Using Wearable Sensors to Measure Interpersonal Synchrony in Actors and Audience Members During a Live Theatre Performance

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Studying social interaction in real-world settings is of increasing importance to social cognitive researchers. Theatre provides an ideal opportunity to study rich face-to-face interactions in a controlled, yet natural setting. Here we collaborated with Flute Theatre to investigate interpersonal synchrony between actors-actors, actors-audience and audience-audience within a live theatrical setting. Our 28 participants consisted of 6 actors and 22 audience members, with 5 of these audience members being audience participants in the show. The performance was a compilation of acting, popular science talks and demonstrations, and an audience participation period. Interpersonal synchrony was measured using inertial measurement unit (IMU) wearable accelerometers worn on the heads of participants, whilst audio-visual data recorded everything that occurred on the stage. Participants also completed post-show self-report questionnaires on their engagement with the overall scientists and actors performance. Cross Wavelet Transform (XWT) and Wavelet Coherence Transform (WCT) analysis were conducted to extract synchrony at different frequencies, pairing with audio-visual data. Findings revealed that XWT and WCT analysis are useful methods in extracting the multiple types of synchronous activity that occurs when people perform or watch a live performance together. We also found that audience members with higher ratings on questionnaire items such as the strength of their emotional response to the performance, or how empowered they felt by the performance, showed a high degree of interpersonal synchrony with actors during the acting segments of performance. We further found that audience members rated the scientists performance higher than the actors performance on questions related to their emotional response to the performance as well as, how uplifted, empowered, and connected to social issues they felt. This shows the types of potent connections audience members can have with live performances. Additionally, our findings highlight the importance of the performance context for audience engagement, in our case a theatre performance as part of public engagement with science rather than a stand-alone theatre performance. In sum we conclude that interdisciplinary real-world paradigms are an important and understudied route to understanding in-person social interactions.

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2474-9567/2023/3-ART27
https://doi.org/10.1145/3580781

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CCS Concepts: • **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: face-to-face interaction, interpersonal synchrony, theatre neuroscience, live performance, audiences, wearable sensors

ACM Reference Format:
Yanke Sun, Dwaynica A Greaves, Guido Orgs, Antonia F. de C. Hamilton, Sally Day, and Jamie A Ward. 2023. Using Wearable Sensors to Measure Interpersonal Synchrony in Actors and Audience Members During a Live Theatre Performance. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 7, 1, Article 27 (March 2023), 29 pages. https://doi.org/10.1145/3580781

1 INTRODUCTION

Wearable devices enable face-to-face social interaction research to be conducted in ecologically valid settings, where stimuli are not limited to the confines of the laboratory. By no means are wearables a replacement for other forms of measurement such as audio-visual and self-report data, but an addition to the information we can collect on understanding implicit and explicit responses to stimuli. Expanding the data set brings challenges on how to set up research spaces to enable realistic social interaction but be conducive to empirical research. Testing the quality of the data we collect is of importance to the present researchers, hence, we created a proof of principle study to trial pre-existing technology and methodological designs within the context of live theatre. In this study researchers collaborated with Flute Theatre ([1]) company who specialise in creating adaptations of Shakespeare for autistic individuals, to create real world social interactions during a public engagement performance for a public audience. This collaboration is a continuation of our ongoing research on autism and theatre using wearable sensors, so the actors were familiar with collaborating with our scientific team [64]. The deconstructed style of theatre that is employed by Flute Theatre additionally allows for specific moments to be extracted from the play and replicated for audiences to have the opportunity to perform with the actors on stage, allowing us to measure the on-stage actor-audience synchrony. Here we measure physiological responses using head-worn IMU accelerometers, behavioural data using audio-visual recordings, and behavioural data using self-report questionnaires. The devices that we use are affordable and easily administered unto large populations. This enables the scalability of our measurement tools to the live theatre space.

Our research aim is to bring together these measurements and use them in the live theatrical space to measure real-world social interactions. We measure three dyads of interaction between: (1) actors-actors, which will reveal the synchrony that occurs when individuals are cooperating as a group to create a live artistic work. (2) actors-audiences which will reveal the synchrony that occurs between performers and observers of that performance; this can be seen as the communicators and receivers of that communication. (3) audience-audience which will reveal the synchrony that occurs between individuals having a group experience which in this case is coming together to watch the same live performance in the same space and time.

Interpersonal synchrony, as an important factor of social engagement, is objectively calculated using participants' movement data by applying cross-wavelet transform (XWT) and wavelet coherence transform (WCT). Wavelet analysis involves using continuous wavelet transform to change time-series signals into the time-frequency domain, making it possible to capture moments of synchrony or temporal coordination, across different frequencies. We extract information via XWT and WCT analysis about the various high and low frequency types of synchronous movement present during actor-actor, actor-audience and audience-audience dyads. We then pair this data with the audio-visual and self-report data to build a picture of what was occurring between dyads during the show, and infer how the audience felt about the show.

[1] https://flutetheatre.co.uk/

2 BACKGROUND

2.1 Face to face social interaction

Research on face-to-face interaction is built on foundations of experiments conducted in controlled laboratory environments where images of humans and avatars have and still are used to investigate social cognitive abilities such as empathy [40] and theory of mind [15]. Nevertheless, we cannot dispute that the most realistic replica of face-to-face interaction is an in-person face-to-face interaction in a naturalistic setting, where humans socialise for a given purpose. Although it can be argued that social interactions increasingly occur online, there is still an importance in building a body of research that investigates in-person social interactions. Our need for face-to-face communication and how this shapes our experience of the world is a topic that is of interest to cognitive scientists [44]. Studies have investigated how this manifests neurally [45] [25], behaviourally [24] and physiologically [10], as displays of communication are driven by seen and unseen processes, with the unseen being accessed through the development of appropriate measurement devices. In the present study researchers focused on a temporal dimension of connection, interpersonal synchrony, and investigated this during a group experience (watching a theatre performance) and during a group interaction (actors performing).

2.2 Interpersonal Synchrony and Performing Arts Research

Interpersonal synchrony is the temporal coordination of endogenous and/or exogenous actions between two or more individuals [68]. This coordination can be interpreted to have social significance, in that the strength of interpersonal synchrony between two individuals leads to cues about pro-social behaviour [8]. Synchronous individuals have been found to demonstrate higher early pro-social behaviour between infants and adults [55], extended self and other agency between adults [42] and cooperation in adults [56]. Temporal coordination occurs in natural everyday interactions and involves the entire body across various frequencies of movements and body parts, such as in movement and speech [46]. Research on interpersonal synchrony has gone beyond the focus of pairwise interactions and has expanded to look at large groups [9].

Group dynamics have been explored in the performing arts [36] with a focus on groups of spectators and performers. The present study also contributes to the investigation of group dynamics within performing arts spaces as we focus on synchrony in a group of actors and a group of audience members. It is of growing interest to the field of performing arts to collect data on their audience responses as organisations want to understand the relationship between their audiences and the work that they produce.

Wearable sensors have been used to measure synchrony during group social interactions [27] at multiple movement frequencies and can capture immediate and continuous responses. Importantly, wearable sensing happens in the background without distracting the audience from the unfolding performance, and does not require retrospective judgement [19]. It is of interest to present researchers to collect both implicit (wearable sensors) and explicit (audio-visual and self-report) data to assess relationships between the two. Whilst implicit data tells us a lot about autonomic bodily responses, self-report data is required to map often less specific psycho-physiological responses onto the subjective experience.

Research on audience physiological responses to live dance performances is increasing, with a wide variety of methods for extracting explicit and implicit feedback from audiences being explored. These include live tablet-based feedback [48, 57], video-based movement analysis [51, 52], and wearable physiological sensing [18, 50, 57, 61]. Recent research in live dance performances has also demonstrated the combination of wearable sensors, self-report and audio-visual data, e.g., [19]. In [19] study, audience members wore triaxial accelerometers in a custom-made device around their necks with acceleration being recorded at 20Hz. Self-report measures included post-show questions about audience members' enjoyment, immersion, mood and whether they would recommend the performance. Researchers found that joint coordination in acceleration variance enabled them to distinguish salient from non-salient moments of the performance, as they could predict self-report responses from acceleration data.

Other wearable devices, such as wrist-worn accelerometers, have been used in dance and movement research to measure whether unitary synchrony (same action at the same time) or distributed coordination (same action at different times) cause group affiliation [60]. [60]'s study was conducted in a dance studio where participants completed simple choreographic tasks (walking/running in circles, falling/tipping into walking and arm swinging) that were designed to produce synchrony or asynchrony among participants without explicit instructions to do so. They also had to complete an online rating task where they rated their experience of the workshop, and their group. In addition to that they completed an opinion task where they physically gave their opinions to survey items by standing in a space that represented 1-7 on a likert scale. Findings revealed that distributed coordination was a predictor of liking and positive feelings towards the group. These studies on live dance performances demonstrate the effectiveness of wearable sensors to collect data at various frequencies from audiences as well as performers. They also show the importance of collecting multi-medium datasets by including self-report data, which is also a practice we follow in this present study. Here we aim to continue building research on interpersonal synchrony during live performances with the difference being live theatrical performances.

Wrist-worn accelerometers have also been used during a theatrical performance in an investigation of interpersonal synchrony between actors and autistic children [64]. Findings revealed that various synchrony dynamics were able to be dissociated from the data, such as repetitive hand movements in time with the actors, twins within the audience synchronising with each other and the actors (although sitting apart at opposite ends of the room), and synchrony between children, the actors and the background music. This detailed breakdown of rich moments of group synchrony evidences the potential of even the simplest wearable devices for studying social interactions. Wearable accelerometers have also been used to investigate socially improvised movements in a public exhibition space where researchers were able to collect acceleration data from various body parts of participants; this data was then fed back into the installation. This highlights the effectiveness of participants' ability to interact and manipulate artistic installations due to the ease of using wearable devices [38]. As seen in these previous studies, there are different devices that can be utilised to measure interpersonal synchrony. The present study is part of an extended body of research where multiple datasets were collected, including data from wrist-worn physiological sensors (Empatica E4). However, the data analysis in this paper is based on acceleration data collected from tri-axial accelerometers in simple IMUs worn on the foreheads of our participants.

