

Article

Real-Time Detection of Laban Effort Factors in Music Performance Using Machine Learning

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Abstract

This article presents a study that applies Laban's Effort theory to detect a musician's expressive intentions during performance. Laban Effort theory was chosen for its capacity to support the observation, description, and interpretation of expressive movement. The aim was to develop interactive musical systems that learn from the embodied expressivity musicians cultivate through practice. The study adopts a multidisciplinary approach, combining Laban Motion Analysis with interactive machine learning. Gesture data, audio, and video were recorded during a performance of Brahms's Clarinet Sonata Op. 120 No. 2. The video was then analysed by an expert annotator observing Laban Efforts. The annotated video was then reviewed in collaboration with the performer to incorporate Effort Phrasing that reflects changes in intensity within Efforts. The annotations were then used as training data, together with motion data recorded during the performance, to train a regression model. The model was evaluated against expert annotations and through qualitative video analysis. Unlike the very linear notation of a Laban analyst, the model reflects the dynamism of human motion by capturing the almost humanly unobservable nuances in Effort variations. This points to the possibility of using machine learning models to reflect a performer's expressive intentions in real-time.

Keywords: embodied cognition; Laban Movement Analysis; effort; machine learning; inner intent; music performance

1. Introduction

Body movement has a crucial role in shaping the expressive nuances of a music performance. It not only conveys expressive qualities to the audience, but it also guides a musician's performance, aiding their interpretation of musical structures and the shaping of phrases. In this article, we describe an attempt at developing methods for analysing the expressive qualities of body movement in music performance. We then apply these methods to the development of an interactive musical system that analyses the movements of a musician in real-time, enabling new approaches to performance with live electronics.

Understanding and classifying the meaning of expressive body movement using machine learning (ML) is a crucial first step towards incorporating real-time detection of motion qualities in performance with live electronics. Achieving this objective requires a multidisciplinary approach that integrates insights from the arts, sciences, and technol-

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ogy. However, the study's aim was not to develop a generalisable model of embodied music performance, but to create a system based on a single performer's body schema. To address the complexity of embodied music performance, the study develops a mixed-method approach, combining qualitative analysis and ML to inform the design of an ML model. To do so, the team used a performance of the first movement of Brahms's Sonata for clarinet and piano, op. 120:2. The choice to use music by Brahms in this study was motivated by Ek's long-term experience of performing this music and an awareness, both from performing and teaching, of how this particular music evokes expressive bodily movements in performance. This choice was supported by several studies showing that musicians performing romantic music exhibit more expressive performance gestures than found in other genres (Wapnick et al. 2004; Huang and Krumhansl 2011; Moura et al. 2024).

We describe a method for detecting manifestations of a musician's expressive intentions while performing. This involves using Laban Movement Analysis (LMA) conducted by an expert, motion sensors to track the musician's movements, and ML. By training ML models using Laban Effort annotations made by an expert, we created a tool for recognising Efforts in human motion during music performance, specifically with a clarinet outfitted with a wireless 9-axis (9-DOF) inertial and magnetic measurement unit attached to the bell of the clarinet. We adopted Laban's theory of Effort since it provides a conceptual framework through which we can observe, describe, and interpret the inner intentions conveyed by body movement. Within Effort theory, inner intentions refer to the underlying motivational impulses that drive qualitative changes within a particular movement. (Kim et al. 2022). This understanding of intentionality aligns with a central concept within embodied music cognition: "an intentional level of musical interaction is established through corporeal articulations and imitations of sensed physical information provided by the musical environment" (Leman and Maes 2015, p. 236), i.e., the assumption that gesture and corporeal imitation are fundamental constituents of musical expressiveness.

The completed model does not access internal states per se but rather provides real-time estimates of Effort-related movement qualities, which can be viewed as traces of musical intentions. We view detecting the embodied manifestations of musical intent as a way to enhance the interplay between human performers and interactive systems. In the following subsections, we review relevant work in three related fields: embodied cognition, LMA, and interactive machine learning (IML).

1.1. Music Performance and Embodied Cognition

The concept of embodiment, as discussed by Clayton and Leante (2013), emphasises the importance of both phenomenological and biological aspects in shaping human cognition and our experience of the world through action. This approach has significantly influenced how scholars perceive and understand musical perception (Godøy and Leman 2009; Leman 2007), highlighting the interconnectedness of physical presence and cognitive processes in experiencing music. This means that the physical act of movements and gestures, as well as the internal sensations associated with them, contribute to understanding and experiencing music. A central concept in embodied music cognition is that "an intentional level of musical interaction is established through corporeal articulations and imitations of sensed physical information provided by the musical environment" (Leman and Maes 2015, p. 236). For example, the assumption that gesture and corporeal imitation are fundamental constituents of musical expressiveness is at the heart of embodied music cognition (Leman 2007).

Music performance is generally recognised as a highly complex process involving several systems within the human body. Flohr and Hodges (2006, p. 8) describe music as a highly interactive process involving "mind, brain and body," integrating mental, cogni-

tive, physical, and emotional aspects. Lehmann et al. (2007, p. 70) prefer the use of the term psychomotor activity during music performance, with reference to how “mental processes mediate motor performance”. Hence, to better understand a performer’s musical intent, it is essential to consider both the representation of the music and the physical action thereof. The interaction between perception and action is the foundation of embodied cognition that, according to Varela et al. (1991, p. 173), develops simultaneously. Referred to as enaction (Varela et al. 1991, p. 173), this concept aligns closely with “musicking” (Small 1998) as simultaneously perception-guided action and action-guided perception, or what Dawson (2013, p. 251) refers to as the sense-act cycle. As the following section will discuss, the theory of Effort relates closely to the physical or outer manifestation of the inner, expressive intent guiding movement.

1.2. Using Laban Movement Analysis to Analyse Music Performance

LMA is a framework developed by Rudolf Laban (Laban 1963), widely used for describing movement and motion qualities, particularly in dance, but it is also well-suited for other types of expressive communication. The LMA approach consists of four categories: Body, Effort, Space and Shape (BESS), providing a rigorous model for describing and analysing quantitative and qualitative characteristics of movement. The quantitative descriptors are found in the Body and Space categories, usually explaining functional aspects of movement. The Body category provides details about body parts and body organisation (the “what” of bodily movement), while the Space category relates to direction in space (the “where” of movement). Effort and Shape categories provide qualitative or expressive descriptors focusing on the “how” (Effort) and body-space relationships (Shape) of movement (Bradley 2009, p. 67). This study focuses on the embodied manifestations of musical intent. The LMA component of Effort is particularly suited to describe the qualitative bodily expressions. Effort, therefore, enables the understanding of more subtle characteristics of movement. In LMA, Effort descriptors reflect the mover’s attitude, inner intent, and the exertion and organisation of energy. “Effort is in constant flux and modulation, with Factors combining together in different combinations ... shifting in intensity throughout the progression of movement” (Studd and Cox 2013, p. 308).

Laban identified four Effort or Motion Factors for describing a particular quality of the movement referred to as Space, Weight, Time and Flow. As further descriptions will elucidate, these Effort Factors reflect a person’s attitude towards space, weight, time and flow and are not static in nature, but highly flexible and nuanced (Bradley 2009, p. 90). Relating to the intention of the mover, each Effort Factor exists on a continuum between polar opposite attitudes characterised as either being accepting (indulging) or resisting (condensing) in nature. Flow Effort describes the fluidity and quality of continuation and control of movements and is often considered the “initiator of action” (Bartenieff and Lewis 1980, p. 55). The intention underlying the manifestation of Flow Effort can also be understood when considering the Jungian influences on Laban’s Effort theory that relate Flow Effort to a sense of progression or underlying feeling (Maletic 2005, p. 10). From the Jungian lens, the inner feeling or intent initiates the movement characterised by Flow Effort. The indulging quality in Flow Effort is called Free Flow, describing a releasing quality to the movement, while Bound Flow Effort refers to a resisting, controlling or restraining quality (Laban and Lawrence 1974, p. 8). These qualities align with the tendency of Free Flow Effort to move away from the centre of the body, while Bound Flow Effort tends to move back to the centre of the body. Weight Effort relates to the extent to which the body activates weight and engages gravity, fluctuating between Light Weight Effort (resisting gravity) and Strong Weight Effort (engaging gravity) (Hackney 2002, p. 240). The Jungian characteristic underlying Weight Effort relates to intention and sensing that relates to a sense of presence of being. Weight Effort is also related to a vertical orientation in Space

(referring to one of the BESS components), and Laban determined that the general Affinity (referred to previously) is to move upwards with Light Weight Effort and downwards with Strong Weight Effort. Time Effort is related to an attitude towards clock time, ranging between an accelerating quality referred to as Quick Time Effort, and a slowing down of motions referred to as Sustained Time Effort (Hackney 2002, p. 241). The spatial affinity determined by Laban for Time Effort is to move forward with Sustained Time Effort and backwards with Quick Time Effort. The Jungian characteristic related to Time Effort is decision, referring to how a person attends to time, ranging between the polar opposites of a sense of urgency or a sense of indulging in time. Space Effort refers to a particular mode of attention to surrounding space. The Jungian influence relating to Space Effort, attention or thinking, clarifies the opposing Effort Elements. Direct Space Effort, referring to attention being directed to a specific point in space and Indirect Space Effort, which represents a more general or multi-focused attention, are the polar opposites on the Space Effort continuum (Studd and Cox 2013, p. 137). In LMA, Space Effort relates to a horizontal spatial organisation, where Direct Space Effort relates to a horizontally closing motion and Indirect Space Effort to a horizontally opening or widening motion. A summary of Effort Factors with the related Effort Elements is summarised in Figure 1.

