Cinema audiences reproducibly vary the chemical composition of air during films, by broadcasting scene specific emissions on breath

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Human beings continuously emit chemicals into the air by breath and through the skin. In order to determine whether these emissions vary predictably in response to audiovisual stimuli, we have continuously monitored carbon dioxide and over one hundred volatile organic compounds in a cinema. It was found that many airborne chemicals in cinema air varied distinctively and reproducibly with time for a particular film, even in different screenings to different audiences. Application of scene labels and advanced data mining methods revealed that specific film events, namely “suspense” or “comedy” caused audiences to change their emission of specific chemicals. These event-type synchronous, broadcasted human chemosignals open the possibility for objective and non-invasive assessment of a human group response to stimuli by continuous measurement of chemicals in air. Such methods can be applied to research fields such as psychology and biology, and be valuable to industries such as film making and advertising.

All living organisms from the smallest plants and bacteria to trees and primates emit chemicals into their local environment1–4. Such chemicals may act as signals, eliciting wide ranging responses5,6. The atmosphere has been shown to be an effective conduit for chemical communication between plants and plants7, plants and insects8, insects and insects9. Yet the extent, or even existence of airborne chemical communication between humans remains controversial10,11. Despite reported chemosignal volatiles in human tears affecting testosterone levels12, armpit and sweat odours interpreted as fear signals13–15, sleeping babies responding to lactating breast volatiles16–18 and menstrual synchronization19, no human pheromone (an evolved chemical signal between humans) has been reliably and reproducibly identified20. Generally, studies reported to date have been small in scale (number of people and measurements), subjectively assessed13,14, and often with unnaturally high concentrations of bioassays, due to the analytical methods available. To screen groups of people for potential emotion signaling molecules at natural levels we have conducted a largescale study involving more than 9500 cinemagoers who viewed 108 screenings of 16 different films (including comedy, horror and romance, see Table 1a). During the films, audiences were subjected to audiovisual stimuli while outside air was directed into the cinema through floor vents and out through ceiling vents (normal operating practice), and in the outflow, the concentration of over 100 trace gas species was measured using proton transfer reaction mass spectrometry (PTR-MS) and infra-red spectroscopy. Data was collected at 30 second time resolution and with sub-ppb (10−9) detection limits to investigate potential causal links between the audiovisual stimuli and audience emitted chemicals.

Of the 872 volatile compounds identified in human breath1, a fraction is thought to be produced endogenously. These compounds can be used to track chemical changes within the body, over long (with age)21,22 and short timescales (medication response, food, disease or exercise)23–25. Within this cinema based study we hypothesize that if films elicit strong emotional responses then volatile products from the internal biochemical response (cardiovascular, skeletomuscular, neuroendocrine, and autonomic nervous system)26,27 may be vented shortly afterwards over the lungs, and observed as transient peaks in concentration in air exiting the cinema. Full details of the experimental set-up and instrumentation is given in the method section.

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### (a) Film Number of Screenings

| Film                             | Number of Screenings |
|---------------------------------|----------------------|
| Buddy                           | 17                   |
| Walking with Dinosaurs          | 15                   |
| The Hobbit – The desolation of Smaug | 15              |
| The Secret Life of Walter Mitty | 15                   |
| The Hunger Games 2              | 10                   |
| Carrie                          | 7                    |
| Suck me Shakespeare             | 5                    |
| The Little Ghost                | 4                    |
| Journey to the Christmas Star   | 4                    |
| Paranormal Activity 6           | 4                    |
| Belle and Sebastian             | 3                    |
| The Counselor                   | 3                    |
| Machete Kills                   | 2                    |
| Cloudy with a chance of Meatballs 2 | 2                 |
| The Physician                   | 1                    |
| Bolshoi: Sleeping Beauty        | 1                    |
| **Total**                       | **108**              |

### (b) Content Labels

| Label             | Sub-label | Relative Frequency |
|-------------------|-----------|--------------------|
| Everyday Life     |           | 0.025              |
| Dream             |           | 0.016              |
| Landscape         |           | 0.040              |
| Conversation      |           | 0.680              |
| Aggressive        |           | 0.008              |
| Conv. Main Actor  |           | 0.321              |
| Action            |           | 0.141              |
| Death             |           | 0.022              |
| Running           |           | 0.031              |
| Recovery          |           | 0.001              |
| Laughter          |           | 0.004              |
| Sleeping          |           | 0.001              |
| Blood (violence)  |           | 0.028              |
| Sex               |           | 0.003              |
| Kissing           |           | 0.009              |
| Crying            |           | 0.007              |
| Main Char. Cry    |           | 0.006              |
| Injury            |           | 0.008              |
| Sudden shock      |           | 0.026              |

