "Low Rate" through to "High Rate," with "Moderate" as the mid point of the scale and assigned values between 0 and 100. For the "source complexity" task, the same five musicians were given the following instructions: "In instrumental (note-based) music, it is common for multiple simultaneous note trajectories to occur. For example, in orchestral music there are usually separate lines played by identical and/or different instruments at any given time. A few separate lines are common for the piano, whereas 1–2 separate lines are common for string instruments such as the violin. Sound-based music (e.g., electroacoustic music) does not necessarily include conventional musical instruments. However, we assume that there are similar variations in the abundance of sound trajectories. On this assumption, in this experiment please continuously rate the abundance of trajectories throughout each excerpt of music." The perceived source complexity scale ranged from "High Abundance" to "Low Abundance," with "Moderate" as the mid point of the vertical scale and assigned values between 0 and 100. Each task took ~30 min to complete.

Continuous Ratings of Perceived Arousal and Valence

In addition to ratings of continuous perceived exertion measured from the sample of participants in the present study, perceived arousal and valence data from two previous experiments were used in our time-series models of affect. First, group mean perceived arousal and valence time-series responses to the Wishart, Dean, and Xenakis *Bohor* excerpts (published in Bailes & Dean, 2012) were used in addition to perceived arousal and valence data in response to the Mozart and Xenakis *Metastaseis* excerpts (published in Olsen et al., 2015). Therefore, in the analyses that follow, only five pieces have arousal and valence time-series responses associated with them: Wishart's "*Red Bird, a political prisoner's dream*"; Dean's "*soundAFFECTS*"; Mozart's "*Piano Concerto 21, K467*"; and Xenakis's "*Bohor*" and "*Metastaseis*." The remaining three pieces were used solely for analyses investigating key aspects of music that may influence the perception of exertion.

Statistical Approach

We have elaborated our approaches to modeling continuous systems in several previous papers, providing tutorials and glossaries concerning the method (e.g., Bailes & Dean, 2012). Most recently we have also illustrated the dangers of comparing pairs of time series without due consideration of their time series serial correlations, and provided methods for overcoming the spurious indications that such a conventional statistical (non time-series analysis) approach can create (Dean & Dunsmuir, 2015). We provide a brief synopsis of the key elements of the approach here. For the purpose of time-series analysis, stationarity of each group-mean time series in response to each stimulus was assessed using the Augmented Dickey-Fuller Generalized Least-Squares test (Dickey & Fuller, 1979), and in each case the time-series required "differencing" to achieve stationarity. Stationarity is essentially the condition in which there is no trend in the data series, and the variances and covariances of events *n* time points apart is constant across the whole series. Differencing creates a new series corresponding to differences between successive values of the original. A series resulting from differencing *seriesname* (e.g., arousal) is here termed *dseriesname* (e.g., darousal).

We use a conservative VARX (Vector AutoRegression with eXogenous variables), allowing the perceptual variables to be mutually influential (i.e., "endogenous"). Vector autoregression with exogenous predictors is a multivariate analogue of univariate ARX that comprises autoregressive modeling of a single dependent variable (DV) (i.e., outcome or "endogenous" variable) with exogenous predictors. In VARX, vectors of perceptual variables (all endogenous) are modeled and assessed for a potentially reciprocal interaction (i.e., a mono- or bidirectional relationship), whereas other variables (e.g., acoustic) are defined as exogenous (that is, they cannot be influenced by the other variables in the system, being physical parameters). In VARX we first define the model order by means of so-called selection order criteria, establishing how many lags of the endogenous and exogenous variables are required. Then we refine this overall model by removing any order of the endogenous variables or lags of the exogenous predictors that are not significant for the component model of exertion and selecting preferred models on the basis of minimizing the Bayesian Information Criterion (BIC).

In the case of the endogenous variables, we also assess Granger causality, which is a statistical correlation (that may be indicative of a causal relationship), in this case, with perceived exertion (Granger, 1969). Granger Causality also assesses the directionality of the relationships in the case of the endogenous (perceptual) variables, allowing for mutual and even reciprocal influences. Note that in some cases this process results in one of the perceptual variables being removed entirely, and if so the VARX model order has to be reassessed and the resultant BIC is no longer comparable with those of the models in which it remained (because fewer variables are being modeled). The BIC was used as the basis of model selection and penalizes strongly for the addition of predictor variables to a model (lowest BIC values are best). Such an approach has been detailed in previous papers (Bailes & Dean, 2012; Dean & Bailes, 2010c, 2011; Dean et al., 2011) and when comparing BIC values between models, if there is an absolute BIC difference ("delta BIC") of >4.6, the evidence in favor of models with lower BIC is normally described as 'strong' and corresponds to a 10-fold difference in probability (Lewandowsky & Farrell, 2011). A delta BIC greater than 1.4 is termed "positive" (a twofold difference in probability), and smaller differences are considered ambiguous as to which model is preferred (Kass & Raftery, 1995).