Indulging Element	Effort Factor	Fighting Element
Free	Flow	Bound
Light	Weight	Strong
Sustained	Time	Quick
Indirect	Space	Direct

Figure 1. Effort factors with their polar opposite Effort Elements.

Due to the complexity of body movement and the intent of a movement, Effort Factors/Elements are never found in isolation. Bartenieff and Lewis (1980, p. 57) explain that “all people in motion are continuously making choices, consciously or unconsciously, to determine what combinations of Effort elements will best serve the purpose of their intent or modify their behaviour.” Combinations of two Effort Factors are called Effort States—they generally describe different moods as indicated by the names. The six possible combinations are called Rhythm or Near, Remote, Awake, Dream, Mobile and Stable States. A summary of the States and the related Effort Factor combinations is reflected in Figure 2. Combinations of three Effort Factors, called Effort Drives, represent “moments of full expressivity” (Bradley 2009, p. 75). As summarised in Figure 3, three Drives contain Flow Effort, collectively called Transformation Drives, are called Vision Drive, Spell Drive and Passion Drive. According to Bradley (2009, p. 80), the absence of Weight Effort in Vision Drive tends to reflect a lack of power and intention, while the absence of Space Effort in Passion Drive displays a lack of presence. She further indicates that the absence of Time Effort in Spell Drive portrays ‘being under a spell’. Effort Action Drives are characterised by the absence of Flow Effort. As illustrated in Figure 4, eight different Effort Action Drives are distinguished and differ in terms of indulging or resisting Effort Elements being part of the collective Effort Elements. The absence of Flow Effort in these drives leads to discontinuity and a “task-oriented” attitude (Bradley 2009, p. 80). The names of these Action Drives are representative of the collective quality of the three combined Effort Elements and are Float, Punch, Glide, Slash, Flick, Press, Dab and Wring.

Effort State		
Weight	Rhythm or Near	Time
Flow	Remote	Space
Time	Awake	Space
Flow	Dream	Weight
Space	Stable	Weight
Flow	Mobile	Time

Figure 2. Effort State combinations.

Effort Drive		
Action Drive		
Weight	Time	Space
Vision Drive		
Flow	Space	Time
Spell Drive		
Flow	Space	Weight
Passion Drive		
Flow	Time	Weight

Figure 3. Effort Drive Combinations.

Effort Element	Effort Action Drives	Effort Element
Float		
Indirect Space	Sustained Time	Light Weight
Punch		
Direct Space	Quick Time	Strong Weight
Glide		
Direct Space	Sustained Time	Light Weight
Slash		
Indirect Space	Quick Time	Strong Weight
Dab		
Direct Space	Quick Time	Light Weight
Wring		
Indirect Space	Sustained Time	Strong Weight
Flick		
Indirect Space	Quick Time	Light Weight
Press		
Direct Space	Sustained Time	Strong Weight

Figure 4. Effort Action Drive combinations.

Fdili Alaoui et al. (2017, p. 1) characterise LMA as “both a somatic and embodied practice as well as an observational and analytical system”. Broughton and Stevens (2012) used LMA successfully as a tool for observational analysis of musicians’ expressive bodily movements. In the last decade, ML algorithms have been used to recognise LMA qualities

in motion capture data (Fdili Alaoui et al. 2017; Silang Maranan et al. 2014; Truong and Zaharia 2017). In recent years, several studies have attempted to use Effort within LMA to detect motion qualities in dance and music, utilising varied amounts of data. Fdili Alaoui et al. (2017) use an accelerometer for Time Effort, Motion Capture for Space Effort and electromyogram (EMG) for Weight Effort. In another study, Silang Maranan et al. (2014) describe a system called EffortDetect using only an accelerometer. Their approach does not outperform other Effort recognition systems fed with richer data. Rather, it assesses the level of Basic Effort Actions recognition achievable using a single accelerometer. However, these systems have tried to detect the occurrence of specific Basic Effort Action Drives. In a more recent study, González-Inostroza and Cádiz (2023) used Effort and Space as a concept in the creation of a fuzzy gestural AI approach for expressive interactivity in multitouch digital musical instruments. Other uses of LMA in movement computing include the procedural synthesis of expressive movements for non-anthropomorphic computer-generated characters (Bisig 2022). The goal of the present study is to continuously estimate each Effort Factor in its constantly fluctuating state on a continuous scale of intensity between -1 and 1 , as opposed to detecting distinct events using classification methods.

1.3. Interactive Machine Learning in Music Performance

In the past two decades, ML techniques have been increasingly adopted by musicians and performing artists as a method for designing interactions between body movement, sound, and other media (Visi and Tanaka 2021). IML is an interaction design scenario which typically involves human gestural input as examples towards the training of a supervised ML model. It privileges small datasets, short training times, and quick iteration with human supervision to interactively create and refine models for interacting with digital media (Fails and Olsen 2003). In the performing arts, such an approach allows practitioners to create interactions with sound and visuals by providing examples of the desired behaviour rather than explicitly programming each interaction. Examples of IML tools used in music include the Wekinator (Fiebrink et al. 2009), MuBu (Schnell et al. 2009), the Gesture Recognition Toolkit (Gillian and Paradiso 2014), ml.lib (Bullock and Momeni 2015), FluCoMa (Tremblay et al. 2019), and Anguilla (Armitage et al. 2024).

Previous works, some of which we reviewed in the previous section, use ML classification methods to detect discrete occurrences of specific Effort qualities. However, Effort is in constant flux (Studd and Cox 2013), and continuous data—as opposed to discrete events—is a useful resource in designing dynamic musical interactions (Visi and Tanaka 2021).

2. Materials and Methods

To gather data to be used to train the ML model, gesture data, as well as audio and video during a performance of Johannes Brahms's Sonata for Clarinet and Piano op. 120 no. 2, was recorded at the Royal College of Music in Stockholm, Sweden. Clarinettist Robert Ek, also author of this article, performed together with pianist Mårten Landström. The video (without sound) was then analysed by Froneman, observing Laban Efforts and fluctuations of Effort intensity known as Effort Phrasing (see Section 2.1.2). The annotations from the analysis were reviewed by Froneman and Ek, fine-tuning the observations with the assistance of video from the performance. The fine-tuned annotations were then converted into training data using a Max patch (see Section 2.2.2). This data was then used together with the gesture data from the performance to train a regression model using the GIMLeT package in Max (see Section 2.2.1). The model was then evaluated by comparing the output of the model with the annotations made by Froneman. Additionally, Froneman manually reviewed the output of the model alongside the video to assess the quality of its

estimations. The video from the performance used in this study, along with the musical score and a timing sheet with Effort annotations, is accessible in an online repository (Ek et al. 2026). In that repository, a Max patch is also found, showing the model output alongside the video with possibilities to focus on smaller segments and single Efforts.

2.1. Qualitative Analysis

To properly understand the different aspects of music perception and performance, a qualitative approach must be used that acknowledges the intricate web of interrelations that cannot always be measured empirically. However, when conducting qualitative analysis of musical performance, the data collected is of a subjective nature. There have been multiple attempts to complement performer-informed analysis with quantitative methods to overcome this weakness (Coorevits et al. 2016; Desmet et al. 2012; Visi et al. 2020). Allowing other researchers to also code the material may provide different perspectives and aid in creating an intersubjective understanding of the data, which Leman (2007) refers to as a second-person perspective.

