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Technology and clinical improvisation – from production and playback to analysis and interpretation

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Introduction

This article illustrates some of the ways in which music technology can be utilised in everyday clinical practice. Presently, digital devices work relatively well together regardless of manufacturer, and there are useful and generally shared standards for digital formats and memory solutions as well. Thus music technology has introduced new possibilities to both clinical practice and music therapy research. Computational improvisation analysis, a key concept in this chapter, is one such relatively new approach in music therapy, and we will present the principles and possibilities of the music therapy toolbox, a computational tool for music therapy improvisation analysis. The chief benefits of computational tools are precision, effectiveness and objectivity. Still, computers cannot produce interpretations, and human-centred qualitative analysis remains an essential part of any successful improvisation-analysis process. The last part of the chapter, then, focuses on the clinical model perspective. The effective exploitation of computational improvisation analysis requires relatively consistent data and large sample sizes, which can represent more of a challenge than the securing of appropriate technology for data analysis.

Music technology in everyday music therapy practice

Digital music instruments, recording equipment and software are increasingly present in music therapy clinicians' everyday work. Thanks to the standardisation of digital formats and the ever-increasing capacity of computers, it is now possible to both store and analyse a large amount of data cheaply and quickly.

Music therapy improvisations, for example, are now simple to record digitally on between one and four different channels, depending on the model of recorder, in most audio formats, including *wav* and *mp3*. A wav file is not compressed and thus takes more space to store, whereas the mp3 format represents some form of compression, depending upon the user's preferences and tolerance for poorer sound quality. Digital recorders typically store date on memory cards, such as SD cards, that are based on industry standards and can be removed and used in computers and other digital devices as well. When determining the desired capacity of a memory card, one rule of thumb rule is that a single gigabyte (1,024 megabytes) represents about three hours of mono recording and about half that amount of time of stereo recording (often the preset setting) in wav format. The mp3 format increases those timeframes by a factor of up to ten, depending on the amount of compression. It is therefore a good idea to acquire a memory card with a capacity of thirty-two gigabytes or more to avoid a sudden stop to one's recording. Digital recorders allow for immediate playback and also include a mini-stereo-plug output, through which one's recording can be listened to using headphones or an external sound system. Music therapy clinicians are therefore able to review and discuss shared improvisations promptly, combining both active and receptive music therapy techniques in the process (see Bruscia, 1998).

Many digital music instruments also include MIDI (Musical Instrument Digital Interface) input and output jacks. The MIDI protocol presents key elements of musical information as numbers. It is important to note that MIDI data is not actually based on real music at all but on variables, which *describe* the music. For example, MIDI information will encompass what key on the keyboard was pressed (number 68 out of 128, say), how long it was held down, and so on. This information can then be used to instruct any compatible device about what to play using its own sounds. The benefit of MIDI information is that it is very 'light' and does not occupy much memory. A computer can process it quickly as well. Furthermore, MIDI information lends itself well to various mathematical, algorithmic operations that can be utilised, for example, in the computational analysis of music-therapy improvisations.

In music-therapy clinics outfitted with musical instruments and equipment, the therapist can take advantage of the more elaborate environment for recording, saving and editing musical material. Musical instruments can be connected directly to computers running digital recording software, some of which can handle both MIDI-based musical information and digital audio. Perhaps the cheapest and most straightforward option for digital music-making is the tablet-based application, but Apple's computer-based Garage Band is also relatively popular among music hobbyists because it enables, among other things, the use of a sample collection for creating accompaniments. There are plenty of other music software makers on the market as well, and their products range from freeware to professional recording software such as Pro Tools and Logic Studio. A workable clinic setup would include a computer and recording software but also an audiocard to accommodate the connection of musical instruments or microphones to the computer. Various makes and models of audiocards range from inexpensive options with only one or two inputs to professional devices with multiple inputs and high class AD (analogue to digital) converters. Audiocards typically incorporate MIDI input and output in addition to analogue inputs and outputs. There are two basic versions of analogue inputs: the so-called line level input (for instruments such as electric guitars and keyboards with quarter-inch jacks) and the XLR input for devices with pre-amplification, so that the audiocard can act to amplify a microphone, for example.

The type and number of instruments to be recorded in a typical music therapy session will determine the type of audiocard needed. If, for example, therapist and client each use an acoustic drum, the audiocard must have two separate analogue input channels to accommodate the two microphones that will be used with the drums. If there are additional instruments or improvisers, there will need to be more input channels. Today's computers, and even laptops, are powerful enough to handle dozens of simultaneous input signals.