Results

The VARX approach was used to select an optimized multivariate model of perceived exertion, perceived event density and source complexity, in conjunction with exogenous (independent) acoustic predictors intensity and spectral flatness. Figure 1 provides an example of such data. Panel A in Figure 1 shows perceived exertion and other features for the Eno piece (Category 1), and panel B the Bach Partita (Category 3). The possibility of a predictive relationship between perceived event density and exertion is apparent from both graphs. Panel A in Figure 1 also shows that the "Eno perceived exertion" model developed below provides a good fit to the data.

In this part of the work, three excerpts were specifically analyzed to understand the factors that may contribute to the measure of perceived exertion (Bach, Beethoven, and Eno excerpts in Table 1). These three excerpts are then complemented in Table 1 by an additional five excerpts of music that serve as stimuli for what we term the "core" time-series models of perceived arousal and perceived valence (see Tables 2 and 3) that include all variables discussed up until this point. In each model of exertion presented in Table 1, Granger causality analyses are used to confirm the significance of the selected endogenous variables for the constituent model of dexertion. Endogenous predictors that fail this test are removed.

Investigating Factors Contributing to Perceived Exertion

First, for illustrative and explanatory purposes, Appendix B presents the complete VARX model of perceived exertion in response to the Bach *Partita* excerpt. This output emphasizes that perceived exertion, event density, and source complexity are si-

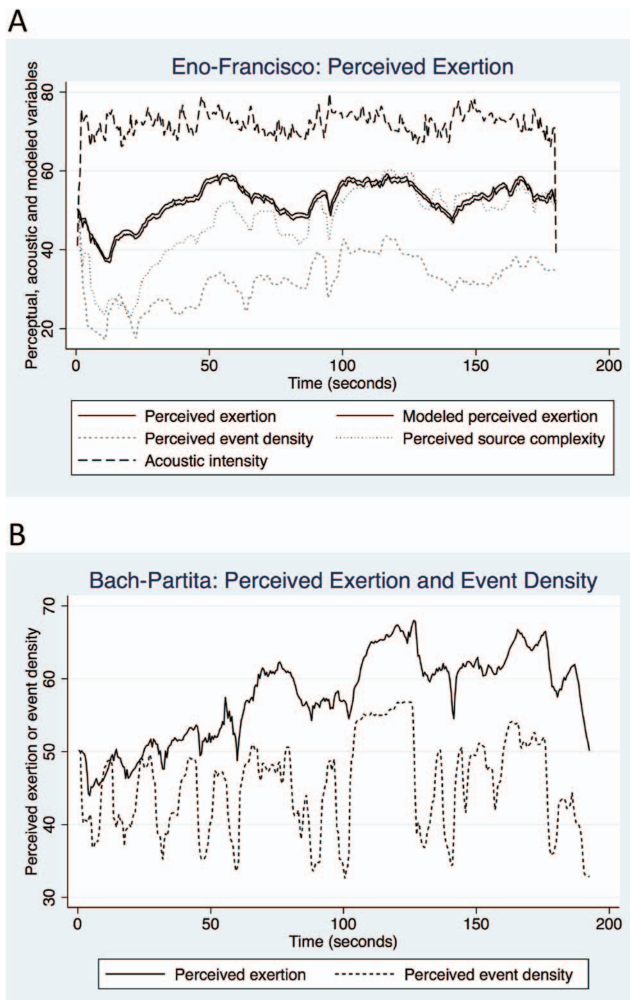

Figure 1. (Panel A) Perceived exertion and its model are shown for Brian Eno's *Francisco* piece (solid lines). The model is offset by −1 to make it more apparent. The intensity profile (dashes) is relatively unvarying. Some aspects of similarity between the exertion profile and both perceived event density (short dashes) and perceived source complexity (dots) are evident. (Panel B) Here only perceived exertion (solid line) and the perceived event density (short dashes) in response to Bach's *Partita* are shown for clarity. It is clear that troughs and peaks in both time series are almost coincident. See the online article for the color version of this figure.