2.3 Theatre as a place to measure face-to-face social interaction

The ease of wearability whilst in public performance spaces is efficient for the theatre space. Theatre is a rich place to study face-to-face social interactions as the co-presence of performers and audience members is a specific feature of this live performing art in comparison to other art experiences such as static art in an art gallery or watching a film. The actors are living and breathing in the same space as the audience, verbally and non-verbally communicating with the audience [30, 37]. Here we can already see three types of dyadic interaction: actor-actor, actor-audience, and audience-audience. It is important to note that all three combinations feed into one another, hence why theatre makers are equally as interested as scientists in the types of interactions that occur within the theatre space. In addition, the bodily and mental experience of their performers and audiences [4] [47]. Social interactions in the theatre are choreographed and reproducible, making them accessible to empirical research as this relies on replicability. Theatre performances are arguably the best approximation of social interactions in the real world, yet allow for experimental control and manipulation. Although it can be argued that the actor may not feel the same during every performance, the plot of a play typically remains the same for every run of the performance. As well as being replicable, the theatre allows for adaptation that can still be seen as ecologically valid. For example, in the present study our show includes a participatory period where some audience members have the opportunity to join the actors on stage as part of the performance, while others remain in their seats. This is ecologically valid for theatrical styles such as forum and immersive theatre [5] [33]. One of the research questions of the wider project was whether audience participants (those who go on stage) have more engagement with the performance compared to audience spectators (those who remain in their seats). Research designs such as ours allow for the theatre industry to explore the effects of different styles of theatre, working outside of the traditional actors on stage and audience members in their seats set-up. Wearable devices mean that the theatre industry can be creative when investigating different styles of theatre because our devices can adapt to the performance. Refocusing on the topic of social interaction, by including a participation period we are able to manipulate the proximity of audience members to the happenings on the stage and investigate whether synchrony levels change between audience participants and spectators at different parts of the performance.

Successfully collecting synchrony data during social interactions within spaces that can cause a lot of artifacts and noise, enables the ecological validity of social interaction research to be improved. It also highlights the technical adaptations that may be required for wearable devices, as well as fine-tuning the methodological paradigms that researchers can explore to truly help us understand real-life social interactions. The richness of movement that is displayed during theatre performances is of interest to researchers as they can be seen as exaggerated or realistic replicas of the dynamics of social interaction including speech, facial expressions, gestures, and body language [3]. To successfully extract various frequencies of synchrony data in these environments will lead to the creation of blueprints for research on social interaction in different real-world settings. This will continue to provide insight into the different ways humans synchronise when we communicate.

2.4 Related work on wearable and social sensing

The automatic sensing and processing of social behaviours - or social signal processing [58] - has attracted much interest due to the availability of cheap wearable and mobile sensor devices (e.g. [39]). One of the early works on social sensing, the Sociometer, used wearable audio, motion and proximity to explore face-to-face interactions [7]. More recently, studies have explored the potential of wearables and mobile devices to recognise different social situations such as, whether people are walking together [17], moving together in groups [20], or simply using social gestures [32]. Similar to the present focus on theatre, wearable physiology and movement have also been used to measure student engagement [16] and attention [69] in the classroom. Electrodermal activity (EDA) and measures of heart rate variability were used to explore the presenter-audience relationship during conference presentations, revealing a link between physiological synchrony and self-reported engagement [18]. Interpersonal physiological sensing has also been used to uncover moments of dyadic connection in patients with dementia [12]. Multisensor wearables have been used to analyse the success of potential partners at speed dating during freestanding conversation [6]. The combination of simple movement sensors and microphones has been shown to reliably recognise collaboration of co-workers during physical tasks [63]. Even the simplest body-worn sensors can be a rich resource for studying complex social situations. With a single accelerometers ability to detect diverse information such as a person's age, gender and height [43], ambulatory activities [34], or surgical skill [31], when scaled to multiple people, the potential for recognising complex social situations is huge [28, 64]. Despite arguments on the limitations of accelerometer-based sensing (e.g. for activity recognition [53]), the present work aims to support the efficacy of wearable accelerometry as a powerful tool for studying complex social dynamics in group environments like the theatre.

2.5 Measuring synchrony

Dyadic body movement coordination has previously been studied using Pearson's cross-correlation [41]. Similarly, linear methods have been used to study cardiographic and respiratory entrainment of audiences during a dance performance [1], or to detect cooperation of workers in assembly tasks [63]. Measures like this are a common way to measure time-series similarity but are limited because, being strictly time-domain,they cannot capture moments of synchrony at different frequencies of interaction. The use of similarity measures like dynamic time warping, for example, used in related work on audience-presenter entrainment [18], is one solution to the problem. However, some information across different frequencies of interaction might still be lost. To capture these rhythmic coordinations more completely, a temporal-frequency analysis can be used. One approach is to calculate the Fourier response of each signal (e.g. Fast Fourier Transform (FFT)) and combine these to produce a measure of spectral coherence [65]. The problem then is that the underlying FFT requires both signals to be stationary (i.e. constant frequency response for the evaluation duration). A typical solution to this is to apply the FFT on short sliding windows. However, windowing leads to the unavoidable loss of low-frequency information, and also a loss of temporal resolution at higher frequencies. Wavelet analysis provides a way of decomposing a signal into its frequency components while preserving temporal information. Obtaining the continuous wavelet transform (CWT) from two signals and then combining these reveals a temporal-frequency response common to both signals. Torrence and Compo [54] introduce the basic premise behind the cross-wavelet transform (XWT) and cross-wavelet coherence transform (WCT). Historically, cross-wavelets were used to study co-variations in weather patterns [35, 54] and in Geophysical time series [22]. Recently, cross-wavelets were used to analyse movement features from dyads in conversation, and revealed how people tend to synchronise with one another at specific frequencies [14, 23, 24]. In a theatrical setting, XWT analysis of video data was used to show how dancers entrain more effectively to one another compared to non-dancers [66]. Wavelet analysis has the advantage of not requiring a sliding window, and is, therefore, free of the time-frequency resolution trade-off, which is well suited to analysing the co-synchrony of two movement signals. Here we measure interpersonal synchrony over time and frequency using wavelet analysis of participant's head movement intensities. The implementation of XWT analysis used in our work, and the adoption of multi-person interaction matrices, builds on an earlier work studying the coordination between actors and autistic children [64].

2.6 Aims

This study is the first to measure interpersonal synchrony in actors and audience members during a live theatrical performance open to members of the public, using head-worn accelerometers. Here we focus on the technology and methodology needed to achieve this. This study is part of a larger body of research entitled 'Deconstructing the Dream' where the extended research team were also the first to measure prefrontal cortex activity and interpersonal coordination in actors during rehearsals with portable functional near-infrared spectroscopy [21].

The present study has two aims, to: (1) demonstrate the use of head-worn wearable accelerometers to record group interpersonal synchrony during a live theatre performance, and (2) assess an interdisciplinary methodological paradigm based on theatre that enables us to conduct real-world, in-person research on social interaction. To achieve these aims, we measure interpersonal synchrony among actors and audience sensor data using Cross Wavelet Transform (XWT) and Wavelet Coherence Transform (WCT) analysis paired with video data and self-report measures. As an additional contribution to this work, the full annotated dataset is freely available to download (see the section on data preprocessing).

3 METHODS

3.1 Participants

28 participants (female = 12) were recruited for this study, with an average age of 36.71. This includes 6 actors from the Flute Theatre company and 22 audience members who bought tickets to watch the show and voluntarily selected to be participants for this study. Audience members were divided into two groups: 5 audience participants (P) who went on the stage to take part in the participatory period of the performance, and 17 audience spectators (S) who remained in their seats throughout.

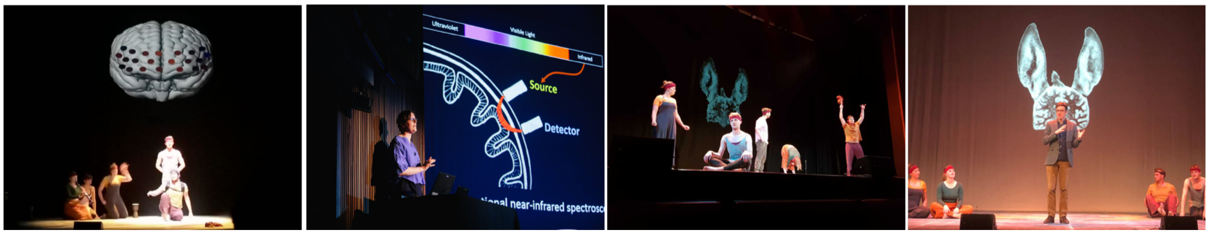

Fig. 1. Four moments during the performance (left to right): Act 1 (with visualisation of an actor's on-stage live brain scan), Science talk 1 (actors not on stage), Act 2 (note sensor-embedded headbands worn by the actors), Science talk 2 (actors on stage, also shows visualisation altered by live audience movement).

The study was ethically approved by the psychology department's ethics committee at Goldsmiths, University of London.

3.2 Design

The event was based around a blend of science talks and an adaption of Shakespeare's A Midsummer's Nights Dream' and took place on two consecutive evenings in May 2019 at Bloomsbury Theatre, London. Although data was collected from two performance nights, technical problems meant that much of the first night's video and labelling data was missing and so only the second night's data is analysed in this paper.

The event was comprised of three elements: acting, science talks and a participatory period. The order of the event was: 'Act 1', 'Science Talk 1', 'Interval', 'Act 2', 'Science Talk 2', 'Participatory Period' ('Game1', 'Game2', 'Game3') and 'Show end'. Figure 1 shows four of these moments (the participatory period is not shown for audience privacy reasons), with the exact timings of the events listed in Table 1.Audiences and actors were given headbands with accelerometers fixed on their foreheads and instructed to wear this throughout the performance. Before the performance, audience members completed a pre-show survey from a paper booklet. During Act 1, the actors performed on stage whilst the audience members were seated in the auditorium [2]. During Science Talk 1, scientist A gave a presentation on stage whilst actors were offstage and the audience members remained in their seats, this was followed by a presentation from the artistic director and then the last remarks from scientist A. In this period, the actors removed their sensors, so there is no data from them at this time. During the interval, everyone was free to roam inside and outside the auditorium. In Act 2, the actors performed on stage while the audience remained in their seats. During Science Talk 2, scientist B spoke on stage whilst the actors were seated on stage. Scientist B initiated synchronised movement (head nodding) with the audience to perform a virtual demonstration on the screen. During this section, some of the audience movement data was live-streamed and visualised on stage. When scientist B finished the talk, audience participants were invited on stage to take part in the games (detailed below). During the participatory section of the performance, audience participants played three games, with every game involving a demonstration from the actors and an explanation from the director before commencing play. Once the last game was over, participants returned to their seats for some closing remarks from scientist B. At the end of the performance, audience members completed a post-show survey from a paper booklet and returned their headbands.