### (c) Genre Labels

| Genre             | Relative Frequency |
|-------------------|--------------------|
| Suspense          | 0.283              |
| Chase             | 0.002              |
| Hidden Threat     | 0.005              |
| Hiding            | 0.002              |
| Comedy            | 0.054              |
| Romantic Comedy   | 0.002              |
| Mystery           | 0.002              |
| Romance           | 0.014              |
| Drama             | 0.019              |

**Table 1.** A summary of the film screenings (a), labels and associated sublabels used in the film scene content (b) and film scene genre (c) annotation.
Results

Figure 1 shows sections of the CO₂ data measured in air from the Mainz Cinestar cinema. In Fig. 1a, large CO₂ peaks can be observed between 26th and 30th December, each corresponding to the screening of a particular film. Prior to a film starting in the empty cinema, CO₂ approximates to background levels (ca. 400 ppm) as ambient air is continually drawn through the cinema from outside. People exhale air with circa 4% CO₂, so that as the audience arrives, CO₂ levels increase, rapidly at first, and then more slowly as the equilibrium value is approached after about ninety minutes, reaching levels between 1000–2400 ppm. This is some 2 to 8 times the current ambient background levels (400 ppm), but well below the European indoor standard limit of 3500 ppm. In effect, the cinema is a small scale analogue of the on-going planetary scale increases in CO₂ in which additional anthropogenic CO₂ sources from fossil fuel usage must equilibrate with the slow uptake rates into the ocean, vegetation and soils28. At the end of each film the CO₂ level falls abruptly as the audience departs, generating a “shark-fin” profile for CO₂.

Figure 1b shows CO₂ measurements and audience numbers for a day on which four films were screened, “Hunger Games 2”, “Dinosaurs 3D” and “Buddy” twice. Those films with higher attendance have correspondingly higher CO₂. Figure 1c displays the CO₂ profile of a single film, “Hunger Games 2”. Clearly the CO₂ trace does not increase smoothly with time, as would be expected from a constant emission source, but rather small peaks are discernable despite the cinema ventilation rate remaining constant. These CO₂ peaks would be generated if the audience’s pulse and breathing rate were momentarily increased in response to scenes in the film. Figure 2 shows measurements from four showings of “Hunger Games 2” on sequential days between December 26th–29th with attendances of 87, 96, 104, and 186 people respectively. Two distinct peaks in CO₂ occurring around 15:00, highlighted by the red vertical lines, are visible on all days, indicating that the physiological response induced in each audience is reproducible. The pattern of CO₂ peaks shown in Fig. 1c was characteristic of the film “Hunger Games 2” and in many cases it was possible to identify the different films from the CO₂ profile by eye.

The mixing ratios of isoprene (C₅H₈) and acetone (C₃H₆O), which are among the most abundant exhaled organic trace gases1,2, are shown with CO₂ for four film screenings in Fig. 2. Acetone is a soluble gas (in blood and water) that has been linked to fat catabolism, while isoprene is an insoluble gas linked to cholesterol synthesis2,23. In Fig. 2 peaks can be seen in the isoprene trace and to a lesser extent for acetone, although acetone mixing ratios were twice as high. Isoprene levels in the cinema are similar to levels reported from aircraft flying low over the...
pristine Amazon rainforest (1–3 ppb) while acetone levels generated by the audience (~8 ppb) are approximately twice that found in forested environments and city air. The two distinct peaks around 15:00 previously noted in CO2 are also visible in isoprene, and additionally a further large isoprene peak is observed at the end of each film (16:00). Breath analyses of individuals on an ergometer have shown that isoprene can be stored in muscle tissue, and that limb movement increases isoprene in breath. The mass exodus of people at the end of the film is therefore the likely cause of the isoprene peak at 16:00 coincident with rapidly falling CO2. However, the two other outstanding peaks in isoprene appear during the film when the audience is seated (15:00 and 15:10). These times correspond to key moments in the film when the heroine’s dress catches fire and when the final battle begins. Previous studies have indicated that breath holding and twitching muscles could potentially enhance isoprene emission over acetone. Another possibility is that isoprene is linked to cortisol production via cholesterol. Whatever the mechanism behind the release, the peaks in isoprene were reproduced in all four screenings of the film at the same time, meaning that each set of cinemagoers broadcasted chemicals into the air in synchrony to on-screen events.