multaneously modeled. Such an analysis also ensures that if, for example, intensity influences perceived event density, then this influence is allowed for in the assessment of intensity's influence on perceived exertion. Each submodel also displays the proportion of variance explained and the coefficients for each predictor, together with their *p* values and confidence intervals. Also note that if, for example, lags of dintensity are included in a model, it may be the case that only some of the lags are individually significant and show substantial coefficients. The additional non-significant lags are required in the model because of the nature of VARX modeling. For ease of interpretation and brevity of data, only the perceived exertion components of the selected VARX models for each piece are presented in Table 1. When interpreting Table 1, it must be noted that an indirect influence of variables (e.g., intensity on exertion) via their influence on an additional variable (e.g., event density) is allowed for.

Table 1 shows that in some cases both perceptual variables representing event density and source complexity are influential on perceived exertion. One exception is the Beethoven *Waldstein* excerpt, where changes in perceived source complexity as the piece progresses are very small, its predictive influence is limited, and it is dropped from the overall model. This relatively homogenous perception of source complexity is perhaps not surprising given that the Beethoven excerpt is a solo piano piece comprising consistently "wide" voicings of chords and melodic lines. Perceived source complexity was also dropped from the model of Xenakis' *Metastaseis* excerpt, which is one of two pieces performed by a large orchestra. Here, source complexity was perceived as almost identical with event density, again not surprisingly given the nature of the work (Dean & Bailes, 2012). Specifically, as a result of the continuity of string glissandi, separable events are contributed by interjections of other instruments and these simultaneously increase source complexity.

Interestingly, perceived source complexity was a strong predictor in models of perceived exertion for electroacoustic sound-sculpting pieces. In the excerpt from Xenakis' electroacoustic piece *Bohor*, source complexity not only replaced perceived event density, but also rendered acoustic predictors unnecessary. In this case, the ongoing timbral molding is presumably perceived as a change in source complexity, more so than changes in event density. This was also the case with the electroacoustic excerpts of Dean's *soundAFFECTS*, which is solely focused on sound-sculpting, and Wishart's *Red Bird*, which includes both sculpting and discrete sound source events such as animate sounds. In both *soundAFFECTS* and *Red Bird*, perceived event density was removed from the models, but acoustic intensity remained a predictor.

These analyses of perceived exertion confirm that, to varying degrees, perceived event density and source complexity contribute alongside acoustic parameters in modeling perceived exertion. However, the models are by no means completely predictive. In other words, there is scope for perceived exertion to have its own influence on other aspects such as perceived affect. Therefore, we proceed to investigate our second aim, which was to determine whether perceived exertion has a complementary predictive role in models of perceived arousal and perceived valence using the same conservative VARX approach as above.

Investigating the Contribution of Perceived Exertion in Time-Series Models of Perceived Arousal

As noted in the Introduction, our earlier work has shown that perceived arousal is usually strongly predicted by the time series of acoustic intensity, and to a modest degree this is modulated by what we take to generate perceived timbral flux, which is the continuous acoustic measure of spectral flatness. Physical exertion, and hence perception of exertion studied here are closely related in the FEELA hypothesis by transduction through the physics of musical instruments and the resultant acoustic intensity profile. Thus, we assess perceived exertion in relation to models of perceived arousal next. In these models of affect, there is again

Table 1
Assessing Possible Predictors of Perceived Exertion (dexertion) by Vector Autoregressive (VARX) Analyses