3.2.1 Audience participation games. The purpose of the participation games was to share with the audience the main components of Flute theatre's theatrical adaptations of their performances for autistic individuals. Their games are a part of the 'Hunter Heartbeat Method' [29] and focus on eye contact, mirroring behaviour and

[2]This section of the performance included a 'World-first' live scanning and public visualisation of an actor's brain using wearable, functional near-infrared spectroscopy (fNIRS), provided by Shimadzu (https://www.shimadzu.eu/).

Table 1. Important moments during the performance

Moment		Time
Show start		19:35:00
Part 1	Act 1	19:35:59
	Science talk 1	20:06:41
Interval		20:42:54
Part 2	Act 2	20:57:14
	Science talk 2	21:16:40
	Participation	21:24:37
	Game 1 starts	21:29:56
	Game 2 starts	21:33:01
	Game 3 starts	21:35:12
Show end		21:54:33

trust. Game 1 portrays the moment when Titania professes her love for Bottom, but Bottom rejects her love. The purpose of the game is about making eye contact a safe, humorous and enjoyable experience. One actor has the role of the fairy queen Titania and the other has the role of Bottom the man with a donkey's head, which is indicated by holding hands to the sides of the head as donkeys ears. Titania moves around the space until she can make eye contact with Bottom and then says 'Doy-yo-yo-yoing; I love thee!' while extending her hands from her eyes in a binocular shape. In response, Bottom becomes alarmed and turns his back on Titania. Titania then moves around the space to capture Bottom's gaze again, and the scene can repeat as many times as needed. Game 2 portrays the moment when Demetrius and Lysander fight over Helena. The purpose of this game is to develop the skills of mirroring and imitation. The game resembles a sword fight where each person has a turn of 'striking' the other person from a distance, and the other person has to dodge the strike. Game 3 portrays the moment when Puck calls out the characters' names in the darkness, making them follow his call. The purpose of this game is to develop trust. One person plays Puck and calls out the person's name, with their eyes closed, the person has to follow the sound of their name.

3.3 Materials

3.3.1 Post-show survey. Participants were asked 12 closed-ended questions about their engagement with the performance. Each question was rated on a 1-5 Likert scale with 1 meaning 'Not at all' and 5 meaning 'Completely'. The 12 questions were used twice, once for the acting element of the performance and secondly for the scientific element of the performance. Table 2 displays the questions and their coded names for data analysis. A pre-show survey was also conducted, but is not analysed here. For both surveys in full, see Appendix.

3.3.2 Sensor data collection. The sensors used in this study are MetaMotionR from MBIENTLAB INC, which benefits from its small size (2.7cm x 2.7cm x 0.4cm) and low weight (2.7g)[3]. MetaMotionR sensors are attached to the head of actors and audiences. The accelerometers were recorded on-device with an (approximate) 25Hz sampling rate and the 3-axis acceleration data were collected throughout the performance. The data is logged and saved to the onboard memory, then downloaded to a laptop via Bluetooth Low Energy (BLE) after the performance.

[3]https://mbientlab.com/

Table 2. Post-show survey questions about the actors and scientists performance

Code	Question
Absorption	To what degree were you absorbed in the performance?
Inhabit	To what extent did you inhabit the world of the performers, lose track of time and forget about everything else?
Emotional Response	How would you characterize your emotional response to the performance? (Weak to Strong)
Bonded	To what extent did you relate to, or feel bonded with, one or more of the performers?
Theraputic	To what extent was the performance therapeutic for you in an emotional sense?
Uplifted	How much did the performance leave you feeling uplifted or inspired in a spiritual sense?
Transcendent	To what degree was it a transcendent experience for you, in the sense of passing into a different state of consciousness for a period of time?
Empowered	To what extent did the performance leave you feeling empowered?
Belonging	To what extent did you feel a sense of belonging or connectedness with the rest of the audience?
Cultural Heritage	To what extent did the performance serve to celebrate and sustain your own cultural heritage?
Outside Exposure	To what extent did the performance expose you to one or more cultures outside of your own life experience?
Social Issues	Did the performance leave you with new insight on human relations or social issues, or a perspective that you didn't have before?

To obtain the magnitude acceleration for further processing, the x,y, and z-axis acceleration signals were combined using the root sum square (Euclidean norm). All the signals are resampled to exactly 25Hz to ensure each sample point has a 0.04s interval before software synchronisation.

Although a detailed analysis is outside the scope of the current paper, additional data was live-streamed to provide live visualisations and sonifications of audience movement during the interval and Science Talk 2. For this purpose each audience member wore an additional sensor which was programmed to transmit a combined acceleration magnitude signal via BLE to a series of Raspberry Pis positioned on-stage, which in turn controlled the theatre visuals and sound using Open Sound Control (OSC) [67].

3.3.3 Procedures for live data collection. Assembling a well functioning team is critical for a successful live performance. This team must work in unison with the front (e.g., performance manager, ushers and box office) and back of house team (e.g., production, directors and technicians) at a venue space. To usher the audience into the live experience, we had a sign in desk where they would retrieve their wristband signifying whether they were an audience spectator or participant. Next, there was a separate sensor team that placed the sensors on the audience members as well as giving them the pre-show questionnaire booklet. There was a sensor team for the actors to ensure they were wearing their sensors before Act 1. Prior to the placing of the sensors on the heads of actors and audiences, scientist B was designated to synchronise all sensors before they were given out. At the end of the performance, the sensor team had to retrieve all the sensors and give the audience a post-show questionnaire to complete.

3.4 Data Synchronisation and preprocessing

It is critical to ensure that individually recorded signals of multiple subjects are accurately temporally synchronised to study the interpersonal synchrony between people. The synchronisation actions, i.e. shaking sensors simultaneously, are performed twice during the performance to generate easily identifiable pattern events in every sensor. Due to technical issues with the availability of actors at the start of the performance, the first syncs for actors and audiences are at different times. The first sync action is for the audience's sensors that happened before the start of Act 1, while the second sync action is performed for the actors' sensors at the interval. All the sensors are shaken together after the end of the show as the third sync action. As shown in Table 3 and Figure 2 (a) at sync action periods, there are large time offsets between raw data from distinct sensors. Therefore, software temporal sync techniques are introduced to reduce the sync time errors, with the use of multiple sync events to align signals.

The simplest synchronisation method is time shifting using kinetic events [2, 64]. One sync event is used to find an anchor point for each signal. The troughs at the third sync action are identified as the anchor points in our data. All signals are then shifted according to the anchor point to align with a selected reference signal. However, the time lags generated by sensors are not constant versus time. The shifting method can only guarantee low error around the sync action used for shifting, and the time errors at the first and second sync actions are still significant due to drift, as shown in Figure 2 and Table 3.

We use signal interpolation to automatically correct for this drift. This is done as follows:

(1) Two anchor points are first selected from the two sync action periods. These are chosen as the first peaks that appear in the signal during each action.
(2) Each signal is cut into the range that starts from the first anchor point and terminates at the second anchor point, ensuring signals start and end simultaneously in the real-world timestamp.
(3) Interpolation, using Matlab function *interp1*, is applied to each signal to allocate the same number of temporal data points between two anchor points. Because our data includes many flat regions with little movement, we choose the Shape-preserving piecewise cubic (pchip) interpolation, which can precisely connect the flat region of signals and avoid overshoots [11].

Table 3. Synchronisation offsets

Sync method	Sync time error (ms)			
	Sync events	1st	2nd	3rd
Raw data	mean	1534.0	3772.5	3107.6
	std	1274.3	2490.6	2936.7
	max	5486.0	8204.0	16538.0
Time shift only	mean	284.3	128.0	15.7
	std	222.4	81.6	12.1
	max	920.0	280.0	63.0
Shift and interpolate	mean	18.2	13.3	16.9
	std	19.9	18.9	19.8
	max	40.0	40.0	40.0

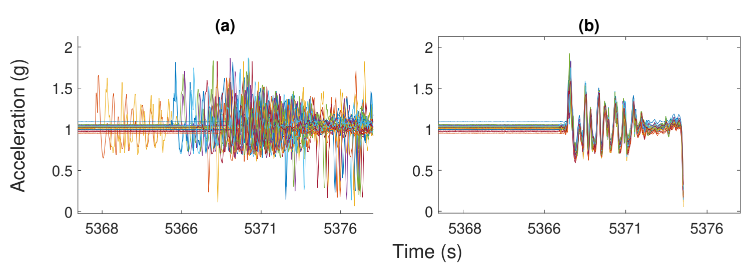

Fig. 2. (a) Raw acceleration data and (b) Software synchronised data by using the proposed method at the third sync event.

The synchronised data are filtered by a 4th-order Butterworth filter with a 10Hz cutoff frequency to remove high-frequency fluctuations after the software sync. Figure 3 shows the synchronised acceleration magnitude for all 28 subjects during the whole performance. Note that because of the difference between the actors' and

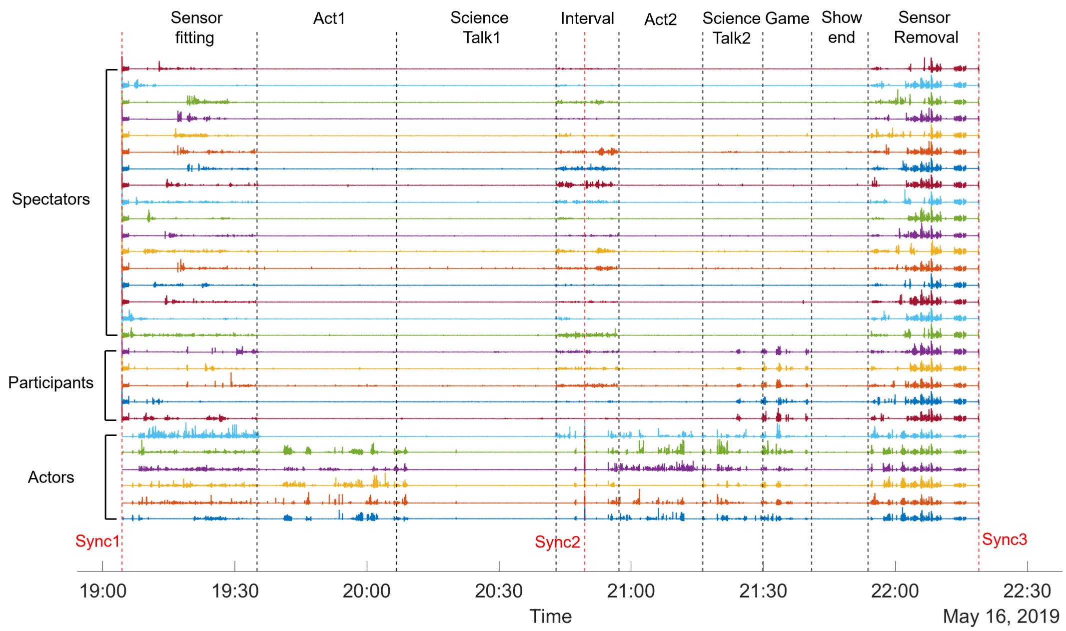

Fig. 3. Synchronised acceleration magnitude of actors, participants and spectators. The black dotted lines present different sections of the show, and the red dotted lines show the synchronisation events.

audience' first sync point, steps 1 to 3 are applied separately to the actors' and audience' signals before shifting to align them all to the final sync anchor point. The sync errors are reduced to tens of milliseconds at three sync events as shown in Figure 2 (b) and Table 3.