Digital recordings of music therapy improvisations offer the following possibilities:

1) Therapist and client can create and edit an entire composition using the available instrumental and vocal performances. In therapy with children and adolescents, in particular, this kind of working method is useful and specifically evokes the therapeutic songwriting method (Baker & Wigram, 2005).
2) Anyone can replay the musical material at any time for any therapeutic reason, with good sound quality.
3) The performances of the improvisers can be separated digitally to accommodate analysis of the features of interaction or for specific attempts at therapeutic microanalysis (Wosch & Wigram, 2007).
4) The sound files can be exported to other applications, such as music therapy–specific computational-analysis applications, in order to create a detailed feature analysis. Musical features, when described as numerical values with specific meanings (see below), can be exported in a data matrix to statistical software for further analysis. In this fashion, a large number of performances from several improvisers can be analysed at once (a so-called batch analysis).

5) The reproduction of recorded clinical improvisations might suggest a shift in the process-oriented work of music therapy. Spontaneous clinical improvisations represent an important tool for achieving unprecedented levels of non-verbal processing of underlying therapeutic themes. Even initially rather primitive material can be processed, and new creative elements can be introduced to round out the end product. This reproduction can be based on both multitrack recording and sound processing. New tones and nuances might appear, to say nothing of new areas and themes for therapeutic processing (Ala-Ruona, 2014).

Music Therapy Toolbox

The music therapy toolbox (MTTB) was created at the University of Jyväskylä, Finland, for the purpose of computational music therapy improvisation analysis. The development work started in 2004 in the context of a research project called 'Intelligent Music Systems in Music Therapy' that was funded by the Academy of Finland. MTTB was designed and developed by Olivier Lartillot and Petri Toiviainen as a set of algorithms and a graphical user interface; it was written in Matlab using the MIDI toolbox (Eerola & Toiviainen, 2004) for the processing of MIDI data. Team members reflected significant experience in music therapy, music psychology, cognitive music research and the computational modelling of music. Whereas their research was initially focused on MIDI data, they broadened their scope to digital audio analysis in the context of a subsequent project using a music information retrieval (MIR) toolbox (see Lartillot, 2007). In the current version of MTTB, both MIDI data and digital audio can be processed.

MTTB was first applied to improvisations created by people with mental retardation and their therapists. The idea was to detect whether the musical features of the given improvisation predict the level of retardation. This study represented the first time a computational analysis was applied to music therapy improvisations to this extent. The large group of features made available through the MTTB demonstrated that the severity of mental retardation affects the client's freedom of musical expression (Luck et al., 2006; Luck, Erkkilä, Toiviainen, Lartillot & Riikkilä, 2007; Luck et al., 2008).

According to the article 'Steps in Researching the Music in Therapy' (Bonde, 2007), the MTTB approach answers many of the needs of music analysis in therapy. Bonde lists five basic categories with which a researcher must grapple: the *trace*, the *scope*, *focus* and *purpose*, the *representation* and the *presentation*. In terms of the *trace*, which refers to the format in which the music exists, MTTB requires music being in MIDI or digital audio format depending on the purpose of the analysis. MIDI format allows doing various precise feature extractions and analyses based on them but it does not enable timber related analyses, for instance. This is due to the nature of MIDI data, which is actually a representation of music, not real music at all. In digital audio, all the aspects of music, such as timbre and dynamics, are included. When these are in the focus of the analysis, digital audio instead of MIDI data is needed. Thus, they are mutually complementary formats, both having their unique qualities. MTTB analysis benefits greatly from verbal comments (therapist's notes and session recordings that include verbal dialogue between therapist and client) as well. In terms of *scope,* MTTB allows the researcher to choose whether to employ a micro-analytical approach (involving the detailed analysis of a short segment of a given improvisation, for example) or to analyse a certain number of improvisations by a single client or many clients (a batch analysis). The advantage of computational methods such as MTTB is that the computer does the work and the computation will always be quick, regardless of the total number of improvisations.