1. Dean *soundAFFECTS*					
dexertion equation R^2		dcomplexity equation R^2		Overall model BIC	
.30		.58		1,183.45	
DV dexertion: predictors (3)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.43	.05	<.001	.34	.52
L1.dcomplexity	.09	.02	<.001	.05	.13
L2.dintensity	.05	.01	<.001	.03	.08
2. Eno *Francisco*					
dexertion equation R^2		deventdens equation R^2		Overall model BIC	
.34		.40		2,173.08	
	dcomplexity equation R^2				
	.34				
DV dexertion: predictors (5)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.33	.05	<.001	.23	.43
L1.deventdens	.13	.02	<.001	.08	.17
L1.dcomplexity	.10	.02	<.001	.05	.14
L1.specflat	−.10	.04	.009	−.18	−.02
L2.specflat	−.14	.04	<.001	−.22	−.07
3. Wishart *Red Bird*					
dexertion equation R^2		dcomplexity equation R^2		Overall model BIC	
.46		.44		2,308.21	
DV dexertion: predictors (3)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.48	.04	<.001	.39	.56
L1.dcomplexity	.26	.04	<.001	.18	.34
L2.dintensity	−.03	.01	.001	−.05	−.01
4. Xenakis *Bohor*					
dexertion equation R^2		dcomplexity equation R^2		Overall model BIC	
.39		.25		584.92	
DV dexertion: predictors (6)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.36	.05	<.001	.26	.45
L2.dexertion	.12	.05	.017	.02	.23
L3.dexertion	.16	.05	.001	.07	.26
L1.dcomplexity	.04	.04	.405	−.05	.12
L2.dcomplexity	.04	.04	.380	−.04	.11
L3.dcomplexity	.15	.03	<.001	.08	.21
5. Bach *Partita*					
dexertion equation R^2		deventdens equation R^2		Overall model BIC	
.20		.31		3,326.54	
	dcomplexity equation R^2				
	.27				
DV dexertion: predictors (7)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.09	.05	.088	−.01	.18
L2.dexertion	.15	.05	.003	.05	.24
L1.deventdens	.12	.02	<.001	.08	.17
L2.deventdens	.02	.03	.359	−.03	.07
L1.dcomplexity	.10	.04	.016	.02	.18
L2.dcomplexity	−.10	.04	.007	−.19	−.03
L2.dintensity	.03	.01	<.001	.01	.04

Table 1 (*continued*)

6. Beethoven *Waldstein*					
dexertion equation R^2		deventdens equation R^2			Overall model BIC
.72		.45			2,585.45
DV dexertion: predictors (6)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.62	.03	<.001	.55	.68
L1.deventdens	.14	.02	<.001	.11	.18
L1.dintensity	.09	.02	<.001	.05	.14
L2.dintensity	.20	.02	<.001	.15	.25
L1.specflat	.35	.09	<.001	.18	.52
L2.specflat	.28	.08	<.001	.13	.43

7. Xenakis *Metastaseis*					
dexertion equation R^2		deventdens equation R^2			Overall model BIC
.73		.70			1,901.96
DV dexertion: predictors (7)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.29	.07	<.001	.16	.42
L2.dexertion	.11	.05	.036	.01	.21
L1.deventdens	.68	.06	<.001	.56	.81
L2.deventdens	−.23	.07	.002	−.37	−.09
L1.dintensity	.06	.05	.226	−.04	.15
L2.dintensity	.30	.05	<.001	.20	.39
L2.specflat	.47	.24	.049	.00	.94

8. Mozart *Piano Concerto 21*					
dexertion equation R^2		deventdens equation R^2			Overall model BIC
.62		.35			229.77
	dcomplexity equation R^2				
	.52				
DV dexertion: predictors (7)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dexertion	.52	.04	<.001	.43	.61
L1.deventdens	1.39	.30	<.001	.80	1.98
L1.dcomplexity	2.45	.41	<.001	1.65	3.25
L1.dintensity	.06	.02	.004	−.01	.14
L2.dintensity	.06	.02	.002	.02	.10
L1.specflat	.15	.07	.044	.00	.29
L2.specflat	.06	.07	.436	−.09	.20

open consideration of all three perceptual variables (exertion, event density, source complexity) as well as acoustic intensity and spectral flatness. A rigorous model selection that strives for simplicity and Granger causality of endogenous variables upon perceived arousal is undertaken (see Method section and references therein for more detail). The five core excerpts of music that comprised a range of exemplars from Classical and Electroacoustic genres were analyzed in models of affect: Dean's *sound AFFECTS*, Wishart's *Red Bird*, Xenakis's *Bohor*, Mozart's *Piano Concerto 21*, and Xenakis's *Metastaseis*.

Let us first consider the two pieces that fall into the category of *Multi-Instrument Orchestral Pieces*. As can be seen in Table 2, model results for the Mozart excerpt showed that perceived exertion was a significant predictor of perceived arousal (and not vice versa), thus complementing the influence of acoustic intensity. The other perceptual (endogenous) variables were ineffective and removed from the model. Spectral flatness remained in the joint model of perceived arousal and exertion, but mainly by virtue of its impact on perceived exertion. For Xenakis' *Metastaseis*, perceived exertion acted in conjunction with perceived event density and acoustic intensity (although again the acoustic variable remained because of its contribution to the component model of perceived event density). The lack of requirement for perceived source complexity as predictor is consistent with the earlier analysis of predictors of perceived exertion for this piece.