The final synchronised dataset, complete with meta-data and questionnaire results, is available to download from OSF. [4]

3.5 Cross wavelet transform analysis

Interpersonal synchrony between people can be analysed by the common time-spectral response of two time-series movement signals. After applying continuous wavelet transform (CWT) to two signals to decompose them into frequency domain while the temporal information remains, combining the two CWT outputs offers a way to acquire the common time-spectral response. Cross wavelet transform (XWT) and wavelet coherence transform (WCT) are the two related methods of combining CWT outputs from two signals. XWT reveals frequencies with high common power, while WCT highlights common frequencies regardless of power in the two signals [54].

The XWT of two time series x_n and y_n (n=1,...,N) is defined as [23]:

$$XWT : W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s) \tag{1}$$

Where s is the scale of the wavelet used in CWT, W^X and W^Y are wavelet coefficient output obtained by applying CWT to x_n and y_n, respectively, n is the sample number (from a total of N samples), and $*$ denotes complex conjugate. The XWT power is further defined as $|W^{XY}|$.

[4]Download dataset: https://osf.io/vr9mn/

WCT power of two-time series is defined as the normalising of two signals' power according to [54]:

$$WCT : R_n^2(s) = \frac{|s^{-1}S(W_n^{XY}(s))|^2}{s^{-1}S(|W_n^X(s)|^2)s^{-1}S(|W_n^Y(s)|^2)} \tag{2}$$

Where S is a smoothing operator(see [22] for details)

CWT is applied to the synchronised signals (Figure 4 (a) and (b)) before the outputs of each pair of participants in the performance were combined using XWT and WCT techniques (Figure 4 (c) and (d)).

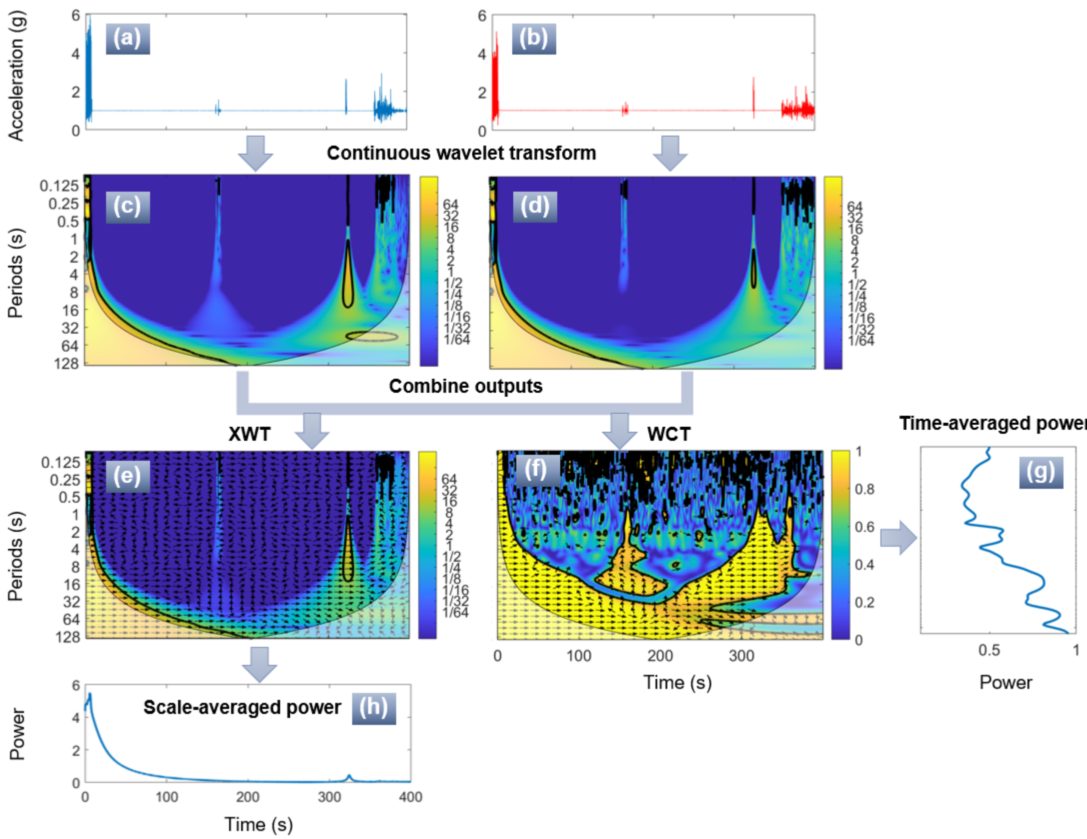

Fig. 4. Cross wavelet transform analysis. (a) and (b) are part of the head acceleration data from actor 0 and actor 1. (c) and (d) are the Continuous wavelet transform outputs of (a) and (b). Combing the outputs (c) and (d) gives the cross wavelet transform (e) and wavelet coherence (f) time-frequency spectral. Scale-averaged power (h) and time-averaged power (g) are calculated from cross wavelet transform power and wavelet coherence power.

The XWT power and WCT power were computed using the MATLAB toolbox from Grinsted et al. [22] and MATLAB function *wcoherence*, respectively, with default Morlet wavelet. To avoid the edge effects, the results of the XWT and WCT were discounted from the 'cone of influence' (COI) (i.e., the pale areas in Figure 4 (c) and (d)).

The XWT/WCT power is averaged across a set of periods for each individual pair to acquire the scale-averaged power against timing within the performance (Figure 4 (h)). Then, the scale-averaged power is averaged across the time course of specific activities during the performance for every combination pairs, which are then used to create interaction matrices (as first used by [64]).

The XWT/WCT power is also averaged over the time course of each section in the performance for each pair of individuals to obtain the time-averaged power over frequencies (Periods) converted from CWT scales (Figure 4 (g)).The wavelet output is truncated in the periods from 0.5s to 60s with a total of 84 different periods. To prevent the synchronisation error from influencing the results, periods smaller than 0.5s are not considered. Some of the sections in the performance (e.g. the three games sections) only last several minutes. Therefore, periods larger than the 60s are also rejected to avoid using results in the region of COI. Finally, the mean time-averaged power and scale-averaged power of different groups of people are calculated by averaging the power in a particular group, ie. actors, participants, spectators, actors & participants, actors & spectators, and participants & spectators.

4 RESULTS

4.1 Interaction matrices

Interaction matrices are utilised to discover the interpersonal synchrony between any combination pairs of actors and audience members for different sections of the show. Act 1 and Act 2, two Science Talks and three games sections are combined into Act, Science Talk and Games sections, respectively. XWT power is used in the interaction matrices since it is more beneficial to see the synchronisation of more significant movements and provide a general overview of the interaction between people [64]). The interaction matrices shown in Figure 5 are calculated using averages across the 5s-60s period (scale) bands since we are more interested in larger movements and the overall level of interaction between actors and audiences for these longer sections of the show. In Figure 5, actors are labelled as A, audience participants as P, and audience spectators as S. There are several interesting findings to be noticed:

(1) The dark blue region in Figure 5 (a),(b) and (c) illustrates that the six actors (A0 to A5) are highly synchronised in Act and Science talk section, and both the actors and participants (P0 to P4) are tightly coupled during the Games section (The values above 0.03 are plotted as a single colour). People are found to interact more when they are on stage. The actors movements synchronised with each other more during the Acts and Science talk sections, while participants and actors movements synchronised more in the games section. The speakers in the science talks were not wearing sensors, so they are not shown in the data.
(2) In the games section, more spectator pairs have higher averaged powers in the 5s to 60s frequency range than in the other sections. This shows that the participatory period not only boosts the interaction between actors and the participants involved in the game but also increases the connection between actors and the seated audience members.
(3) Interaction pairs can be clearly spotted from the interaction matrices. For example, A4 and S12 form a pair in the Science talk and Game sections.
(4) People who have relatively high synchronisation with one person tend to have relatively high power with any other individual pairs. For example, A4 appears to have relatively higher power with the audience members in Act, Science talk and Games sections. It is worth noting that actor A4 was particularly visible during Science talk 2 and can be clearly seen to the centre left of the speaker in Figure 1. Relatively Higher power can be seen in all four sections for P2. In contrast, S3 rarely interacts with the audience members during the performance.

This kind of data can be valuable for indicating the reactions between audiences and performers to analyse audience members' overall experience.