2.1.1. Stimulated Recall

The qualitative method of stimulated recall, frequently used in fields like human studies and the humanities, was first introduced by Bloom (1953) as a way to gather data by prompting memory through recorded media. Participants report on recalled thought processes as they revisit situations via video or other stimuli. Across the last decades, the method has been adapted to music research and further developed by adding gesture analysis (Coorevits et al. 2016; Visi et al. 2020; Östersjö et al. 2023). In the present study, the clarinet performer returned to the video of the performance to conduct stimulated recall analysis of the segments reviewed by Froneman. We adopted stimulated recall to analyse the video of the performance to see if the output of the model aligned with our interpretation of the piece.

2.1.2. Laban Movement Analysis

LMA is regarded as a subjective form of analysis, where the observer assigns specific descriptors in terms of BESS to particular movements within particular contexts. A study by Bernardet et al. (2019) assessed the reliability of the LMA system using all the BESS components for analysis by expert movement analysts (Certified Movement Analysts (CMA)) to observe different variations of video-recorded knocking-on-a-door gestures by the same person. The study found a greater agreement between the different CMA's in variation descriptors within the Space and Phrasing components than in the Effort and Shape components, which can be attributed to the more qualitative changes these components describe. Effort observations are often influenced by the observer's own preferences and movement characteristics, and in many cases, CMA's collaborate when analysing to address possible biases. However, within the LMA approach, the interactions between the different BESS categories can in themselves be a generalisability strategy due to the concepts of affinities and disaffinities that will be addressed in the Effort section below. Furthermore, following the results of two case studies discussing the implementation of LMA as a strategy to enhance function and expression in classical pianists, Froneman and Munro (2023) suggest that an understanding of the instrument and the body movement requirements dictated by the technical or functional aspects of playing a particular instrument is paramount when CMA's engage with musicians. Although suggested within a movement education context, analysing instrumentalists also requires knowledge of movements inherent to the nature of playing the instrument in determining the functionality or expressivity of a particular gesture. Laban's concept of Effort was refined during World War II when the British Government hired Laban to develop the productivity of

the female factory workers who had to continue the work traditionally done by men (Adrian 2008, p. 5). This implies that Effort, although generally considered qualitative or expressive, can also contribute to functionality, as in the case of movements specifically relating to the playing of a particular instrument. Therefore, the theory of Effort lends itself well towards observing and describing expressive elements of musical gestures in music performance.

2.2. Model Training and Evaluation

In these sections, we will describe the techniques we have adopted for annotating Effort Factors on the video recordings of the performance, how we converted the annotations into training data, and how this was paired with motion sensor data to train a regression model using ML.

2.2.1. Annotating Efforts in Video

Using the LMA theory with a specific focus on Effort, the initial analysis of the video recording was done over a period of two weeks. At first, the video material was viewed several times, both with and without the score, to obtain a general sense of the movement as attached to specific segments, phrases or passages. The analytical annotation was conducted without sound, as perception can be convoluted by Effort qualities embedded within the sound. Effort notations were organised using time indications, specific Effort combinations and Effort Phrasing. Discussions between Froneman and Ek resulted in further analytical observations aimed at a more detailed analysis of the nuances of Effort. The video data was revisited over a period of four weeks, where the analysis focused on smaller segments and phrases. Although the analytical annotations focused on Effort combinations and the phrasing thereof, each Effort factor was analysed individually in the smaller segments to assign a value of intensity to each Effort separately to provide detailed data on each Effort. The analytical observations were documented using a timesheet indicating Effort Phrases of the Effort combinations (see Figure 1) used as training data.

Additionally, and not used as part of the training data, an Effort analysis using only the audio of the recording was notated using the score (see Figure 5). LMA theory is used to analyse body motion, and as already indicated, Effort refers to the qualitative intention of the movement. However, considering that tonal changes can be perceived in terms of rhythm, melody and harmony, motion is inherent to music. Froneman correlates the different Effort Factors (often referred to as motion factors) and changes perceived in musical motion in terms of dynamics, pulse, texture, timbre, and articulation (see Table 1).

Table 1. Effort Factors and their relations to musical descriptors according to Froneman.

Effort Factors		Related Musical Changes and Descriptors	
Indulging Element	Condensing Element	Indulging	Condensing
Light Weight	Strong Weight	Softer dynamics	Louder dynamics
Sustain Time	Quick Time	Rhythmic deceleration	Rhythmic acceleration
Free Flow	Bound Flow	Open, light texture. Less observable control of breath	Dense texture. More observable control of breath
Indirect Space	Direct Space	Legato articulation	Staccato or marcato articulation

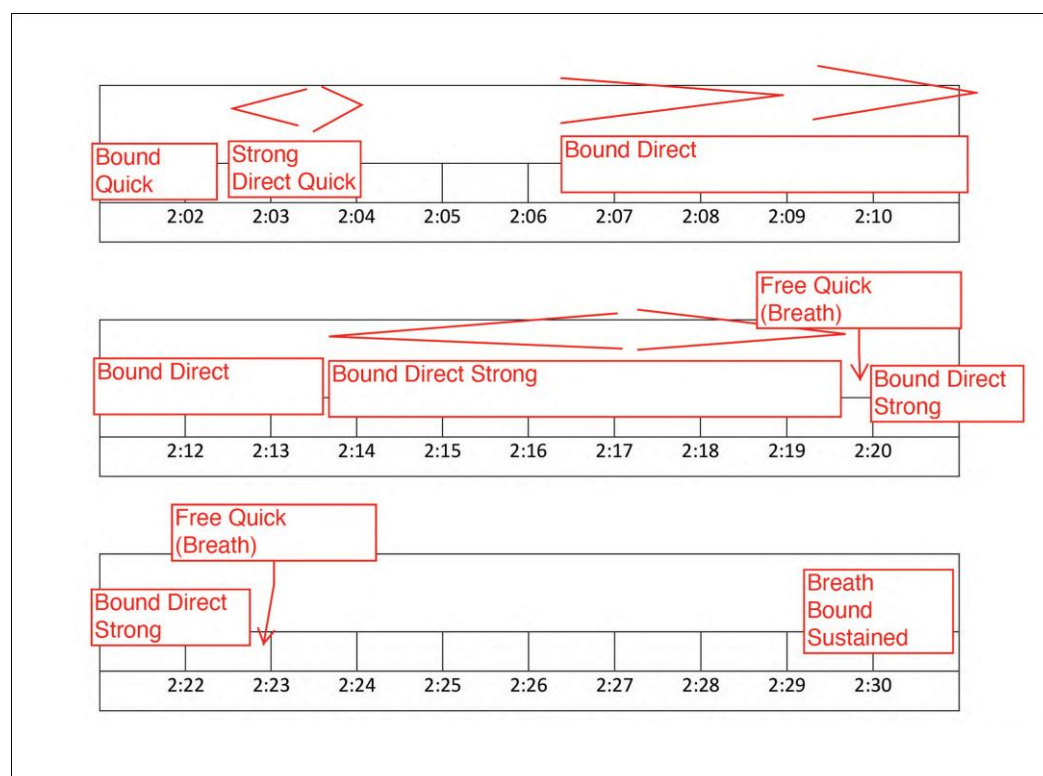


Figure 5. Part of the timesheet with Effort annotations.

Froneman related Weight Effort to dynamic qualities linking Light Weight Effort to a softer dynamic and Strong Weight Effort to louder dynamics. Similarly, Quick Time Effort was related to a perceived acceleration and Sustained Time Effort to perceived deceleration. Flow Effort was related to texture and timbre, with Free Flow Effort related to a more open, light texture in the music, while Bound Flow Effort was related to a dense quality in the music. Breath control also influenced the perception of Flow, as passages requiring more breath control were perceived as tending towards Bound Flow and passages where breath control was less observable tended towards an experience of Free Flow Effort. Space Effort was linked to articulation, with Indirect Space Effort being experienced as legato passages, with Direct Space Effort being an indication of staccato or marcato-like passages. Froneman used these descriptions and annotations to relate the data from motion or gestural analysis to the musical intentions of the performer. This relationship is important when reviewing the output of the model and will be referred to in the results section.

2.2.2. Converting Annotations to Continuous Data

The recording of Brahms is 8 min 51 s long. Froneman annotated all Efforts she found prominent in the video. In total, Froneman annotated 121 segments, ranging from 0.6 to 5 s, adding up to 4 min and 30 s of annotated segments. Some of these annotations are shown in Figure 5. The team reviewed all of the 121 annotations. During this work, the video from the performance was used as a reference. In the initial annotations, only the presence of a particular Effort quality or combination of Effort qualities was documented. In reviewing the shorter annotations, each Effort was assigned a value to reflect the intensity of each Effort in a particular annotation, as their intensity differed with each occurrence. This process was a significant refinement of the annotations to reflect specific nuances of Effort. To transform the qualitative annotations made by Froneman into numerical data that could be used to train the ML model, we implemented linear ramps between annotated values for each Effort throughout each analysed segment. We sampled the

value of the linear ramps at 100 Hz, resulting in 27,000 data points for the whole training set.