Next we consider the three electroacoustic works: Models of Xenakis's *Bohor*, in contrast to his orchestral piece *Metastaseis*, show that perceived event density was key to modeling perceived arousal, and furthermore, the roles of the acoustic predictors were subordinate and they largely operated through their impact on perceived event density. The lack of contribution of source complexity was consistent with its importance for perceived exertion, which did not influence perceived arousal. For Dean's *sound AFFECTS*, perceived exertion was similarly ineffective (as were the other perceptual variables) and only spectral flatness was useful among acoustic predictors. Thus, the two electroacoustic works with the least apparent human agency were also pieces in which the continuous perceived exertion response was not a pre-

Table 2
Vector Autoregressive (VARX) Analyses of Perceived Arousal (darousal) for the Five Key Excerpts of Music: Endogenous and Exogenous Predictors

1. Dean *soundAFFECTS*

darousal equation R^2		Overall model BIC
.25		1,007.41

DV darousal: predictors (3)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.darousal	.48	.05	<.001	.39	.57
L2.specflat	.50	.19	.008	.13	.87
L4.specflat	.32	.19	.089	−.05	.68

2. Wishart *Red Bird*

darousal equation R^2	dexertion equation R^2	Overall model BIC
.47	.61	2,251.54

DV darousal: predictors (8)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.darousal	.42	.04	<.001	.33	.51
L1.dexertion	.18	.05	<.001	.10	.28
L1.dintensity	.08	.01	<.001	.06	.10
L2.dintensity	.09	.01	<.001	.07	.12
L3.dintensity	.04	.01	.002	.01	.06
L4.dintensity	.01	.01	.292	−.01	.03
L5.dintensity	.04	.01	.001	.02	.06
L1.specflat	.03	.06	.605	−.09	.15

3. Xenakis *Bohor*

darousal equation R^2	deventdens equation R^2	Overall model BIC
.16	.36	947.92

DV darousal: predictors (5)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.darousal	.30	.05	<.001	.20	.39
L1.deventdens	.24	.06	<.001	.13	.36
L3.dintensity	.02	.02	.245	−.01	.06
L5.dintensity	−.01	.02	.447	−.05	.02
L3.dspecflat	.05	.06	.401	−.07	.17

4. Xenakis *Metastaseis*

darousal equation R^2	deventdens equation R^2	dexertion equation R^2	Overall model BIC
.24	.65	.71	2,761.67

DV darousal: predictors (5)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.darousal	.17	.07	.016	.03	.32
L1.dexertion	−.08	.04	.051	−.17	.00
L1.deventdens	.25	.05	<.001	.15	.35
L1.dintensity	.05	.04	.242	−.03	.13
L2.dintensity	.03	.04	.440	−.05	.11

5. Mozart *Piano Concerto 21*

darousal equation R^2	dexertion equation R^2	Overall model BIC
.17	.59	1,798.85

DV darousal: predictors (7)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.darousal	.24	.06	<.001	.13	.35
L1.dexertion	.15	.05	.007	.04	.25
L2.dintensity	.05	.03	.073	−.00	.11
L3.dintensity	.09	.03	.002	.03	.14
L1.dspecflat	.02	.09	.855	−.15	.18
L2.dspecflat	.11	.11	.307	−.10	.33
L2.dspecflat	−.03	.10	.798	−.23	.17

Table 3
Vector Autoregressive (VARX) Analyses of Perceived Valence (dvalence) for the Five Key Excerpts of Music: Endogenous and Exogenous Predictors

1. Dean *soundAFFECTS*

dvalence equation R^2	dexertion equation R^2	Overall model BIC
.10	.21	1,349.89

DV dvalence: predictors (3)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dvalence	.28	.05	<.001	.18	.38
L1.dexertion	.25	.12	.029	.03	.48
L4.dintensity	−.05	.03	.104	−.11	.01

2. Wishart *Red Bird*

dvalence equation R^2	dcomplexity equation R^2	deventdens equation R^2	Overall model BIC
.48	.53	.50	3,590.23

DV dvalence: predictors (10)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dvalence	.60	.04	<.001	.52	.67
L1.deventdens	−.09	.04	.036	−.17	−.01
L1.dcomplexity	.12	.05	.011	.03	.22
L1.dintensity	.07	.04	.074	−.01	.14
L2.dintensity	.59	.14	<.001	.30	.87
L3.dintensity	−.02	.01	.021	−.04	−.00
L4.dintensity	−.05	.01	<.001	−.07	−.03
L5.dintensity	−.05	.01	<.001	−.07	−.03
L6.dintensity	−.03	.01	.020	−.05	−.00
L7.dintensity	−.03	.01	.004	−.05	−.01