In terms of *focus* and *purpose*, the researcher is free to choose his/her theoretical standpoint in relation to the music analysis enabled by the MTTB. Of course, MTTB does not read the music in a 'human' way and is therefore limited. It cannot easily, if at all, extract musical aspects such as melody and phrasing, for example. If one wants to go beyond those features that MTTB *can* extract from the music, one must turn to traditional music analysis methods. In terms of *representation*, MTTB offers the possibility of graphic notation (see figure 2). A sequence within an improvisation, or an entire improvisation, can be readily visualised, and furthermore the user can specify the musical features to be captured there. This is a convenient way to look at the interaction patterns between the client and the therapist, trace meaningful moments from an improvisation, or simply prepare an overview of the improvisation itself. The rendering of several improvisations across different therapy sessions allows for an overview of changes or evolution in the music as well. This kind of visualisation serves clinicians in their everyday clinical practice as well as qualitative researchers who want to look at the improvisation second by second and possibly connect their findings to other data sources. Quantitative researchers, in turn, are generally more interested in the data matrixes created by MTTB for further statistical operations.

In terms of *presentation*, MTTB encompasses certain extra-musical possibilities for interpretation which enhance its applicability to other professions. Specifically, MTTB features are not always related to purely musical considerations. Features such as density, velocity and pulse clarity, for example, are more or less interdisciplinary and have various connotations. This characteristic of MTTB may help in the conversion of certain findings into general language for health care professionals.

How MTTB helps in improvisation analysis – a micro-analytical perspective

MTTB is based on mathematical algorithms that compute statistical and musicological analyses based on the raw symbolic data provided by MIDI files, as well as raw audio data. There are algorithms for various music-related aspects such as time, register, dynamics, tonality, dissonance, timbre and pulse (for more information, see Luck et al., 2006; Erkkilä, 2007). For the purpose of microanalysis, the clinician can arrange a closer look at any excerpted portion of the improvisation, investigating the rhythmic synchronicity between the improvisers, for example (see figure 1):

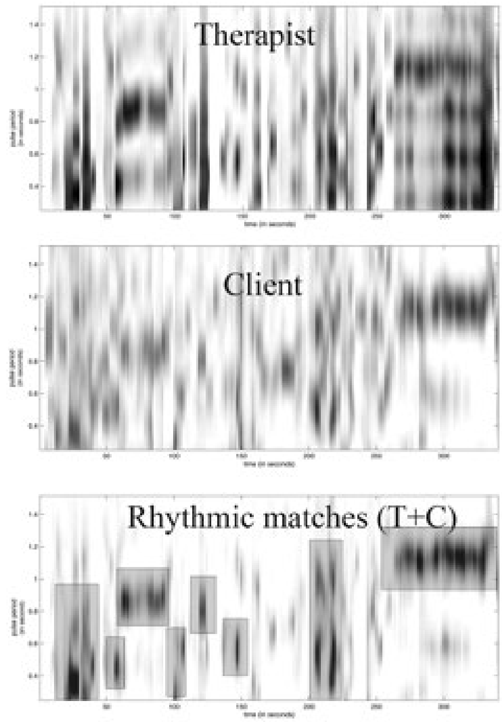

Figure 1(a,b,c): *An example of a pulse diagram created by MTTB. The temporal evolution of the improvisation is spread along the horizontal axis. Detected pulsations are shown in black, vertically ordered according to their periods: fast pulsations are at the bottom, slow pulsations at the top. Figure 1c shows the pulsations that are common to both client and therapist.)*

In figure 1, the darker spots signal greater rhythmic clarity – that is, more rhythmically precise playing – and the lighter colours or spots signal the opposite.
The lower box indicates the points of greatest rhythmic synchronicity between the therapist and the client, a young boy with Asperger syndrome who also suffers from delayed development and resides in an institution for disabled individuals. Rhythm and even basic pulse have an important role in music therapy for individuals with these kinds of problems, because they are seen as basic and primitive elements of music, which do not presuppose high level of cognitive skills for understanding (Wigram, 2007). In general, then, this excerpt shows that the therapist's rhythmic clarity is greater than the client's. With some clients, it may be clinically relevant to focus on rhythm-related aspects of ordinary improvisation, so as to work to improve rhythmic expression via selected techniques and interventions and then track the progress via the MTTB. By using the toolbox to analyse several improvisations representing different phases in the music therapy process, one quickly gains an objective overview of rhythmic development in terms of synchronicity and preciseness point of views, for instance – if these phenomena are under specific interest and relate to the goals of the therapy. MTTB visualizations on couple of the early improvisations and couple of the later ones allow comparing them and finding out whether any lasting improvement has happened.