Figure 6 shows interaction matrices using XWT and WCT from two examples from part of Act 2: an instance of dancing (a-c), and an instance of sword fighting (d-f). These activities lasted just under 1 minute, so the period range chosen for consideration is the average from 0.5s to 5s. (Note that A2 is not on stage during Act 2, so

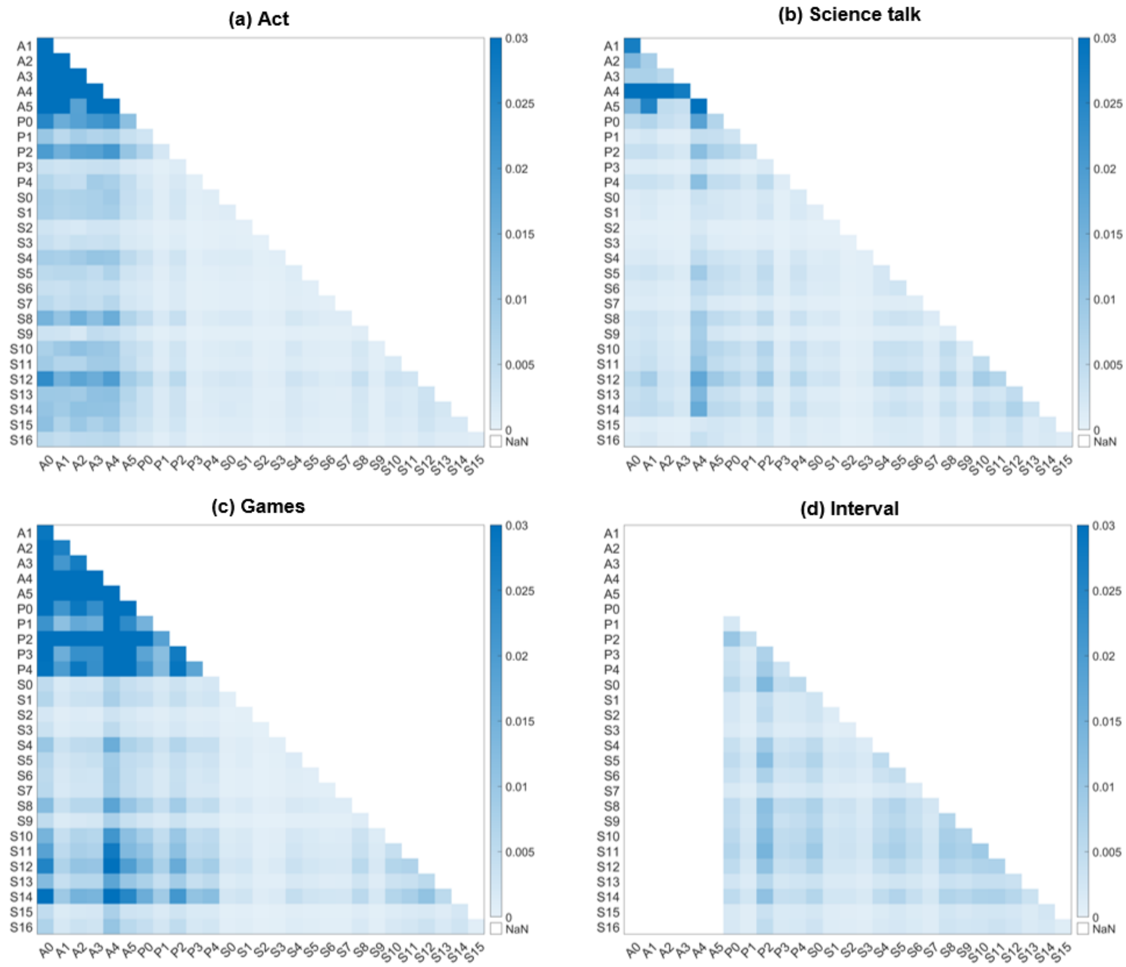

Fig. 5. Interaction matrices using XWT power for different sections of the show.

the interaction matrices do not include A2.) We compare the effectiveness of XWT and WCT techniques for identifying interaction pairs in these two activities.

For dancing, shown in Figure 6 (b), $A0$ and $A3$ danced together, which is reflected in the high XWT and WCT power between them (Figure 6 (a & c)). A1, A4 and A5 were fairly still for most of the time, while A5 played the guitar. WCT captures the coherence of smaller movements from $A4$ as they watch $A5$ play, shown in Figure 6 (c). Coherence is also apparent with $A1$ as they watch (and subtly move with) $A4$ and $A3$.

There is much more movement happening during the fight sequence, shown in Figure 6 (e), where $A0$ and $A4$ fought while $A3$, $A1$ and $A5$ watched on. Note how the relative stillness of $A1$ watching on is reflected in their comparatively low XWT but high WCT power when compared to $A3$, $A4$, and $A5$. That is, A1 was actively watching, but not moving as much as the others (only small head movements). This is revealed in their high

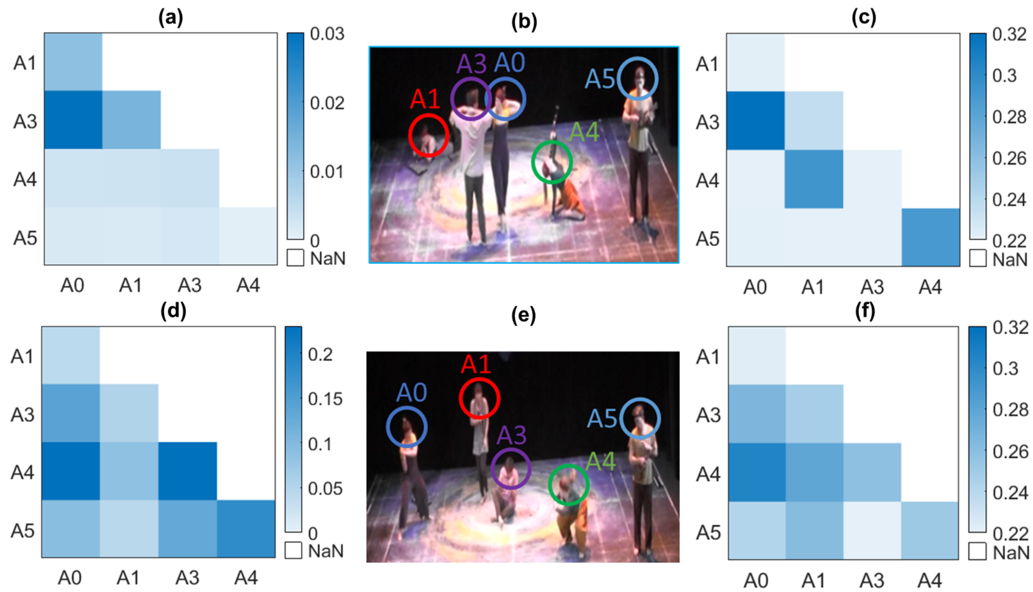

Fig. 6. Interaction matrices (IM) between actors pairs for two short periods of activities during Act 2. (a) IM using XWT power, (b) photo and (c) IM using WCT for the Dancing period, (d) IM using XWT, (e) photo and (f) IM using WCT for the Sword fighting period.

coherence values using WCT (Figure 6 (f)), but lower values for XWT (d). Conversely A3 has high XWT synchrony with A4 (they were in the middle of the fight, facing A4, and would move out of the way occasionally).

Sword fighting involves rapid reactions and more powerful movements, while dancing is more gentle; therefore, the XWT power of sword fighting is much higher than that of dancing. In contrast, WCT analysis outputs power on the same scale, which is not affected by the activities' strength, so different scenarios can be easily compared. The XWT method is more suitable for seeking correlation of more significant movements (e.g. synchrony between actors on stage), but not good at finding the correlation between signals with lower power. WCT is more useful for determining interpersonal synchrony involving small movements, especially movements that cannot easily be evaluated by eyes.

4.2 Time-averaged power

The time-averaged WCT powers of different groups of people are compared for different performance sections as shown in Figure 7. WCT power is used since it can spot synchronisation between people regardless of the power of their movements. In the two Acts and Science Talk sections, audience participants and audience spectators are all seated, so they are regarded as audience members. It should be noted that the speakers in the Science talks were not wearing sensors and actors were offstage during Science Talk1. As expected, the WCT power between actors is found to be dominated for most of the activity periods during two Acts and Science Talk2 sections (Figure 7 (a),(d),(e)), since they were on stage at these moments and had many interactions. In contrast, the WCT powers between audiences and between actors and audiences are similar and relatively stable for the 0.5s to 60s period range during these sections.

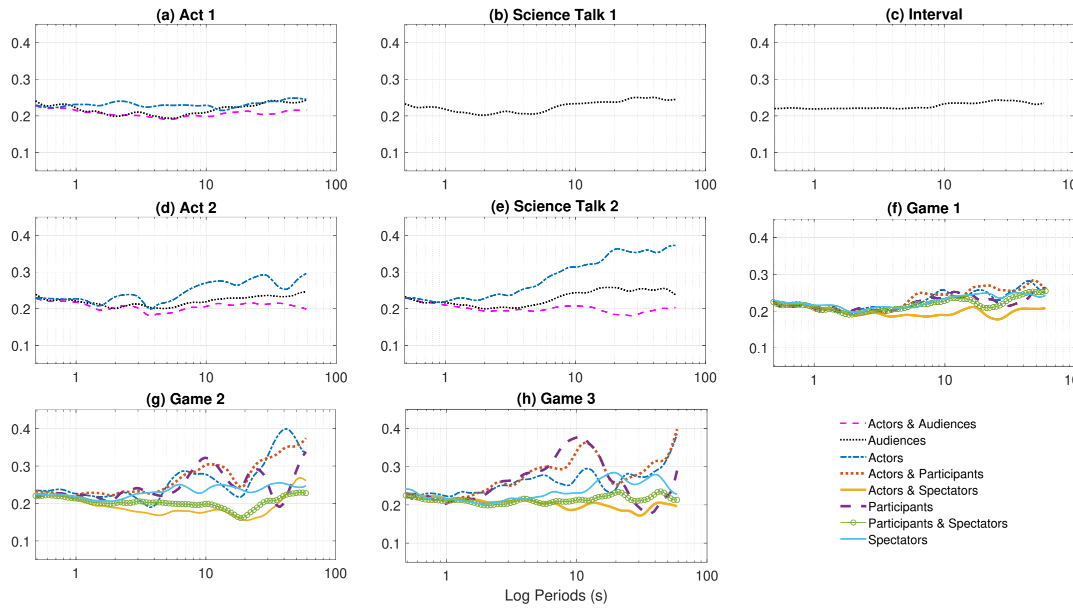

Fig. 7. Time-averaged WCT power is shown for different sections of the show. The means of time-averaged WCT power of appropriate groups of people for the different sections are calculated, i.e. actors, audience as a whole, audience participants and audience spectators. For example, the game sections have the audience separated into participants on the stage and spectators, which is not the case for Acts and Science talks. Periods are plotted in log scale with the range from 0.5s to 60s.