Figure 6 is an example of a segment between 02.10.800 and 02.12.600 (1.8 s long) where the change in each Effort can be viewed. Space Effort training data is decreasing from 0.5 (a moderate intensity of Direct Space Effort) down to 0.33 (a low intensity of Direct Space Effort). Weight was not annotated in this segment. Time is increasing from 0, representing a neutral Time Effort, to 0.15, representing a very low intensity of Quick Time. Flow Effort is at a static level of 0.5, representing a moderate Bound Flow Effort. With regard to the Flow Factor in this segment, due to the design of the Max abstraction, a small value difference had to be added for the model to receive data, which was decided to always be 0.01 lower than the end value. The data was eventually used to train a regression model that outputs continuous change in each Effort factor in real-time. This is preferable over a classifier, as Effort factors continuously change in performance. We randomly excluded 11 of the annotated segments, leaving 110 segments used to train the model. Since the main goal of the study was to use the analysis of Laban Efforts and ML in artistic applications, the team chose to evaluate the model primarily from a qualitative perspective. It is standard practice for Certified Movement Analysts to incorporate a whole-part-whole approach to analysis, often relating the analysis of a specific segment to a bigger segment. In our study, Froneman was asked to choose three longer segments exhibiting prominent Effort qualities. These three segments are discussed in Sections 3.2.1–3.2.3. In these segments, we can see how the model behaves both in parts that have training data (dotted lines) and in parts that do not have any training data. In Section 3.2.3, however, the displayed training data (dotted lines) was one of the annotated segments excluded from the training data.

time frame in ms		Space		Weight		Time		Flow					
130,800	132,600	0.5	0.33	1800	0.0	1800	0	0.0	0.15	1800	0.49	0.5	1800

Figure 6. Example of annotations of Effort converted to quantitative training data for the segment 2 min 10.8 s (130,800 ms) to 2 min 12.6 s (132,600 ms).

2.2.3. The Music in Motion Sensor System

For the retrieval of gesture data, we used a specially designed clarinet bell fitted with a sensor system called Music in Motion, MiM (Ek 2024). The benefit of adding the sensor to the bell of the clarinet is that this can be done on an extra bell, and then that bell can be easily replaced when not needed. The heart of this device is a Bosch Sensortec (BNO055) 9 DOF sensor capable of delivering sensor data over Wi-Fi at a rate of 100 Hz. The sensor sends raw data in three axes from each of the three parts of the sensor: accelerometer, gyroscope, and magnetometer. It is also equipped with onboard sensor fusion that calculates quaternions, which represent spatial orientation and rotation of elements in three-dimensional space. Unlike Euler angles, quaternions are not subject to problematic singularities such as gimbal lock (Brunner et al. 2015). The movement data is transferred over Wi-Fi to a host computer, where a Max patch collects and stores the data synced with the audio and video recording. The main reason for not expanding the data collection with camera-based motion capture and EMG for higher accuracy is that the model created is intended to be used in live performances with minimal intrusions for the performer.

2.2.4. Training the Model

We trained a regression model that takes data from the MiM sensors and outputs continuous estimates of the four Effort Factors. To do so, we built a training dataset that included three-dimensional acceleration, angular velocity, jerk (i.e., the first-order derivative of acceleration), and the fluidity feature (Piana et al. 2016) obtained from the MiM sensor paired with the corresponding data for the four Effort Factors (see Section 2.2.2). This resulted in a dataset with a total of 10 inputs and four outputs. Training was done using the GIMLeT package for Max, a set of patches for gesture analysis, IML, and gesture-sound interaction design. The package includes a Max external object called rapid-max (Parke-Wolfe et al. 2019). The object implements basic ML algorithms, such as multi-layer perceptrons, k-nearest neighbours, and dynamic time warping, to allow Max users to quickly employ ML for regression or classification tasks. It is a wrapper around RapidLib (Zbyszyński et al. 2017), a C++ and JavaScript library for creative, IML applications in the style of Wekinator (Fiebrink et al. 2009). Here, we used a multilayer perceptron (MLP) neural network with one hidden layer to train a model and perform regression and output estimation of the four Effort factors based on the 10 input features obtained from the MiM sensor. The hidden layer has 10 units while the output layer has four (the number of Effort Factors). We used sigmoid activation functions, and the model was trained for 500 epochs using gradient descent backpropagation with a weighted difference as the loss function.

3. Results

Results are structured in three parts. In the first part, we look at how the model we trained performs by comparing its output with the Effort annotations done by Froneman. This was done for two excerpts of the performance: one in which the output of the model aligns with the annotations, and a second one in which the output of the model deviates from the annotations. This is not a systematic validation of the model's performance. Rather, we use the two excerpts as a starting point for a qualitative appraisal of the model's behaviour and its usefulness in live electronics performance.

In the second part, we look at how the model performs on longer segments of the piece. This allowed us to assess the original annotation done by the CMA in the context of musical phrases. This provides an assessment of the original annotations usually done by the CMA. In these longer segments, there are sometimes annotations by Froneman to compare with, but since the 121 annotations do not cover the whole performance, they are not present throughout the complete segments. This part of the analysis also assisted in interpreting the results, as it required the CMA to return to the video to explain whether and why the model differed from the original annotations. For these longer segments, the performer (Ek) conducted a stimulated recall analysis of the recorded video and audio to unpack the connections between the clarinetist's embodied performance of the piece and the expressive intentions of his interpretation.

Since the aim of the study was to develop an ML model for real-time analysis of expressive embodied performance that can be used in the design of interactive musical systems, the evaluation of the model included a series of artistic applications within such systems. This part of the evaluation is discussed in the third and final part (3.3).

We adopted a "small-data mindset" (Vigliensoni et al. 2022) in creating our own training dataset and model. As explained by Vigliensoni et al. (2022), preventing overfitting may not align with the purpose of some creative applications, yet it may still be desirable in some cases. This resonates with our use case, as our goal here was to obtain models that capture the expressive idiosyncrasies of a single performer rather than aiming for generalisation.

3.1. Comparing Human Annotations and Laban Effort Model Output

A comparative analysis of the training data and the Laban Effort model output was conducted to assess how closely the model output aligns with the training data. In this article, we examined two of these segments in detail. We used average RMSE (Root Mean Squared Error) to select two segments with different levels of accuracy. In the first segment, the model output follows the training data relatively well, with an average RMSE = 0.17, SD = 0.04. The second has a higher average RMSE = 0.29, SD = 0.17. In that case, Froneman returned to the video material for possible clarification and explanation of the model's performance.

3.1.1. Alignment with Annotations, 14,000–15,000 ms

In the first segment 14,000–15,000 ms (see Video S1), Space Effort training data is decreasing from 0.5 (a moderate intensity of Direct Space Effort), down to −0.33 (a low intensity of Indirect Space Effort). This gradual change is represented by the purple line (see Figure 7). The blue line reflects the behaviour of the trained model when activated in the same segment.

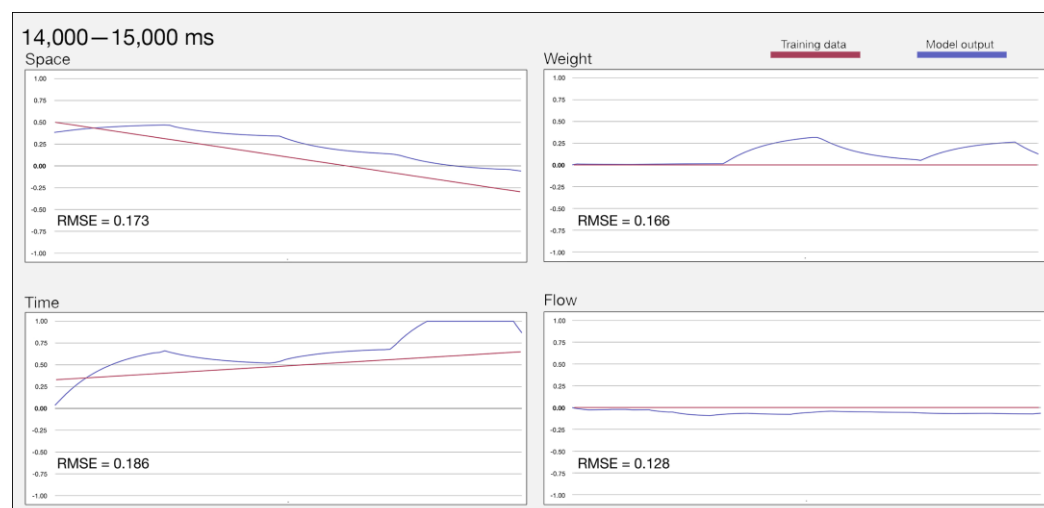


Figure 7. Training data from a segment compared with Laban Effort model output.