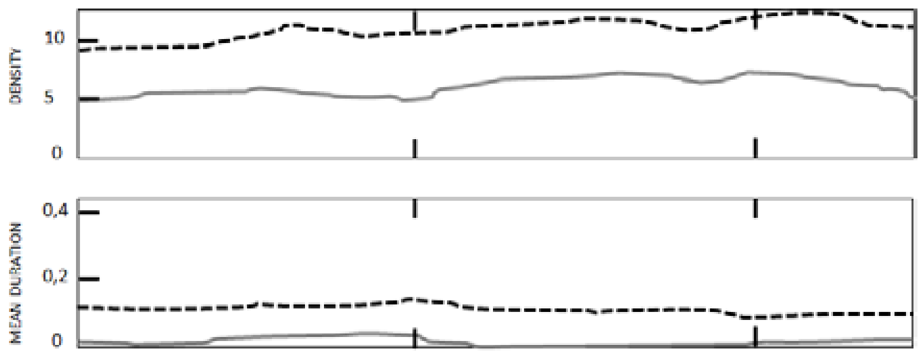

***Figure 2**: An example of density and mean duration graphs from the MTTB showing improvisations of client (dashed line) and therapist (solid line).*

Another example (see figure 2) demonstrates how MTTB can be used to explore two improvisers' musical behaviour according to a specific musical feature. Regarding density (above), the upper dashed line reflects the client's play, which is obviously very busy, and the lower solid line reflects the therapist's play. In MTTB, one can adjust the moving time window within which the calculations are made. In figure 2, for example, the time window is a duration of six seconds, and it is moved every half second: the first window starts at time t = 0 seconds, the second window at t = .5 seconds, and so on. The shape of the line thus shows how the improviser's musical behaviour regarding a given musical feature changes over time. Likewise, one can use the MTTB to explore potential interactions between the improvisers in terms of any musical feature. In figure 2, the client is a young boy with Asperger syndrome who played the therapist's electric piano by using both hands and pressing down on many keys at once, which produced a clustered, chordlike improvisation. This is why the density of the client's music is greater than the therapist's music, most of the time.

The two examples above depict a microanalytical perspective, which is valuable to everyday clinical needs when a music therapist wants a quick overview of what is going on in the music. It also supports single or multiple case-study research where there is an interest in emphasising microanalytical or process-related musical aspects.

How MTTB helps in improvisation analysis – a process-analytic perspective

In a recent case study (Erkkilä, 2014), fifteen music-therapy improvisations involving a depressed client and her music therapist were initially analysed using MTTB to produce a data matrix of their musical features. All of the improvisations were played on a pair of digital xylophones, which allowed for easy comparison, and they were created during a therapy process, which lasted for about three months. With this much data, a microanalytical approach was deemed to be less useful than statistical methods for processing. One way to compress the MTTB data that accompanies multiple sessions and/or musical features is to run a principal-component analysis (PCA). This statistical method determines what kinds of components, which consist of several individual musical features that have something in common, explain changes in the data. In other words, a component is an independent entity consisting of several factors, in this case of musical features, which vary concurrently and are thus like relatives to each other. It is the task of a researcher then to try to conclude why certain factors (musical features) seem to belong together and to form an independent component. If many of the factors (musical features) of a component seem to have something to do with rhythm, we could conclude that rhythm related phenomena seem to be in the core of expression and (one of) the main source of musical variation. The therapist's, or the researcher's, task is also try to understand why rhythm has this kind of salient role in a client's musical expression, how rhythm related expression has been used for different expressional needs, and what it might represent symbolically in relation to the illness, for instance. After running the PCA in the aforementioned case study, the first three components turned out to explain 75 per cent of the change. When there are three salient components, as in the example here, the question becomes how the components differ from one another – that is, how they explain different aspects of the data. A challenging task now is to try to understand what is common with the factors of a component and is it possible to name the component in a way that is relevant to clinical music therapy.

When each of the components consists of musical features that correlate with each other (either positively or negatively) it is helpful to name the component based on a musical aspect which best describes it. This is the so-called interpretative part of PCA, and it demands questions such as the following: 'What does it mean from a musical-behavioural point of view when these musical features appear to interact in this way?' In our example, the first component with the highest loading was named 'Activation-Harmony', the second, 'Variation-Static', and the third, 'Tonality', based on the musical features of the components and their interaction. High loading refers to the amount of explanatory power, i.e., how much a component explains the change in data in percents. If one knows each of the musical features of a component, it is possible to see whether and how each of the components is or is not present in individual sessions. This is done by creating a graph consisting of the values of the component factors (musical features) for each of the fifteen improvisations, for example, the Activation-Harmony component (AHC) as is shown below (see figure 3):