3. Xenakis *Bohor*

dvalence equation R^2	Overall model BIC
.05	964.70

DV dvalence: predictors (5)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dvalence	.07	.05	.174	−.03	.16
L2.dvalence	−.11	.05	.033	−.20	−.01
L3.dintensity	−.05	.03	.054	−.11	.00
L5.dintensity	−.07	.03	.016	−.12	−.01
L5.dspecflat	.24	.09	.008	.06	.42

4. Xenakis *Metastaseis*

dvalence equation R^2	deventdens equation R^2	Overall model BIC
.32	.73	1,805.27

DV dvalence: predictors (10)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dvalence	.26	.06	<.001	.13	.39
L2.dvalence	−.02	.06	.708	−.18	.10
L1.deventdens	−.12	.05	.030	−.22	−.01
L2.deventdens	.18	.05	.001	.08	.29
L1.dintensity	−.03	.04	.405	−.11	.04
L2.dintensity	−.07	.05	.145	−.16	.02
L3.dintensity	−.11	.05	.036	−.21	−.01
L4.dintensity	−.20	.05	<.001	−.30	−.10
L5.dintensity	−.18	.04	<.001	−.27	−.10
L6.dintensity	−.03	.04	.369	.11	.04

5. Mozart *Piano Concerto 21*

dvalence equation R^2	Overall model BIC
.05	907.71

DV dvalence: predictors (3)	Coefficient	*SE*	*p*-values	95% confidence intervals	
L1.dvalence	.09	.06	.123	−.02	.21
L3.dintensity	.08	.02	<.001	.04	.13
L3.dspecflat	.17	.09	.054	−.00	.34

dictor of perceived arousal. In contrast, for the Wishart excerpt that included examples of human and animate activity intermittently throughout the excerpt, perceived exertion and the previously well-established influence of intensity were powerful predictors. Overall, these results show that for excerpts with reasonably apparent human agency, nonmusicians' perception of exertion required in producing music was pertinent to the perception of arousal.

Investigating the Contribution of Perceived Exertion in Time-Series Models of Perceived Valence

Given the demonstration above of significant roles for perceived exertion in some models of perceived arousal, we assess whether it contributed also to perceived valence. Consistent with previous time-series models of perceived valence in response to the same musical excerpts, the predictors used in the present time-series models did not result in strong models of perceived valence in response to Mozart's *Piano Concerto* excerpt and the Xenakis *Bohor* excerpt (with $R^2 = \sim 0.05$) (see Table 3). Models for perceived valence in Dean's *soundAFFECTS* were only slightly better ($R^2 = \sim 0.1$). A reasonable model was obtained for the orchestral Xenakis *Metastaseis* excerpt ($R^2 = 0.32$), with perceived event density retaining a role together with acoustic intensity. As is often observed in our earlier work, a good model was also obtained here for the highly characterful Wishart *Red Bird* excerpt ($R^2 = 0.48$), in which both perceived event density and source complexity retained predictive roles with acoustic intensity. In sum, the time-series models of perceived valence shown in Table 3 did not indicate any important role for perceived exertion, and models were in several cases very poor. In the two reasonably well-modeled pieces, Xenakis's *Metastaseis* and Wishart's *Red Bird*, there were some indications of roles for perceived event density and source complexity.

Discussion

The present paper investigated listeners' real-time continuous perception of exertion required to produce Classical and Electroacoustic music, and assessed the role that this aspect of perceived musical performance has in time-series models of affect. An in-depth analysis of the possible influences on perceived exertion was undertaken, and results show that acoustic intensity, source complexity, and event density contributed to models of perceived exertion to varying degrees, but with no models completely predictive of perceived exertion. Time-series models of affect included the perceived exertion measure and the "FEELA" hypothesis formed the underlying conceptual framework: the Force and Effort (realized here throughout as physical exertion) required for a performer to produce a musical sound, the Energy of the resulting sound (realized as acoustic intensity), and the experience of the listener in the form of perceived Loudness and Arousal are all hypothesized parts of communication and perception of affect in music (Dean & Bailes, 2010a, 2010b; Dean et al., 2013). Previous time-series models of affect and arousal in particular have reported the significant role of listener engagement (Olsen et al., 2014), perceptual loudness (Olsen et al., 2015), and acoustic intensity (Dean & Bailes, 2010c; Dean et al., 2011). The results from time-series models in the present paper complement and strengthen previous models and show that given reasonably apparent human agency in the production of classical or electroacoustic music, nonmusicians' perception of exertion required in producing music is pertinent to the perception of arousal and to a lesser extent, valence. With the more abstract sound-sculpted electroacoustic pieces of music, listeners could identify exertion when required, but it was not influential in their perception of arousal.