Weight Effort was not annotated in this segment, and that can be viewed in the flat purple line. However, in the model output, there is a small amount of Weight Effort showing up like two bumps. After revisiting the video of the performance, Froneman assumed that the model was able to detect changes in a single Effort that she did not consider prominent in that specific segment. This assumption implies that the model was able to detect changes within a single Effort, even when not considered as prominent by the analyst.

Time Effort was annotated to increase from 0.33 to 0.67 during the segment. The model output (purple) follows the overall direction of the originally annotated data (blue). Revisiting the performance in the video, Froneman considered that fluctuation as a more nuanced and detailed reflection of the expressive human movement and expressive aspects related to musical interpretation.

Similarly to Weight Effort in this excerpt, Flow Effort was not annotated in this segment, although some fluctuations of Flow Effort, predominantly towards Free Flow Effort, can be observed within the model output. Fluctuations in Flow Effort reflected by the model align with the theory that Flow Effort is the baseline of human movement that other Effort Factors develop from and return to (Bartenieff and Lewis 1980, p. 55; Hackney 2002, p. 239).

The comparison between the model's output data and the training data in this segment reveals similar tendencies in terms of changes in intensity of Efforts (or Effort Phras-

ing). As Effort is qualitative in nature, exact replication of quantitative indicators as used for training of the model is not expected. The success of the model, from a qualitative perspective, is in this case the similarity in terms of changes in intensity of single Efforts, or Effort States, which, in the case of this short example, shows a high level of similarity.

3.1.2. Deviation from Annotations, 24,500–27,000 ms

In the segment 24,500–27,000 ms (see Video S2), the model reflects some activity in all the Effort Factors. The annotations of the training data (see Figure 8), however, did not reflect any Space Effort. However, the fluctuations by the model in the graph above indicate some deviations to Direct Space Effort in the first half of the graph, as well as to Indirect Space Effort (to a lesser extent than Direct Space Effort) in the second half of the graph.

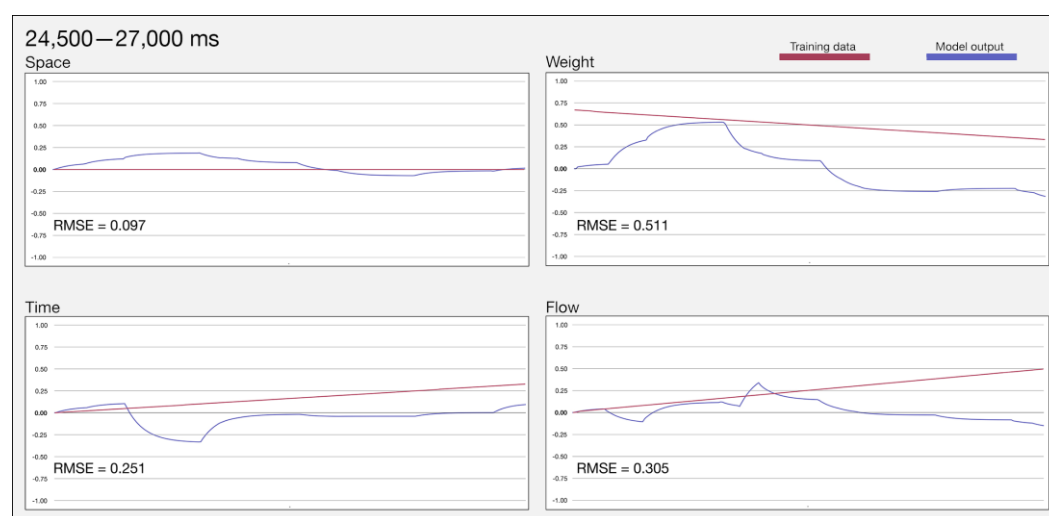


Figure 8. Training data from a segment compared with Laban Effort model output.

The training data for Weight Effort reflects the most intense deviation (RMSE = 0.511), decreasing from approximately 0.7 to 0.3 in Strong Weight Effort. The output of the model commences with almost no inflexion, then deviates in intensity to about 0.5 in Strong Weight Effort, and thereafter it moves towards a slight intensity in Light Weight Effort (at approximately −0.25). Although the exact intensities do not relate between the training data and the model's output, the curve and general trajectory of the intensity do overlap.

The training data for Time Effort reflects a slight intensification towards Quick Time Effort from 0 to 0.33 approximately. The response by the model, however, reflects a slight intensification towards Sustained Time Effort, before it gradually intensifies towards Quick Time Effort to an intensity of approximately 0.1. Similar to Weight Effort, the model's interpretation does align with the curve and trajectory of the training data.

In the graphic representation of Flow Effort, the training data reflects an increase in intensity towards Bound Flow Effort from 0 to 0.5. While the model's output generally aligns with the increase in intensity towards Bound Flow Effort in the first half of the graph, it decreases in intensity of Bound Flow Effort and moves towards an intensification of Free Flow Effort in the second half of the graph. In the second half of the graph, the training data and model indicate opposite motions.

Changes in terms of intensity of Effort in this example are difficult for the analyst since the excerpt is less than three seconds in duration. In the original analysis, changes in Effort were notated in terms of Effort Phrasing that resulted in analysing segments where changes continued. In comparing the model output to the training data, it seems that the analyst's reading fits into a bigger phrase of Effort change, while the model seems to detect the smaller segment as an entity. This is to be expected given that we adopted a

feedforward architecture that has no temporal memory. Froneman deemed the Effort changes in this segment as an accurate representation when returning to review only this short example.

3.2. Evaluating the Laban Effort Model

Within the analytical process, CMA's frequently use a whole-part-whole approach. Within the Body category of BESS, it refers to viewing a part of the body in relation to the whole body. However, in the analytical process, it refers to viewing smaller segments in relation to larger segments in order to identify tendencies of movement, as movement is considered a manifestation of human behaviour or expression. In evaluating the Laban Effort model based on the initial analysis and annotations (see Section 3.1), the whole-part-whole approach seems important towards evaluating how the model reflects shorter and longer segments. This is important as a single moment of one to three seconds is unable to be representative of the musical intent of the performer.

3.2.1. Musical Phrase with Build-Up, 00.47.000–00.53.000

The musical score of this segment can be viewed in Figure 9, (see also Video S3) is a build-up to the first forte in the movement. The large phrase consists of four sub-phrases, of which the last three are in this segment (see Figure 9). The first sub-phrase in this segment consists of four notes at the end of measure 12 and the beginning of measure 13, where, oddly enough, Brahms has marked the second note as the goal point with a crescendo from the first to the second note and then a diminuendo. In the stimulated recall, Ek notes how “without that marking, I would have gone for the fourth and last note in this sub-phrase”. Ek continues by relating the physical gesture to the musical shaping:

“You can see this interpretation in my physical gestures when I’m changing direction on the second note. This goal point is also not that defined, it’s a soft one and without edges. I try to smear the notes in this small crescendo diminuendo, making it as legato as possible”.

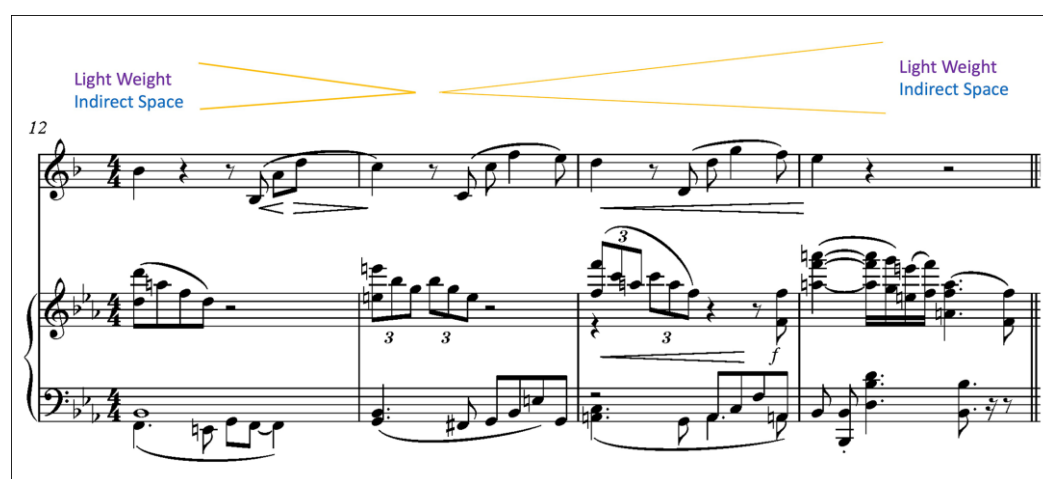


Figure 9. Part of the music score showing measures 12–15.