The game sections ((Figure 7 (f),(g) and (h)),) involve participatory activities with participants joining on stage, so that we can see the WCT power between participants and between participants & actors rises, which is higher than the power between actors at specific periods. The power peaked between participants (thick dash purple line) and between actors & participants (thick dot red line) at the period around 10s during Game 2 (Figure 7 (g)) and Game3 (Figure 7 (h)), respectively. Higher power is observed between actors and participant groups (thick dot red line) in Game 2 and Game 3, while the power between actors and spectators (thick yellow line) stays at the lowest level in all three game sections. During the game section, participants were paired with an actor or another participant. Synchrony may have peaked in Game 2 due to the style of the game but also due to participants becoming more acquainted and perhaps comfortable with each other and the actors. Whilst Game 1 requires dynamic movement of the arms being extended from the eyes of one person as they try to gain the affections of the other person, Game 2 and 3 require dynamic movement from both persons as Game 2 is a mirroring exercise of fighting movements. The entire body engages in combat, as you anticipate where one person will strike and respond to that strike. In contrast, Game 3 requires one person to move into a space and call the other person's name and the other person has to follow the sound by walking with their eyes closed. All three games require different bodily motions as there are different social reactions, i.e., eye contact, mirroring, and response to your own name/sound. The power may be low between actors and spectators during all games due to the fact that spectators were watching rather than participating.

There are more variations in the game sections for the larger period range. Hence, in the next section, we will investigate the scale-averaged power in the games sections along the timeline over the 5-60s period range using both XWT and WCT techniques.

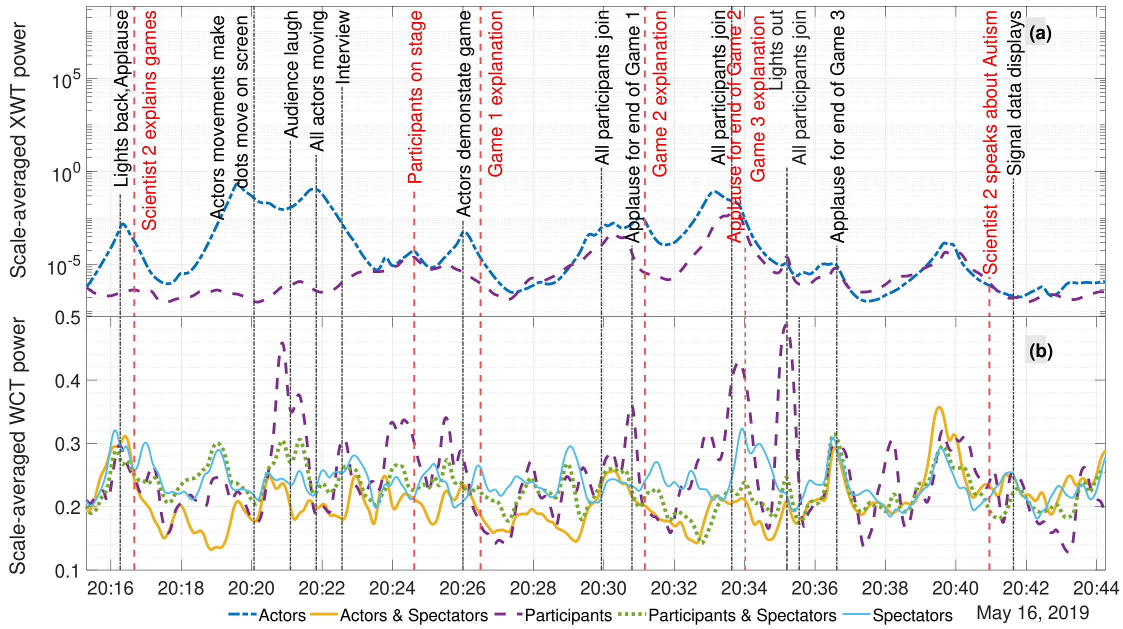

Fig. 8. The mean of scale-averaged power of groups during the games sections is shown in (a) using both XWT and (b) WCT power for comparison. The scale-averaged XWT power is calculated between actors and participants, while the scale-averaged WCT power is computed between participants, actors & spectators, participants & spectators, and spectators. The period range used for average is from 5s to 60s. Vertical lines show the important timestamps during game sections.

4.3 Scale-averaged power

The scale-averaged power is computed to investigate the interpersonal synchrony between different groups of people against the timeline of parts of the performance. XWT power is used to explore groups of people with similar strength of movements while the movements are relatively big. (e.g. actors and participants play games on stage). In contrast, WCT power is applied to groups with notable differences in their movement power (e.g. between participants who play games on stage and spectators who remain seated) or groups with relatively small movements (e.g. between seated audiences).

Figure 8 displays the power between different groups of people during participatory periods utilising both XWT and WCT analysis. The scale-averaged XWT powers between actors and between participants are revealed in Figure 8 (a). The power between actors remains high because actors always stay on stage, who demonstrate and play the games with continuous and extensive strength of movements. It is also clear that the participants' power is lower before they go on stage and increases after they join the games, aligning with the power between actors. Figure 8 (b) compares the WCT power between 4 groups of people, which shows a significant expansion in power between participants after they are on stage and during the games sections. However, the rest of the groups' WCT powers are relatively stable before and after the participatory periods, fluctuating slightly all the time.

During applause periods, we can see growth in the power of both XWT and WCT between all groups of people. Nevertheless, it is more apparent to capture by WCT power because applause is associated with slight movements of heads. It is also interesting to note that the power between participants in the three games differs in XWT and WCT analysis. Game 1 and 2 involve more large movements (e.g., jump, turn and sword fighting), and Game 3 contains slow walking in the darkness with smaller head movements but continuously. The XWT bias towards higher power is reflected by the corresponding peaks in the first two games while reaching a shallower peak in game 3. In contrast, the WCT power between participants achieves the highest value in game 3.

Next, we investigate the synchrony between the audience in more detail within a smaller time range, so the scale-averaged WCT power is averaged over 05.s-5s period ranges for part of Act 2 (Figure 9). A prominent peak is observed when the audience laughs, which can also capture by WCT power using a 5-60s period range (Figure 8 (b) between 20:20-20:22). But this is not seen explicitly in the XWT power (Figure 8 (a) between 20:20-20:22), due to the strength of the head movement being small during laughing. The scale-averaged power also reaches a peak when $A3$ speaks to the audience, indicating the connection between the audience and the actor when the fourth wall (the metaphorical wall blocking direct communication between actors and audiences) is briefly broken and the actor communicates directly to the audience. In addition, an increase of the WCT power during intense emotional periods can be observed, e.g., $A3$ argues with $A1$ and after $A3$ screams, which proves the link between audience interactions and strong emotional periods.

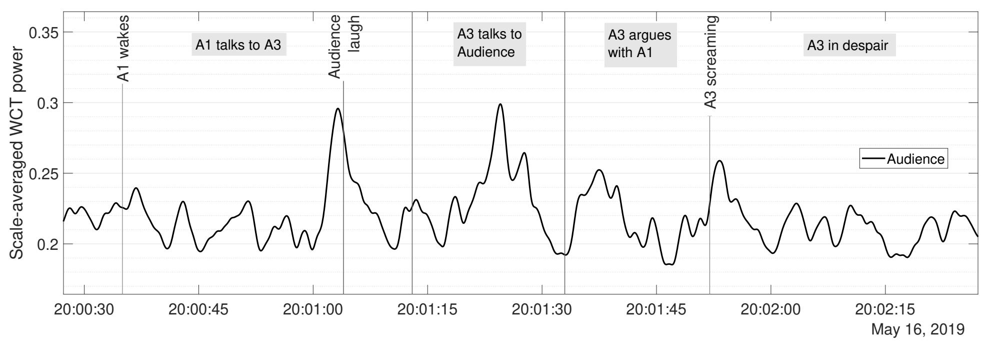

Fig. 9. The mean of scale-averaged power between audiences during Act 2. The period range chosen for average is from 0.5s-5s in order to observe more details interactions.

4.4 Survey

4.4.1 Actor-Audience. A total of 18 audience members completed the post-show survey, of which 15 are used in this analysis due to missing data. Acceleration data was collected from the actors and audience members, but not from the scientists. We combine the synchrony data from Act 1 and Act 2 in a single analysis (as used in the Act interaction matrix of Figure 5).

Actor-Audience synchrony at XWT and WCT short (0.5-5 seconds) and long (5-60 seconds) periods are calculated during the Acting sections, and these are compared with audience survey responses on the actors performance using Pearson's correlation (using Matlab function *corrcoef*). We found moderate positive correlations to XWT (long) synchrony with survey response 'Inhabit' (p=0.0773), and significant correlations to 'Emotional Response' (p=0.0121), and 'Empowered' (p=0.0209). See the correlation data for XWT (long) presented in Table 4. No other significant correlations were found for either XWT short or WCT long and short (the data of all correlations for XWT and WCT long and short periods can be found in the Appendix).

4.4.2 Audience members self reports for the actors performance and scientists performance. A paired samples t-test was conducted between all audience members responses to each item of the survey for the actors performance

Table 4. Pearson's correlation between all audience to actors synchrony at XWT long (5-60 seconds) with audience spectators' survey responses for the actors performance (N = 15). Significant correlations are in **bold**.

Questioniare item	Correlation coefficient	P_value
Absorbed	0.2657	0.3386
Inhabit	0.4697	0.0773
Emotional Response	**0.6284**	**0.0121**
Bonded	0.2098	0.4529
Theraputic	0.2609	0.3476
Uplifted	0.1334	0.6355
Transcedent	0.1738	0.5356
Empowered	**0.5887**	**0.0209**
Belonging	0.1783	0.5250
Cultural Heritage	0.2071	0.4589
Outside Exposure	-0.1728	0.5381
Social Issues	0.0247	0.9304

Table 5. Descriptive and difference statistics for the audience survey responses. Means and standard deviation (SD) shown for audience responses to the actors and scientists performance (N = 15). Paired samples t-test shown for the difference between the responses to the actors and scientists performance also shown (df = 14), with significant (p < 0.05) differences shown in **bold** (indicating slightly higher ratings for the science presentations).