In earlier work we have addressed the question of whether a continuous variation in acoustic intensity in music (a physical-parameter time-series) is nothing more in time-series models of affect than the source of continuously perceived loudness. In spite of the early single-excerpt case that impelled us to investigate this particular question (Bailes & Dean, 2012), a more detailed and broad follow-up investigation has recently been completed (Olsen et al., 2015) and clearly shows that with a diverse set of excerpts from Classical and Electroacoustic genres, acoustic intensity *and* perceived loudness have complementary roles in time-series models of perceived affect, even though loudness is overall more powerful a predictor. This leads us to consider whether an analogous proxy situation could exist in the present work in relation to perceived exertion: could it be that the role of the continuous exertion in time-series models reflects nothing more than the contribution of perceived loudness? We assessed that here and chose two extremes among the pieces we studied, those by Mozart (orchestral) and Wishart (electroacoustic). VARX analyses were conducted on both pieces, in which perceived exertion and perceived loudness (originally reported in Olsen, et al., 2015) were allowed as predictors and could compete or complement each other in models including acoustic intensity as potential predictor. Results (not shown) indicated that in both cases, loudness did not show Granger causality on perceived arousal while perceived exertion did, and that loudness did not enhance models when exertion was included. Furthermore, the role of acoustic intensity (as shown in the Table 2) was important but did not change. Overall, we conclude that perceived exertion is a perceptual parameter of direct significance for models of perceived arousal within these pieces, subsuming the important role of intensity and loudness when included in time-series models of perceived affect.

There is now a growing body of research investigating real-time aspects of perceived musical affect (Bailes & Dean, 2012; Dean & Bailes, 2010a, 2010c, 2011; Dean et al., 2014a, 2014b; Farbood & Upham, 2013; Juslin & Sloboda, 2010; Krumhansl, 1997; McAdams, Vines, Vieillard, Smith, & Reynolds, 2004; Olsen et al., 2014, 2015; Salimpoor, Benovoy, Longo, Cooperstock, & Zatorre, 2009) that includes approaches based on machine learning and music information retrieval (Coutinho & Cangelosi, 2011; Deng & Leung, 2015). Taken together with this preceding work, strong evidence now exists showing that listeners' perception of the force/effort required to produce a musical sound, coupled with music's acoustic intensity profile and its associated real-time experience of loudness, all significantly contribute to prediction of perceived affect in response to classical music, and to a lesser (yet still significant) extent, electroacoustic music. Time-series analysis of perceptual and acoustic variables has provided evidence of all key aspects of the FEELA hypothesis, and more specifically, has shed further light on the complex causal interaction between a performer's actions and affective intentions, the sonic outcomes of such actions and intentions, and listeners' cognitive engagement and perceptual experience. Indeed, all these factors play a crucial role in determining affective elements perceived by listeners as expressed by music. This is the case when music is created and performed with human agency and instrumental sound sources, as well as sculpted sound sources without obvious human agency. Therefore, we argue for the strength of the FEELA process in the real-time perception of musical affect; the present correlational studies, even though involving continuous responses, will need to be complemented by further causal intervention studies. The question remains as to whether such a process is realized in the context of continuous real-time psychological and bodily emotional response (the so called "felt-affect"). Further behavioral and psychophysiological research targeting the plethora of key indicators of emotional response to music from a range of musical genres and cultures is needed to thoroughly investigate this important question.

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Appendix A

Pilot Study: Subjective Strategies for Continuously Rating Perceived Exertion ($N = 7$)

This pilot study asked seven nonmusician participants who did not participate in the main experiment to describe strategies used for rating perceived physical exertion (effort) required to create the music they had listened to.

Participant 1: "I think I was rating the loudness of the pieces. When the music sounded loud it sounded like it took more effort to produce. I think also the tempo or the speed was a factor—the sounds that sounded like they were being played faster sounded more effortful. Also I wasn't sure how to rate the second piece (with the pressure sounds) as it didn't sound like it was produced by a human. I couldn't imagine how to rate the non-human sounds so I couldn't imagine the amount of effort required."