The annotated data (see Figure 10, dashed lines from 00.49.200 to 00.51.600) presents an increase in intensity to 0.67 in Direct Space Effort and an increase in intensity in Quick Time Effort to 0.5 (see Figure 10), resulting in an Effort State configuration called Awake State. The graphic representation by the model relates closely to the original observational analysis that indicated an increase in Direct Space Effort, while not reflecting the original increase in Quick Time Effort. The increase in Bound Flow Effort and Direct Space Effort in the model’s output can be reflective of Ek’s intent to “smear the notes”. Bound Flow

Effort can be considered a conscious attempt to control the articulation in binding notes together, while the Direct Space Effort may be representative of the focus on the more functionally driven intent of connecting specific notes.

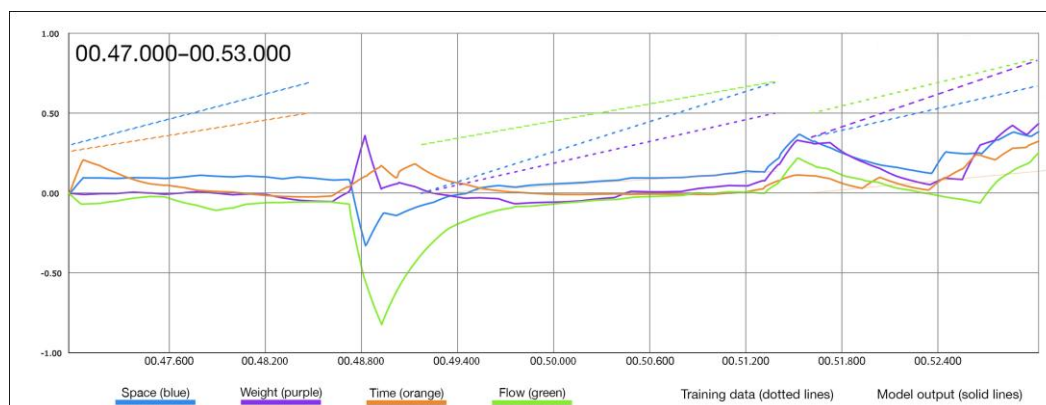


Figure 10. Overview of a segment where both training data and Laban Effort model output are present.

The output of the model in this segment is particularly interesting when related to the originally annotated data. It reflects a sudden increase in the intensity of Free Flow Effort in the fourth column, initially intensely and then gradually releasing towards an intensity of Bound Flow of approximately 0.25 in column 8. After this point, it releases again towards Free Flow Effort of approximately 0.1 in column 10, followed by a release towards Bound Flow Effort (of an intensity of approximately 0.25 at the end of column 10). Although the trajectory of intensification towards a particular Flow Effort Element is consistent with the annotated data, the rather sudden increase in Free Flow Effort to an intensity of approximately -0.85 by the model required further engagement with the original material. In revisiting the video material in search of an explanation for this reaction, it was interesting to note that a quick inhalation occurred at this point (at the quaver rest in measure 13). The occurrence of a high intensity of Free Flow Effort in general human behaviour is extremely rare, as the anatomical/physiological nature of movement mostly requires a large amount of control. However, at this moment, the clarinettist is attempting to take in the maximum amount of air within a very short period of time. The assumption is that in this case, the intent of taking in optimal air in terms of Free Flow Effort outperforms controlling the movement related to this action. Supporting this argument is the simultaneous peak of intensity of Strong Weight Effort (to approximately 0.4), and Indirect Space Effort (to approximately -0.3), resulting in a Transformation Drive called Spell Drive. Strong Weight Effort supports the dynamic intensity of the inhalation, while Indirect Space Effort supports the intention to inhale air to maximise lung capacity. Ek did not comment on this moment in the stimulated recall, probably given the functional and technical nature of breathing for the clarinettist. The output of the model in this particular example also reflects the LMA theme of Function/Expression, which states that movement can be simultaneously functional and expressive. The way that the model interpreted this motion was indeed more representative of detailed fluctuations in the functional context of this split-second activity, whereas this was an unconscious intent of the clarinettist and while CMA considered the motion within the larger phrase as more important.

In the second sub-phrase (end of measure 13 going into measure 14), the pattern changes, notated as a continuing crescendo over five notes. Ek describes the passage: “I see now that I also change body language from moving side-to-side in the first sub-phrase, which for me is a sense of indirectness or smearing, to a more directed gesture”. This can be viewed in the video as a more vertical physical gesture directed towards the goal point,

which here is the last note. In this sub-phrase (from 00.49.200 to 00.51.600 in the graph), the training data reflects an increase in intensity from 0.33 to 0.67 in Bound Flow Effort, an increase in intensity from 0 to 0.67 in Direct Space Effort and an increase in intensity from 0 to 0.5 in Strong Weight Effort corresponding closely to the graphic representation of the model's output indicating an intensification of Strong Weight, Bound Flow and Direct Space Effort (this combination of condensing Efforts is a Transformation Drive called Spell Drive). Although similar in intensity, the model's output reflects a less intense intensification than the original training data. In this sub-phrase, the model's output reflects both the changes in the individual Efforts and meticulously reflects the Spell Drive originally annotated by Froneman. The last sub-phrase is the most intense one. Ek comments on this:

"This last sub-phrase ends in the first forte of the movement, and at the same time, I give over to the pianist to continue. My timbre over these four sub-phrases has gone from open sound and warm to more directed and almost a bit harsh".

In the training data for this sub-phrase (from 00.51.800 to 00.53.200), Bound Flow Effort increases in intensity from 0.5 to 0.8, Strong Weight Effort increases in intensity from 0.33 to 0.8, while Direct Space Effort increases in intensity from 0.33 to 0.67. While the model output follows the general tendency of intensification of Bound Flow, Strong Weight and Direct Space Efforts (a Spell Drive combination of condensing Efforts), it also indicates an intensification in Quick Time Effort reaching an intensity of approximately 0.35 at the end of the graph from approximately 0.0 in one second. Froneman revisited the video material to explain this phenomenon and concluded that it might be possible that Quick Time Effort is added at that moment. The combination of all four Effort Factors or "full effort combinations" is rare and usually encountered during moments requiring maximal function or expression (Bartenieff and Lewis 1980, p. 63). However, unless the video speed is adjusted to play extremely slow, this fluctuation, inclusive of all Effort Factors, is not observable to the human eye. In this case, the detailed output of the model is probably more accurate than the observation of the CMA.

3.2.2. Visible Goal Point, 01.54.000–02.04.210

This segment (see Video S4) is a single phrase with an extended build-up. It begins in a *sotto voce*, *dolce*, dreamy state that is also present in the preceding phrase. This closely aligns with the original analysis (see Figure 11), indicating Indirect Space Effort in the first half of the phrase that is reflective of a general, open-spaced attitude towards the surrounding performance space. The Bound Flow and Indirect Space combination, annotated initially, is also called Remote State, and reflects the "dreamy" quality Ek refers to in his stimulated recall. Throughout this phrase, the music intensifies, going to a forte in the end. In a stimulated recall by clarinetist Ek, he comments on this phrase:

"The timbre, in the beginning, is deliberately loose and unfocused but gets more and more centred towards the end. I can see how I begin this phrase by moving from side to side, which indicates a will to perform the phrase very legato. The speed of change between left and right picks up speed instantly, and 2/3 into the phrase, it results in a still moment just before going over to a vertical gesture marking the goal point".

This goal point is clearly visible in the model data (see Figure 12).