To determine whether causal links exist between levels of all chemicals measured and events in the film, it was necessary to annotate the films with scene content labels. A set of scene labels (Table 1) was defined based on genres in the IMDB database (e.g. comedy), on objective subheadings (e.g. chase) and psychological studies (happy to sad and excited to calm). These labels were applied to the films by ten individuals independently (see method for details). All data were then statistically normalized and random forests were constructed for each mass and CO2, for each 30 second timestep within a 10 minute window, and for each label. Each random forest based model was generated based on a randomly selected subset of two thirds of the data and then evaluated on the remaining third. This procedure was then repeated 15 times, using the Mainz Mogon supercomputer. A set of models were trained in a process called backward prediction to determine how well the present label was predicted by the future mass (in the next 5 minute time window). Figure 3a shows film scene labels plotted against AUC (Area Under Curve, see method) which expresses the ratio between true positives (when the model correctly predicted labels based mass decision trees) and false positives. A random prediction produces an
AUC value of 0.5. Many of the labels showed a significant relationship with measured masses. The highest AUCs observed were for the labels “injury” (0.85), “hidden” (0.83), “mystery” (0.81) and “hiding” (0.79), all of which were subcategories of the label “suspense” which itself showed an AUC value of 0.75. The label comedy was also predictable based on the measured chemicals (AUC = 0.78). In contrast, the label “chase” (AUC = 0.55) could not be predicted by the model.

In parallel we investigated the ability of an individual mass to be predicted by the labels (forward prediction). The performance of this prediction versus the real value for VOC mixing ratios is given as the Pearson’s correlation coefficient (r). High correlation coefficients indicate the predictive model was successful for that particular species, and not that all species with high correlation coefficients are inter-correlated.

Figure 3. Shown are the results when two thirds of the whole film screening dataset is randomly selected (15 times) and the resultant model tested on the remaining third. The boxes indicate the extent of 25% of the data either side of the median (solid line). The dashed vertical line represents the lowest/highest datapoints that are still in the 1.5 interquartile range while the circles are outliers. (a) shows AUC which expresses the ratio between true positives (when the model correctly predicted labels based on mass decision trees) and false positives (backward prediction). A random prediction produces an AUC value of 0.5. (b) shows the ability of an individual mass to be predicted by the labels (forward prediction). The performance of this prediction versus the real value for VOC mixing ratios is given as the Pearson’s correlation coefficient (r). High correlation coefficients indicate the predictive model was successful for that particular species, and not that all species with high correlation coefficients are inter-correlated.
predicted and measured water sensitive reagent clusters m21 and m39. Both water and CO2 are introduced to the cinema primarily by breath. Among the best correlated masses was isoprene (r = 0.91), which is presented qualitatively for the film "Hunger Games 2" in Fig. 2. Some masses with high correlations have not been observed or identified in previous studies (e.g. 105.93, r = 0.92) while other masses exhibit no significant correlation.

Table 2 shows the best correlated masses and labels based on backward prediction. A filter of AUC > 0.5 and significance level < 0.05 was applied to all data. “Significance” here is the result of a statistical T-test (between an evaluation based on all masses and an evaluation with one mass omitted, this mass is given in Table 2). Therefore higher AUC and lower significance values indicate stronger potentially causal links. The labels with the highest overall causal link to the measured species were “injury” and “comedy”. Among the chemicals linked to injury scenes are methanol (mass 33.03), acetaldehyde (mass 45.03), 2-furanone (mass 85.03), and butadiene (mass 55.06). These compounds have all been previously detected in human breath1. Although the masses 100.93 and m73.94 were also significantly linked, no plausible identification could be made based on combinations of C, H, and O. Curiously, the mass 374.08 also shows a causal link to injury scenes despite being
associated with polysiloxane which is found in cosmetics and conditioning shampoo. This may be related to emotionally induced body temperature variations rather than to breath. The film labels “chase” and “romance” both did not show significant causal links with any measured masses.

**Discussion**

Interestingly, the two film scene labels with the most significant linkage to chemicals measured were “suspense” and “comedy”. These could be interpreted as an evolutionarily advantageous alert/stand-down signal, if perceivable by others34. Humans possess a very well developed sense of smell35, and new evidence suggests that recall is more effective36, and our perception of faces changes with odours present37. Therefore the chemical accompaniment generated by the audience has the potential to alter the viewer’s perception of a film.