Questioniare item	Actor		Scientist		Paired t-test	
	Mean	SD	Mean	SD	t	p
Absorbed	3.6	0.828	3.93	0.961	-0.892	0.388
Inhabit	3.07	0.799	3.53	0.915	-1.825	0.089
Emotional Response	**3.33**	**0.816**	**4.07**	**0.884**	**-3.214**	**0.006**
Bonded	3.2	1.082	3.2	1.014	0	1
Theraputic	2.87	1.187	3.33	1.047	-1.825	0.089
Uplifted	**3.53**	**0.743**	**4.2**	**0.775**	**-3.162**	**0.007**
Transcendent	2.47	1.125	2.87	1.407	-1.871	0.082
Empowered	**2.8**	**1.014**	**3.53**	**1.187**	**-2.442**	**0.028**
Belonging	2.93	1.223	2.93	1.1	0	1
Cultural Heritage	3	1.558	3.07	1.335	-0.25	0.806
Outside Exposure	2.8	1.265	3.13	1.302	-0.734	0.475
Social Issues	**3.13**	**1.457**	**4.27**	**0.799**	**-3.238**	**0.006**

and scientists performance. There was a significant difference between mean ratings for 'Emotional Response,' actors (M = 3.33, SD = .816) and scientists (M=4.07, SD = .884), [t(14) = -3.214, p = .006 < .05] 'Uplifted,' actors (M = 3.53, SD = .743) and scientists (M = 4.2, SD = .0775), [t(14) = -3.162, p = .007 < .05] 'Empowered' actors (M = 2.8, SD = 1.014) and scientists (M = 3.53, SD = 1.187), [t(14) = -2.442, p = .028 <.05] and 'Social Issues,' actors (M = 3.13, SD = 1,457) and scientists (M = 4.27, SD = 0.799), [t (14) = -3.238, p = .006 < .05]. See Table 5 for the full list of descriptive and paired t-test statistics comparing audience responses to actors and scientists for each question.

5 DISCUSSION

5.1 Studying group interpersonal synchrony in theatre

Our findings firstly show that it is possible to record implicit responses from performers and spectators during a live theatrical performance. This supports the movement of social-cognitive research to real-world spaces such as the theatre [64], and provides a further example of how the field of social neuroscience can create paradigms that allow more space for ecological validity. We used XWT and WCT analysis on our recorded data to spot movement synchrony between people. Therefore aligned with previous research in dance [19, 36, 57, 60] and public visual art [38] spaces, we were able to extract various frequencies of movement, and through time stamps and video footage were able to dissect the movements that were occurring to make observations about human social behaviour.

Our findings reveal interactions between audience members and actors during the scientific talks - when actors simply sat quietly at the back of the stage - and when actors were performing. Synchrony across different movement intensities and frequencies shows large individual differences in synchronous behaviour among groups of people. Synchrony varies across the specific activity that people are doing. These activities include: dynamically moving together, interacting for the purpose of the narrative, or sitting together. We also found that some actors had stronger synchrony levels with individual audience members during the acting parts of the show, for example during the Act performance A1 had high synchrony with audience members P0, P2, S8 and S12.

Our analysis revealed that as expected, audience members exhibited higher movement synchrony with the actors when they participated in the performance. This was expected because the audience members were performing extracts from the performance with the actors, coordinating their movements in a game-styled performance, made for the purpose of encouraging social interaction [29]. To find that there was synchrony between actors and audience members shows that we can successfully research social interaction in real-world spaces and that theatre can be used to create stimuli to help us investigate real-world social interaction. Interestingly we also found that during audience participation spectators who remained in their seats also had high synchrony with the actors (as shown in Figure 5-c, e.g., for S10-14). This finding is consistent with the idea that watching dance (or theatre) can involve action simulation [8], since performing and watching actions can elicit similar responses in the brain via mirror neurons [45]. This finding is insightful for the theatre industry because it may show that audiences can have physiological connections with performances of different styles. To participate in a performance or to watch others participate in a performance can elicit the same physiological responses. However, to know which style of performance audiences prefer, or whether audiences would like to have a moment of participation in a performance can be revealed through self-report measures. We did not ask this exact question, but are highlighting that self-report measures alongside physiological data can help the theatre industryunderstand how their audiences are connecting with their performances.

Our self-report post-show questionnaire asked audiences the same 12 questions, once for their opinions about the actors performance on stage and once for their opinions about the scientists performance on stage. We felt it was important to make this distinction as the performance was a combination of scientific talks/demonstrations and acting. We correlated audience survey responses to the actors performance with available actor-audience XWT synchrony data (unfortunately, we lost data from the scientists and were not able to evaluate that correlation). Significant positive correlations were found for both audience's emotional response to the performance, and the extent to which the performance left audiences feeling empowered.

This is consistent with the idea that watching a theatrical performance can be an emotionally moving experience where you are drawn into the world of the performers (linking to our 'Inhabit' positive correlation although it was not significant) and process the varying emotions they portray on stage. The narrative presented on stage should be strong enough to capture audience members attention and focus, where sometimes it feels like as the audience member you can feel what the characters are feeling. For future work it would be interesting to collect open-ended question responses on what exactly about the performance was emotional or empowering. This would lead to insight into whether it was a message relayed in the narrative, or the act of coming together to watch actors perform.

When comparing audience survey responses between their views on the actors and scientists performance we found that audience members found the scientists performance more emotional, uplifting, empowering and left them with more insight into social issues than the actors performance. This may have occurred due to the fact that scientists A and B were always speaking directly to the audience so there was no fourth wall at all between the scientists and the audience. The scientific message presented was that the work we do can lead to more discoveries about actors' creative processes as well as autistic children's social cognitive skills. Perhaps the message the scientists delivered was emotionally striking and highlighted social issues more than the actors performance, as it directly related to the real world (the world outside of the theatrical space that audience members must return to after the show). Lastly, it can also be suggested that by having a performance that is half-theatre, half-science communication rather than pure theatre could lead to findings such as this. Hence, it could be proposed that audience members understood the performance as for the purpose of science, so perhaps they needed a longer time to watch the acting segments. These propositions can be tested in future research.

5.2 Multi-person data synchronisation and coordinated movement extraction

During the data collection, we found two limitations of the MetamotionR sensor: the memory size and download time. When the logging mode is selected, the maximum recording time is limited by the memory capacity rather than the battery life. The estimated recording time to full log mode is around 5 hours, with the accelerometer operating at 25Hz. The sensor recording time of this live theatre performance is approximately 3.2h, and it requires several hours to download the data from each sensor over BLE.

Moving on to the data preprocessing stage, we compared the traditional time shift-only method and the proposed shift and interpolation-based data synchronisation technique. The proposed methods can reduce the time sync error to tens of milliseconds at several sync events several hours apart. We recommend using some form of interpolation in multi-sensor wearable data recordings, especially for those with long recordings where device clocks tend to drift. For this to work, additional synchronisation actions (i.e. shaking sensors) at both ends of the recordings are required. One limitation of the synchronisation used here is that only a proportion of the sensors were shaken together at the first and second sync actions, which ultimately leads to difficulties when performing the interpolation. Because we only have one camera facing the stage, there is a lack of video information about the audience. So we do not have enough labels to discuss the connection between the cross-wavelet analysis and the actual interaction between each audience pair. It is necessary to set up several cameras to cover an adequate breadth of view, ensuring the participants' behaviour and moments of synchrony can be seen clearly. This would allow us to better synchronise the video and sensor data to guarantee more precise timestamps for analysis.

Finally, The cross-wavelet and wavelet coherence transform techniques are found to be useful for measuring interpersonal synchrony between people using movement signals. WCT is well-suited for capturing interpersonal synchrony regardless of the power of the signals themselves, which is good at finding the correlation of smaller movements, e.g. analysing the audience's signal when they are seated and watching the performance or communicating with each other. One downside of this agnosticism to signal power is the risk of amplifying the influence of even the tiniest of movements, which may lead to difficulties interpreting the wider interactions - particularly if analysing over a long period of time.

In comparison, XWT power is biased towards finding high common power between signals, but the information about low power synchronisation might be lost. XWT is, therefore, unsuited to time-averaged power analysis since it outputs much higher power for longer-period signals, which will not deliver any valuable comparison between power at different periods. XWT is nonetheless a powerful method that provides a straightforward way of finding the pairs with strong movements correlation, such as the interaction pair between actors during the performance and the participants during the games periods. One limitation to bear in mind is that when pairing one person with relatively small movements to several others with 'equal' synchrony but different strengths of movement, those with the biggest movements will unevenly dominate the XWT output. Hence, when the groups of people have significant differences in the power of their activities, XWT is not a good option.

XWT and WCT analysis can be broken into different frequency bands. Analysing the signals in the time-frequency domain is beneficial since it offers a way to investigate the synchrony of different types of interaction. The scale/frequency bands are selected differently to apply in distinct scenarios. In our research, we use a larger (5-60s) period range to provide a general overview of different interactions during hours of performance and activities with long duration. Shorter period ranges (0.5-5s) can be applied when discovering short activities and rapid reactions (e.g., when the audience laughs).

We present some insight into using XWT and WCT methods for studying interpersonal synchrony. XWT and WCT have their own pros and cons suitable for different applications. It might also be helpful to combine both XWT and WCT to tackle different problems in one scenario. Thus, choosing the appropriate method and period range to analyse interaction is crucial. XWT/WCT techniques provide flexibility in analysing particular social activities involving specific movement frequency ranges.

5.3 Lessons learned

Creating live performances for psychological and neuroscientific research is a promising avenue for research in social interactions but requires interdisciplinary collaboration between performing artists and scientists. In our study, theatre makers, actors, neuroscientists, experimental psychologists, engineers, and creative coders worked together to bring to fruition all the elements of our multi-faceted performance. Despite, and perhaps as a result of, this diversity of interests and tasks, our study suffered at times due to necessary multi-tasking (e.g., a presenting scientist was also involved in setting up the sensor system - and then, inevitably, forgot to put a working senor on himself). It is important that there are clearly delegated roles within the team as the task load should not be underestimated - particularly in the heat of a live performance involving dozens of people. Our performance was not solely for experimental purposes but it was also open to the public as both entertainment and an exercise in science engagement. Therefore, we don't only operate as scientists but as theatre makers. This process is an important learning curve as we learn how to fuse resources and to work in a more effective interdisciplinary manner.

Outside of the practicalities of putting this performance together, there are factors to be assessed in our methods of data collection. One limitation of our data analysis is that it is based only on a single night's performance (having video and labelling data for only one out of the two performances). Ideally, multi-day performance data would allow us to explore patterns that are intrinsic to the overall structure or choreography of the work as independent from specific audiences [26]. However, the current work demonstrates the feasibility of our approach, and we leave it for future research to explore the generalisability of specific findings across multiple performances.

Another limitation is the lack of sensor data from the non-actor presenters. Therefore we could not compute correlations between audiences-scientists and audiences-artistic director. It is highly recommended that to create a rich data set with multiple social interactions, all audience members and all persons who have a part to play in the performance should wear sensors so that all interactions can be measured and analysed.