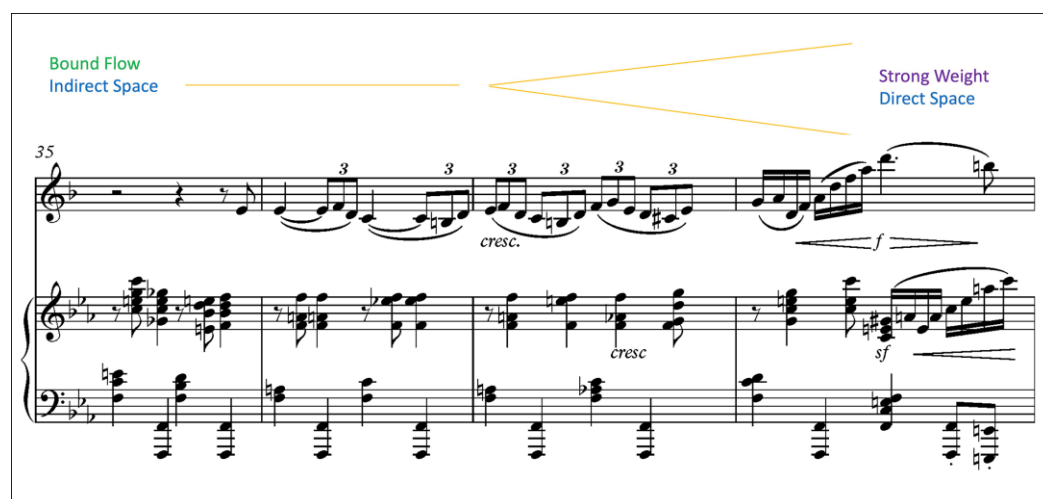


Figure 11. Part of the music score showing measures 35–38.

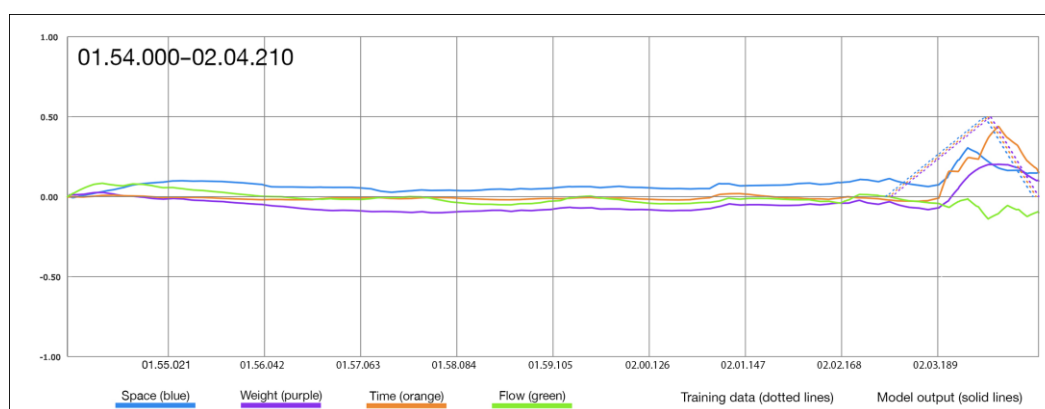


Figure 12. Overview of a segment where both training data (dotted lines) are present at the end of the segment.

In the original analysis, a simultaneous intensification of Quick Time, Strong Weight and Direct Space Efforts from 0. to 0.5 as represented by the straight lines in the last two columns of Figure 12. After 0.5 is reached, these Efforts resolve back to 0. again. Of interest is that the specific combination of Efforts, here referred to as a Punch Action Drive. The model output of this specific moment reflects the intensification of the Effort Element within the Punch Action Drive, but presents Time Effort, Weight Effort, and Space Effort differently. As mentioned in the previous example, these fluctuations are not detectable by the human eye. Although the general curve of the graph of the model reflects a similar contour, Froneman regards the detail of the Effort annotation by the model as more reflective of nuance than human perception. Further interest within the graphical representation of the model's output is the fluctuation of Flow Effort at this point (in the last two columns). In revisiting the video material, the inclusion of a slight intensification towards Free Flow Effort seems accurate, as two clear moments containing a release of controlled motion appear—once when releasing to gravity and a final release when the clarinet is released from playing position at the end of the phrase.

When relating the motion data with the auditory Effort annotations, the overall trajectory of the intensification of Space Effort and Weight Effort is similar. However, whereas the auditory analysis reveals a gradual intensification to Strong Weight and Direct Space (a combination referred to as Stable State, indicated in Figure 11), the motion analysis only reflects the intensification at the end of the phrase. The absence of Quick Time Effort in the auditory analysis can be attributed to the fact that the note values are

shorter and smaller, providing acceleration in the music, although it is not an expressive variation, but a functionally notated acceleration. However, the presence of Quick Time Effort in the movement analysis at the end of this phrase is representative of the intention of the notation itself to speed up. Furthermore, the inclusion of Free Flow Effort in the model output at this point also reflects the intent of Ek's musical interpretation to intensify dynamics and tempo towards a release of tension in the clarinet part, although the piano part takes over the intensity at this stage.

3.2.3. Segment Excluded from Training Data, 04.57.000–05.09.000

Musically, this segment is the last phrase before the theme comes back (see Video S5). It is interpreted with a light dolce character (see Figure 13), it moves towards a lighter and lighter ending, adding a sense of weightlessness. In Froneman's annotation of Effort in the music (auditory data only) of this segment (see Figure 13), a decrease of Bound Flow and Indirect Space Efforts (called Remote State) is reflected. From a musical perspective, Froneman considers the release of Bound Flow Effort, interpreted as less control of breath and a more gradual release of air pressure, as more important than Light Weight Effort, prominent in the movement annotations. All the goal points here are soft in nature, and in the video, it clearly coincides with an elevated clarinet representative of the need to convey a light texture. The first sub-phrase (04.57.000 to 05.00.000) is quite short with a clear crescendo–diminuendo shape. Ek comments:

“There is a sense of weightlessness here right after the goal point where the small crescendo turns into a diminuendo. I can see in the video that I do this sub-phrase lifting the right foot along with elevating the clarinet”.

Figure 13. Part of the music score showing measures 98–101.

The initial observation by Froneman reflects a Stable State configuration where Light Weight Effort and Indirect Space Effort align with Ek's intent as expressed in the stimulated recall passage. The Spatial Affinity of Light Weight Effort to move upwards is observed in the upwards motion of the clarinet and right foot, which is interpreted as an attempt to resist gravitational pull. The 'sense of weightlessness' referred to by Ek (in the previous paragraph) is observed by Froneman as an expansion of attention to a broader surrounding performance space. The graphic representation of the model's output reflects the finer nuances and fluctuations that Ek refers to and continues into the second part of this phrase. The second sub-phrase (05.00.000 to 05.04.000) starts just after releasing the first.

“I immediately start to build up to the second goal point. I can see how I start this one with bending my knees, usually this is a sign of me wanting to empha-

sise something, but here it is more a way of being able to go up once again for the next goal point”.

The last sub-phrase (05.04.000 to 05.09.000) is mostly a diminuendo, but there is a small emphasis on each of the two dotted crotchet notes reflected in the movement of the knees and the clarinet. However, the more gradual fluctuations can be attributed to the more circular up-and-down motions of the clarinet in the second half in relation to the more linear up-and-down motions in the first half of this example. The subtle inflexions in Time Effort and Flow Effort of the graphs (see Figure 14) align with the theory that Flow Effort is an initiator of action, as Flow Effort follows a similar motion to that of Weight and Space Efforts. Time Effort is also represented as leaning towards momentarily Sustained Time Effort within the more dynamic motion in this excerpt, possibly related to the crescendo-diminuendo fluctuations by Ek.

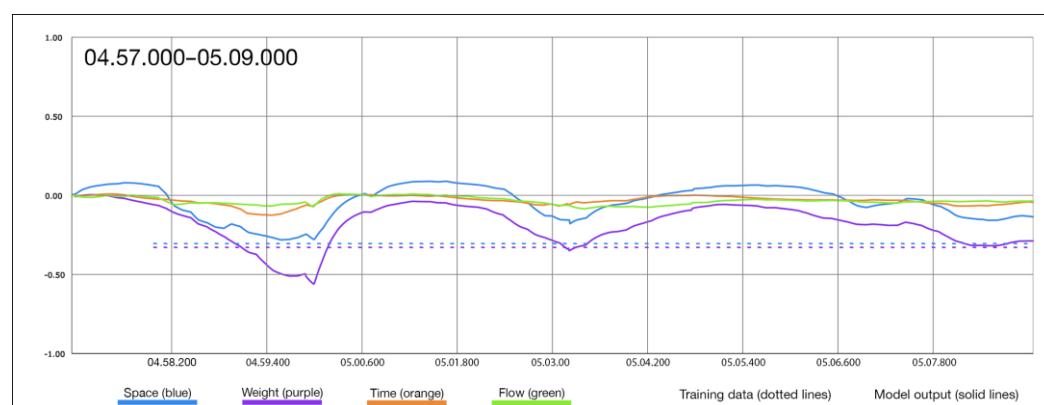


Figure 14. Overview of a segment where the training data displayed was excluded when training the model.