There are several important consequences of our finding that human beings respond to audiovisual cues through breath emissions. Firstly, in the field of medicinal breath analysis, where chemical markers for diseases such as cancer are being sought2, emotionally induced emissions have the potential to confound disease marker identification. The strong response found here for “suspense” suggests that a patient’s state of anxiety should be taken into account in future medicinal breath studies. These findings also have obvious industrial applications where an objective assessment of audiovisual material is sought from groups of people, for example, in advertising, video game design or in film making.

**Method**

**Cinema/Movie Theater.** All data were recorded at the Cinestar Cinema complex in Mainz (Fig. 4a), Germany between 1st December 2013 and 14th January 2014. Of the 14 screen multiplex, two separate screen rooms were used (see Fig. 4b, Cinema 2 capacity 230, and Cinema 7 capacity 230). During a film the entrance doors were closed and ambient air was circulated from outside into the room through vents under the banked seating and out via ceiling mounted openings so that the screening room was flushed entirely circa 6 times per hour. The measurement instruments (PTR-ToFMS and the CO2 detector, see below for details) were located outside the screening room (to avoid possible noise disturbance), in a technical room that contained the outgoing air vents (75 × 75 cm square stainless steel) and associated control systems for all auditoriums, see Fig. 4c. An inlet was inserted into the midpoint of the exit flow vent and a 10 L/min flow was drawn through ¼” OD (0.625 cm) Teflon line continuously, see Fig. 4d. The films viewed and the number of screenings are given in Table 1a. This is a study of ambient air and the chemical changes within it caused by entirely anonymous groups of people in a public space. No personal data concerning the cinemagoers was collected, no individuals identified, only the number of people present were recorded by way of the ticket sales.

**Proton Transfer Reaction Time of Flight Mass Spectrometer.** Volatile Organic Compounds (VOC) were measured using a commercial PTR-ToFMS (Proton Transfer Reaction Time of Flight Mass Spectrometer, PTR-ToF-MS-8000, Ionicon Analytik GmbH, Innsbruck, Austria)38,39. The measurement technique is based on the low pressure (ca. 2 mbar) protonation of molecules with a proton affinity higher than water by H3O+ ions (691 kJ mol−1) that are generated in a hollow cathode discharge chamber flushed with water vapour. All protonated molecular ions are accelerated by an electrical field to the same kinetic energy such that the resultant velocity of the ions depends on the mass-to-charge ratio. Hence, the time-of-flight is used to measure the velocity,
from which the mass-to-charge ratio can be determined. The TOF was configured in the standard V mode with a mass spectrum of approximately 3700 m/Δm. Mass spectra were collected ranging from m/z 10–400 with a TOF acquisition sampling time per channel of 0.1 ns. The instrument was operated with a drift pressure of 2.20 hPa (EaN 137 Td) and a drift voltage of 600 V. For mass calibration, 1,3,5-trichlorobenzene was used as an internal standard by permeating 1,3,5-trichlorobenzene into a 1 mm section of 1/8" (1.58 mm) Teflon tubing used in the inlet system. Data post-processing and analysis was performed by using the program “PTR-TOF DATA ANALYZER”, which is described elsewhere46. The PTR-ToFMS was calibrated with a commercial pressurized gas standard mixture (Apel-Riemer Environmental Inc., Broomfield, USA) of known mixing ratio. The overall uncertainty was 15%. The calculated detection limit (3σ of the noise) of identified masses was between 15 ppb and 155 ppb. Signals were normalized to H3O+ ions and the first water cluster H2O(H3O)+ by means of the following formula:

$$\text{[R+]} \text{ncps} = \frac{\text{[R+] cpu x P x T}^2}{500 + \text{[m39]} x 250}$$ (1)

here [R+] ncps is the normalized counts per second, [R+] is the reagent ion, P the pressure, T the temperature, [m21] the counts per second of the O18 isotope of H2O+ and [m39] the counts per second of the 18O isotope of the first water cluster of the primary ion. The signal is normalized to a temperature of 298.15 K and a pressure of 2 mbar. The humidity dependence of the PTR-ToF-MS sensitivity was tested for a suite of compounds including key breath species such as isoprene and acetone shown in Fig. 2. The sensitivity was weak, varying in the order of 3% for the ambient conditions in the cinema and therefore we can exclude humidity dependent variations in sensitivity as the cause of the peaks shown.