A further limitation was our missing survey data. We were unable to conduct a contrast analysis to assess the differences between audience spectators' and audience participants' subjective responses to the actors performance and scientific talks/demonstrations. However, as stated in our aims section, this study was a part of a large research project, and data was collected comparing heart rate (via wearable wrist sensors) and the questionnaire data, with contrast analysis on audience participants and spectators. To tackle this in future research it would be important to check the questionnaire booklets before participants leave the auditorium to ensure that they did not accidentally forget to complete the questionnaires. Furthermore, as stated above, increasing the number of participants also means that if there is missing data, it would have fewer effects on a large participant pool compared to a small participant pool. The questions items of the surveys also need to be improved. It would have been useful to collect the audiences responses to different elements of the performance rather than the overall performance. Our performance combined acting, science talks/demonstrations and audience participation, but spectators only completed one survey at the end of the show. Future studies should include separate measures for separate parts of the show, although this will have to be carefully selected to not create a lengthy survey. Creating an online survey that can be completed on participants phones instead of booklets may also be more efficient and environmentally friendly. When evaluating the design of the performance, it could be argued that a replication of this design should focus only on having an Act 1, Interval, Act 2, Participatory Period and and Act 3. The inclusion of another act after the participatory period may also allow a comparison to be made of synchrony before and after the participatory period. The wider purpose of the study meant that the performance had aspects to it such as live science talks, which you wouldn't traditionally have in a theatrical performance. It would be interesting to see if applying this traditional design results in clearer effects.

Despite our limitations and propositions for future improvements, we have accomplished the creation of a live theatre production for the public, where we measured interpersonal synchrony between actors-actors, actors-audience and audience-audience. We used head-worn movement sensors, audio-visual data and self-report measures to understand the connection between those in a live theatre space with each other and the performance. Our research paradigm can be used as a blueprint as to how fields might collaborate to understand human behaviour.

5.4 The benefits of interdisciplinary research

The implications of this research extend beyond one field. For the theatre industry research such as ours provides insight into the actors and audiences experience of live performances. We are able to see how actors interact on an implicit level gaining behavioural and physiological correlates of an actors experience and performance. For audiences, we can understand better audience engagement and this feeds into theatre companies audience development and content creation. For neuroscientists and experimental psychologists, we are able to advance research investigating real-world social interactions using wearables and theatre as a laboratory [62]. Research designs such as this can be replicated across various types of social interaction research to improve ecological validity. For engineers, these reports of the usefulness of wearable sensors in the study of human social interaction can lead to development and updates to the wearable technology that is available for researchers. One specific engineering challenge that arises from this work, for example, is the need for more accurate time synchrony between separate wearable devices. Future challenges might also involve ways of detecting measures like interpersonal synchrony in real-time, perhaps building on earlier work on the distributed peer-to-peer analysis of groups [20]. Overall, a feedback loop is created within different disciplines with the aim of understanding more about human behaviour.

Future replications of this research will explore creating self-reports that capture the information from audiences that can tell us about their explicit responses to various elements of the performance (e.g. in real-time, as in [48]). Also, we will look into more ways of measuring the bodily movements of the actors and audiences as previous researchers have used motion-capture to collect bodily movements in real-world settings [59] and on performers [49]. This will enrich the interpretation of synchrony data. Another fruitful avenue is to expand the study by looking at audience physiology and eye movements [13, 26, 50]. We would highly encourage researchers looking at a live performance to include wearable, self-report data and video footage in their research designs.

6 CONCLUSIONS

In this paper, we provide an interdisciplinary method of how to investigate group face-to-face interactions in a live theatrical setting. Wearable technology that measures acceleration, the audio-visual and self-report measures, provided researchers insight into the types of synchrony present during actor-actor, actor-audience and audience-audience interactions. Cross Wavelet Transform (XWT) and Wavelet Coherence Transform (WCT) analysis enabled moments of synchrony at different frequencies to be analysed, revealing the implicit interactions different members of the theatrical experience have with each other. Survey data provided insight into audiences explicit experiences of watching an interdisciplinary performance. Our study demonstrates how theatrical organisations can utilise multi-medium measurements to gain insight into the implicit and explicit connection between their audiences and the work they create.

ACKNOWLEDGMENTS

We would like to thank Kelly Hunter MBE and the cast and crew of Flute Theatre, including Charlie Archer, Sam Jenkins-Shaw, Paula Rodriguez, Hephzibah Roe, Holly Musgrave, Joshua Welch, as well as Lynne McConway, Jenny Roxburgh and Heather Cooper. Thanks to the team at University College London, including Daniel C. Richardson, Paola Pinti, Gregory Thompson, Charlotte Lange and Sara Din. Thanks also to Terry Clark and Edmund Oetgen at Goldsmiths.

This work is supported by funding from UCL Grand Challenges and Goldsmiths Research & Enterprise Committee. GO and JW are supported by funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No. 864420 - Neurolive). JW is funded by a Leverhulme supported grant from The British Academy, Royal Academy of Engineering and Royal Society (APX\R1\201093).

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A COMPUTATIONAL COST OF THE PROPOSED ALGORITHM

Table 6. The computational cost of WCT and XWT analysis for one pair of participants

	WCT analysis	XWT analysis
Processing time (s)	24.1	11.9
memory (MB)	255.6	528.5

The averaged computational time (on an AMD Ryzen 7 4800HS CPU) for XWT and WCT algorithms are 11.9s and 24.1s respectively for a single combination pair (two individuals) with 3.2h acceleration recording (291870 data points). For our study, 28 participants are involved; therefore, 378 different combinations are required, resulting in a total calculation time of around 157.5mins for WCT (88mins for XWT) without using parallel processing. Note that the WCT analysis produces the XWT matrix first and then constructs the WCT coefficient based on that, so the processing time of WCT is always longer. Another critical parameter to be considered is memory. One individual pair's XWT and WCT matrix occupies approximately 529MB and 256MB (based on the frequency range chosen and length of recording). How many combination pairs can be processed in parallel will be limited by the computer's memory.

B SURVEYS

B.1 Pre-show survey

All surveys were answered on a Likert scale 1 (disagree strongly) to 5 (agree strongly).

I see myself as someone who …

(1) Is reserved
(2) Is generally trusting
(3) Tends to be lazy
(4) Is relaxed, handles stress well
(5) Has few artistic interests
(6) Is outgoing sociable

(7) Tends to find fault with others
(8) Does a thorough job
(9) Gets nervous easily
(10) Has an active imagination

B.2 Post-show survey

Seat No?
What is your age?
What is your gender? Female, Male, Non-Binary, Other
What acting and/or directing experience do you have?
How often do you go to the theatre per month? 0-1, 2-4, 5+
Are you familiar with Shakespeare's Midsummers Nights' Dream? Yes, No
Is this the first adaptation of Midsummers Nights Dream you have seen? Yes, No

We would like to ask you about two aspects of this evening : your experience during the actors performance, and your experience during the scientists performance. Surveys were mostly answered on a Likert scale 1 (not at all) to 5 (a great deal).

In regards to the actors performance

(1) To what degree were you absorbed in the performance?
(2) To what extent did you inhabit the world of the performers, lose track of time and forget about everything else?
(3) How would you characterize your emotional response to the performance? (Weak to Strong)
(4) To what extent did you relate to, or feel bonded with, one or more of the performers?
(5) To what extent was the performance therapeutic for you in an emotional sense?
(6) How much did the performance leave you feeling uplifted or inspired in a spiritual sense?
(7) To what degree was it a transcendent experience for you, in the sense of passing into a different state of consciousness for a period of time?
(8) To what extent did the performance leave you feeling empowered?
(9) To what extent did you feel a sense of belonging or connectedness with the rest of the audience?
(10) To what extent did the performance serve to celebrate and sustain your own cultural heritage?
(11) To what extent did the performance expose you to one or more cultures outside of your own life experience?
(12) Did the performance leave you with new insight on human relations or social issues, or a perspective that you didn't have before?

In regards to the scientists performance

(1) To what degree were you absorbed in the performance?
(2) To what extent did you inhabit the world of the performers, lose track of time and forget about everything else?
(3) How would you characterize your emotional response to the performance?
(4) To what extent did you relate to, or feel bonded with, one or more of the performers?
(5) To what extent was the performance therapeutic for you in an emotional sense?
(6) How much did the performance leave you feeling uplifted or inspired in a spiritual sense?
(7) To what degree was it a transcendent experience for you, in the sense of passing into a different state of consciousness for a period of time?
(8) To what extent did the performance leave you feeling empowered?
(9) To what extent did you feel a sense of belonging or connectedness with the rest of the audience?
(10) To what extent did the performance serve to celebrate and sustain your own cultural heritage?

(11) To what extent did the performance expose you to one or more cultures outside of your own life experience?
(12) Did the performance leave you with new insight on human relations or social issues, or a perspective that you didn't have before?

C PEARSON CORRELATION

The full table of correlations between audience-actor synchrony and survey responses (for XWT and CWT short and long) are shown in Table 7.

Table 7. Pearson's correlation between all audience to actors synchrony at XWT short, XWT long, WCT short and WCT long with audience survey responses for the actors performance ($N = 15$). CC means correlation coefficient

Questioniare item	XWT short		XWT long		WCT short		WCT long	
	CC	P_value	CC	P_value	CC	P_value	CC	P_value
Absorbed	0.2908	0.2930	0.2657	0.3386	0.2657	0.3335	0.1264	0.6536
Inhabit	0.4340	0.1061	0.4697	0.0773	0.4697	0.5838	-0.0074	0.9791
Emotional Response	0.1494	0.5950	0.6284	0.0121	0.6284	0.9035	0.2508	0.3672
Bonded	0.2035	0.4669	0.2098	0.4529	0.2098	0.7710	0.1467	0.6018
Theraputic	0.2944	0.2868	0.2609	0.3476	0.2609	0.8432	0.3667	0.1789
Uplifted	-0.2134	0.4450	0.1334	0.6355	0.1334	0.4292	-0.3774	0.1654
Transcedent	-0.1611	0.5664	0.1738	0.5356	0.1738	0.6318	-0.3890	0.1518
Empowered	0.4132	0.1258	0.5887	0.0209	0.5887	0.7185	0.4201	0.1190
Belonging	-0.1076	0.7026	0.1783	0.5250	0.1783	0.6643	0.1139	0.6862
Cultural Heritage	-0.0986	0.7266	0.2071	0.4589	0.2071	0.8134	-0.0909	0.7474
Outside Culture	-0.2920	0.2910	-0.1728	0.5381	-0.1728	0.5100	-0.3233	0.2399
Social Issues	-0.0656	0.8164	0.0247	0.9304	0.0247	0.7116	-0.3184	0.2474