In this example, it is important to note that the original Effort analysis and annotations by Froneman were not included in the training data. To be able to validate the performance of the model, besides the cross-reference between training data and model performance, we excluded 10% of the segments annotated by Froneman from the training set. This segment was one of them, so the lines representing the annotation are used as a reference representing the original annotation, while not being used as part of the training data. Considering this aspect, the model output generated for this segment illustrates the model's ability to efficiently reflect changes in Effort intensity when related to the annotation by Froneman.

3.3. Using the Laban Effort Model in Live Music Performance

Ek has used the Laban Effort model in several artistic collaborations since its completion. One of those projects was the collaborative artistic laboratory cut-cut. The idea was to develop a space for exploration without a pre-determined goal, such as a public performance, instead focusing on openness to the unknown. It is this openness that Spatz claims “characterises the epistemic integrity of a process” (Spatz 2020, p. 108). The primary focus of the laboratory was to explore embodied music performance, focusing on gestural space and the agencies at play in the connection between the clarinet and the body. To explore these embodied connections, Ek invited a composer and a choreographer: The composer Kent Olofsson focused on the musical manifestation of embodied music performance, whereas the choreographer Lidia Wos focused on the physical manifestation. Hereby, in the laboratory, we explored embodied practice from these two perspectives, juxtaposing them as a driving force in the collaboration. The entire working process was filmed by videographer Emmalisa Pauly.

At one point in the workshop, the choreographer asked Ek to use the clarinet as a pendulum while playing (see Figure 15). After some discussion with the composer Olofsson, we decided to use two multiphonics as material. The choreographer Was also asked Ek to start very close to the camera and move slowly backwards. Ek ended up playing for over 15 min, gradually moving farther and farther away from the camera. This seemingly simple setup conveyed a great deal of expressiveness, both visually and sonically. Ek pendular movement affected the dynamics of the multiphonics, giving each swing an extra push. This happens because the abdominal muscles change during pendulum motion, and multiphonics, in general, are quite unstable and require extremely controlled airflow. Instead of trying to minimise this effect as if it were unwanted, Ek instinctively made the dynamic changes larger. All three others in the group said after this episode that it looked like the body was driving the sound, which, of course, always is the case, but not in a visible way like this. Due to the long reverberation in the hall, the different pitches in the multiphonics remained and blended together in the space, creating a harmonic material that sparked Olofsson's interest, an aspect that was later picked up and developed electronically in the studio work that followed.



Figure 15. Multiple merged photos depict the pendular motion.

During this workshop, Ek also recorded the model's output. Because the model was trained on movement data from a conventional performance of Brahms' Sonata, Ek was unsure how it would respond to this choreographed episode. Ek was asked to annotate the Laban Efforts present in the workshop video. When comparing the annotations with the model's output, Froneman, as a CMA, observed that the model generally follows the contour of her analysis. Similar to earlier evaluations, the model outputs Effort in far more detail than the human eye can perceive. The model also presents an analysis of segments where Froneman does not deem that specific Effort important at that moment. In general, Efforts occur in combinations of two or three at a time. The combination of four Efforts is actually a rare event, but as the model only picks up on the clarinet motion, it cannot take the "bigger" picture into account to evaluate which Efforts are prominent and which are "in the background".

The pendular movement described above inspired Olofsson to write a new piece for clarinet and electronics. In *Pendulum Songs and Swings*, which premiered in April 2025, the pendular motion, combined with the model and multiphonics, forms the core elements of the piece. The four parameters output by the model (Space, Weight, Time, and

Flow) were mapped to four settings in the same software audio effect that Olofsson used for the tape parts. The effect, a VST plugin called GRM Evolution, can be considered a spectral sample-and-hold. It captures snapshots of the input's frequency content and morphs between them, creating a continuous sound that retains the original timbre but shows minimal dynamic variation. The timbre can be entirely frozen, and its character can be manipulated in various ways.

Ek describes working with the model in this piece as intuitive. He goes on to state that “in many ways I can foresee how the model will behave, but at the same time it also has its own agency, outputting data that surprises me. This balance between predictability and surprise creates a creative resistance in the system”. The decision to use the same audio effect across various parts of the electronic setup, both in the tape part and in the live electronics, was an important reason the finished live electronics, as experienced by several audience members, felt so homogeneous. The live clarinet, the live-processed clarinet, and the clarinet in the tape parts blend together, making it difficult to distinguish the different parts.

4. Discussion

The Laban Effort model we have developed serves as a bridge between the low-level bodily features of the performance and the high-level intentions of the performer. We adopted LMA because it enabled us to examine higher-level qualities of expressive movement. Evaluation of the model output by a CMA has validated the approach. Although this is beyond the scope of the article, the process has also highlighted how such a method could potentially become a tool for more fine-grained analysis of expressive movement in music performance, thereby contributing to improving the depth of LMA of music performance.

The data output by the Laban Effort model is rich in information related to the embodied manifestation of musical intentions, requiring both the performer and the CMA to explore these intentions further, especially regarding musical phrasing. It also illustrates the advantages of employing a mixed-method approach in both the design and evaluation of ML models, as the quantitative data reveals variables or differences between the training data and the model's output. By engaging with the qualitative data and relating it to the quantitative data, the qualitative approach offers interpretations aimed at describing and clarifying the similarities and differences. The “accuracy” and success of the Laban Effort model regarding individual Efforts are due to its training on Effort Phrasing and changes in Effort intensity. However, the output we compare against uses a “statistical” or quantifiable measurement, whereas Effort is a quality of motion that is not truly meant to be “quantifiable”. Therefore, when relating human analysis to the Laban Effort model's output, the two are not expected to be identical but should show similar tendencies.

4.1. Possible Contribution to LMA of Music Performance

The graphs representing the model's depiction of Effort (as presented in Section 3 above) are indicative of Effort's ever-present and continuously changing characteristics. In line with Laban's theory of Effort, the representation of Effort in the graphs is continuously and dynamically fluctuating. Unlike the very linear notation of the analyst, the model reflects the dynamism or ‘aliveness’ of human motion, capturing almost the humanly unobservable nuances in the variations of Effort. The model's reflection of smaller gestural/motion nuances and more extended musical nuances lends itself as a tool to the CMA to further extend observations to include and refine unobservable inflexions and nuances inherent to musical performance and gesture. The added granularity provided by the Laban Effort model magnifies details of the movement that would otherwise be

impractical to analyse. This allows the analyst to consider smaller scales of expressive movement and reflect further on the subtle dynamics in which such movements unfold.

4.2. Artistic Possibilities with the Laban Effort Model

As demonstrated in both the Laban analysis by Froneman and the stimulated recall analysis by Ek, the Laban Effort model effectively reflects artistically nuanced interpretations. Ek's use of the model in his artistic practice has demonstrated how it can access musical intentions in real-time and translate them into higher-level descriptors that can be used to develop interactive musical systems for mixed-music performances. In this way, the performer can concentrate on expressing themselves with their instrument, engaging with all the nuances of music performance, while still conveying expressive information about musical intent through the intermodal translation to the live electronic system.

5. Conclusions and Future Work

This study reports on the successful integration of LMA with ML techniques to facilitate real-time interpretation of expressive movement qualities in music performance. By combining qualitative movement analysis, based on Laban Efforts, with gesture data collected with motion sensors and IML approaches, the team has developed a system capable of translating embodied musical expressions into continuous control data. This data can subsequently be used to design live electronic interactions.

The findings indicate that ML models can capture nuanced fluctuations in movement qualities associated with musical phrasing and interpretation. The model frequently revealed subtleties that can be difficult to perceive through manual observation alone, suggesting that computational analysis may complement and extend traditional LMA practices.

The study further demonstrates the value of combining qualitative and quantitative methods in the design and evaluation of interactive musical systems. Qualitative analysis provided interpretive insight into the expressive meaning of movement, while ML enabled continuous, real-time estimation of Effort dynamics. This mixed-method approach enabled the system to serve as both an artistic tool for performance and a research instrument for investigating embodied musical interaction.

Although the model was developed using data from a single performer, the methods presented here may have broader applicability to music performance and movement analysis. A possible continuation could be to have other clarinetists use the model and assess how much the model output differs from the findings presented in this article. Such a study could identify areas that are more general and could be transferred to future, more general systems for real-time estimation of expressive movement qualities. Overall, the study highlights the potential of ML to support embodied approaches to music performance and interactive system design. Evaluations of the model's use in artistic practice indicate that it aligns effectively with the performer's musical intentions, reinforcing the concept of musical instruments as an extension of the human body.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/arts15070157/s1>.

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