**Carbon Dioxide (CO2) measurement.** CO2 was measured at 1 Hz using a commercially available Li-COR Li-7000 system. The Li-7000 monitor was calibrated using a standard containing 509 ± 10 ppmv of CO2, ppmv (Air Liquide, Germany) before and during the campaign. The instrument specifications state that the response is linear up to 3400 ppmv. Post campaign the linearity of the response was confirmed to 3400 ppmv using a second standard gas (10% CO2, Air Liquide, Germany).

**Film scene annotation.** In order to assess the data for relationships between film scene content and trace gas behavior it was necessary to annotate the film scene content at high time resolution, from a set of preselected labels. Although several approaches to film scene annotation have been reported, including scene change frequency and both audio and visual cues40-43, as yet no standardized procedure exists. Suitable independently derived time resolved annotations were also not available from film censor boards nor from the subsequently published film DVDs. Instead, ten volunteers individually viewed the films and allocated descriptor annotations as a function of the film duration using a custom made interface. Each film was labelled at least five separate times. Three different types of scene labels were used. The first set was general in nature and described the film genre using terms from the Internet Movie Database (IMDb). These included terms such as “comedy”, “suspense” or “romantic.” The second set was more specific and referred directly to the scene content such as “chase”, “laughter” or “kiss”, “house pet” or “injury”. These terms were kept deliberately objective to minimize potential labelling differences between individuals caused by personal perception. Finally, we have adopted an emotional assessment scheme that has been previously used by psychologists44. It consists of two separate five point scales, one ranging from happy to sad and the other from excited to calm. The labels produced by the individual volunteers were then averaged and used only when two thirds of the individuals agreed. The labels were created to match the datapoint frequency (1 every 30 seconds). A full list of scene labels is in Table 1b,c and a comprehensive description of all data mining approaches applied to the dataset given by Wicker et al.33.

**Data Mining.** This study was designed to determine whether causal links exist between levels of volatile organic compounds and CO2 emitted in a cinema auditorium and events in the film. While it is easy to examine the variance with time of a single molecular species for a single film by simple graphical methods (see for example Figs 1 and 2), to analyze the entire suite of measured masses (including unidentified mass species) at thirty second intervals with all the labels from all the films for causal relationships and possible interdependencies requires a more sophisticated and systematic data mining approach. Full details of the data mining algorithms applied are given by Wicker et al.33, however, the generalized approach is summarized below. Data mining algorithms were applied to analyze the VOC and label data within a 10 minute window around a given measurement datapoint (5 minutes backwards and 5 minutes forwards). The first method applied was forward prediction, whereby the VOC mixing ratios are predicted based on regression from past VOC mixing ratios and the film labels. The second method was termed backward prediction, as it used VOC changes ahead of a given point in time to predict the current associated label. In order to evaluate the coherence of the two types of models, the forward prediction model and the backward prediction model, we used the predictions of the forward prediction model as an input to the backward prediction model and compared the resulting predicted values with the actual values. The overall product of the backward prediction are tables of VOC signal intensities (measured as mass-to-charge ratios in the mass spectrometer) that are associated with a given label and the error in the prediction expressed as the area under the receiver operating characteristic (ROC) curve (AUC, sometimes also called AUROC, see Table 2) and a significance. The AUC expresses how well a classifier (in this case the label) ranks the cases of one class before those of another class (in our case: those of one scene label before those of all others). An AUC value of 1 would mean that the label was predicted perfectly from mass signals, while a value of 0.5 indicates that the predictive performance was equivalent to a random selection45. The p-value results from a statistical test that compares the performance of a machine learning model using all masses as input to the performance of a model using all but one mass as input. The difference between these two cases is tested using a corrected paired t-test46. The t-test returns a significance measure in terms of p-values, the lower the p-value, the more probable is a relationship
between the left out mass and the target label. Whereas in most cases, an adjustment like Holm–Bonferroni should be performed on the tests, this is not necessary in this case, as we only searched for indications for further analysis, which we also can get from uncorrected values. The results of the two (significance level and AUC in Table 2) expresses the significance of the relationship with low number of p-values and high numbers of AUCs indicating higher degrees of dependence.

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**Author Contributions**

J.W. conceived the experiment, made measurements and wrote the paper. B.D., C.S., E.B. and T.K. made the measurements, calibrated the systems and worked up the data to ambient concentrations. S.K., J.W. and N.K. conceived and performed the data mining analysis.

**Additional Information**

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