Participant 2: "I would imagine the movements required to generate the music and then judge how much exertion would be required to make that sound."

Participant 3: "Picturing an orchestra; listening to the loudness; listening to the number of instruments; listening to when it got faster/more hectic."

Participant 4: "I mostly based it on the complexity of the music (how many instruments) and the tempo (the quicker the tempo the more effort I think is required)."

Participant 5: "I focused on the intensity, number of instruments, and the speed. The strategy/focus depended on the music I was listening to. Piano: speed. Electric: how many different types of sounds. Violin/orchestra: number of instruments and intensity."

Participant 6: "I was listening for the number of diverse instruments/sounds in each of the pieces. The greater the number the more effort required to play in 'sync'. If there was just one instrument I judged [perceived exertion] by the pace of the melody."

Participant 7: "For the orchestral music I determined the amount of physical exertion on the speed, complexity, and loudness of the music. For example, if the music was quite loud and fast with many notes being played at once, I would assume that it would be quite physically demanding than only playing a few slow notes softly. In terms of the electronic music again I focused on the complexity and speed but not the loudness. This is because I was imagining how this may have been produced perhaps by pressing various buttons or key[s], so the faster or more buttons that were pressed at the same time, the more physical exertion that may have been used. I did not contemplate loudness for the electronic music as that may involve a volume scale rather than more physical movements."

(*Appendices continue*)

Appendix B

A Complete Vector Autoregressive (VARX) Model Output of Perceived Exertion

Bach *Partita*

Modeled DVs (endogenous variables): dexertion (perceived exertion); deventdens (perceived event density); dcomplexity (perceived source complexity)

Predictors: autoregressive lags(1/2) of the endogenous variables; IVs (exogenous variables) lags(1/2)dintensity

BIC = 3,326.54 (Table B1).

L1 and L2 indicate lags 1 and 2 respectively, and dseriesname indicates the first difference form. The output first describes the parameters, overall fit (R^2), and probability (p-values) of the three components of the VAR model, the models for dexertion (perceived exertion); deventdens (event density); dcomplexity (source complexity). Secondly, the output presents the coefficient for each predictor and its standard error, significance, and confidence intervals. Note that the three DVs are modeled together, and hence a predictor may be essential for one of the DVs and have a highly significant coefficient, but also be unimportant with a nonsignificant coefficient for the others. However, by design the three components share the same predictors. The models did not include an intercept (they are not normally required for models of differenced variables).

Table B1

Vector Autoregressive (VARX) Model Output of Perceived Exertion

Equation	Parameters	R^2	p-values		
dexertion	7	.20	<.001		
deventdens	7	.31	<.001		
dcomplexity	7	.27	<.001		
	Coefficient	*SE*	p-values	95% confidence intervals	
DV dexertion: predictors					
L1.dexertion	.09	.05	.088	−.0127925	.184487
L2.dexertion	.15	.05	.003	.0503122	.2408051
L1.deventdens	.12	.02	<.001	.0761627	.1696503
L2.deventdens	.02	.03	.359	−.0262434	.0724405
L1.dcomplexity	.10	.04	.016	.0177008	.1760547
L2.dcomplexity	−.11	.04	.007	−.1877782	−.0295188
L2.dintensity	.03	.01	.000	.0118445	.0413796
DV deventdens: predictors					
L1.dexertion	−.49	.10	.640	−.2534894	.1558155
L2.dexertion	−.33	.10	.001	−.5297568	−.1345323
L1.deventdens	.54	.05	<.001	.4458146	.6397775
L2.deventdens	−.05	.05	.306	−.1557879	.0489562
L1.dcomplexity	.03	.08	.745	−.1370389	.1915054
L2.dcomplexity	−.12	.08	.161	−.2816865	.0466617
L2.dintensity	.03	.02	.069	−.0022406	.0590373
DV dcomplexity: predictors					
L1.dexertion	−.07	.06	.273	−.1895255	.0535466
L2.dexertion	.13	.06	.037	.0077748	.2424851
L1.deventdens	−.07	.03	.012	−.1316364	−.0164485
L2.deventdens	.03	.03	.417	−.0356439	.0859466
L1.dcomplexity	.53	.05	<.001	.4333929	.6285041
L2.dcomplexity	−.16	.05	.001	−.2596202	−.0646255
L2.dintensity	.03	.01	.004	.0085891	.04498

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