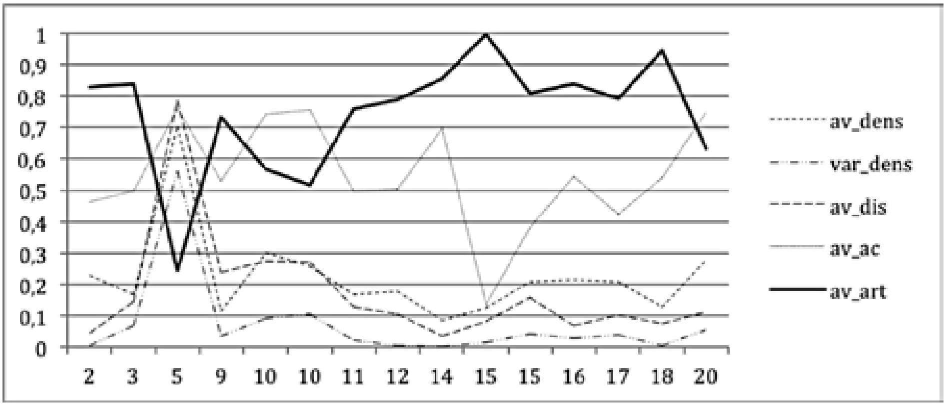

Figure 3: Activation-Harmony component as it appears in the therapy process of a client with depression. The scale of the Y axis is based on normalised values (0–1) of each of the musical factors in the component. A high value means a more dominant role for the musical feature, such as average dissonance. In the X axis, the session numbers are presented. For example, in sessions 10 and 15, two improvisations which were included in the analysis were created. The figure 3 is based on both improvisers' playing (client + therapist).

AHC consists of five musical features: average density (av_dens), variation in density (var_dens), average dissonance (av_dis), average pulse clarity (av_ac), and average articulation (av_art). We can see that in most of the sessions, musical density, variance of density and average dissonance is rather low. This tells us that the improvisations were generally rather 'peaceful', with little drama and few dissonant outbursts. This resonates with the character of the client, who was a rather calm and peaceful person with no tendency to dramatic behaviour. The high articulation values indicate that the improvisations were typically based on staccato rather than legato expression. In most of the improvisations, the pulse clarity is high, which suggests a rather stable rhythmic progression.

The exception to the typical state of affairs is the session 5 peak in the component, but there is an explanation. The client was working on her inability to be spontaneous and throw herself into life situations. It was also difficult for her to show negative emotions, such as anger or aggression – she typically kept these feelings inside, which caused a kind of repressed negativism. It also led to situations where some of her close relatives and friends were very dominating in relation to her, because she could not show her real feelings. In session 5, the therapist took on the role of a dominating friend and symbolically dominated her musically. He later wrote in his journal:

> *I took the role of the annoying relative in the improvisation. I intentionally disturbed the patient's play by playing in a loud, dissonant way (i.e., trying to be annoying in a symbolic way). However, this did not affect the patient's play, which was a picture of her life. This was exactly her problem: not being able to react in a spontaneous, authentic way.*

One way to utilise computational improvisation analysis methods in psychiatric context is to look at the graphical outliers in relation to the human context of the therapy.

For larger quantitative studies, the MTTB offers another perspective as well: a batch analysis – a statistical analysis of a large number of improvisations at once – can encompass many clients with a large number of sessions. Instead of graphic, visual representation of the improvisations, MTTB can create a data matrix. Each of the relevant musical features is depicted as single numeric value, which may be the mean, standard deviation or variation, for example. If the improvisation is not divided into sections, there will be only one numerical value per musical feature per improvisation; mean of musical density concerning whole improvisation, for instance. In this kind of representation, unfortunately, precision of micro-analytical analysis is sacrificed and the data are reduced and compressed, but it remains useful when one is dealing with big samples and trying to locate general trends across the musical features and client population under consideration.

Pros and cons of computational improvisation analysis

While computational improvisation analysis methods such as MTTB enable the analysis of a large amount of data, and the result of the analysis is clearly objective, the work is still being done by a machine with obvious limitations. The MTTB, for example, cannot interpret its findings. If musical density, one of the many features that the MTTB can extract from improvisational data, is high in the client's play, as was the case in figure 2 for the client with Asperger syndrome, it might indicate high energy and much activity in general; strong feelings about something, based on positive or negative emotional loading; or simply a physical limitation that forces the client to improvise using clustered voices. Thus the clinician or researcher will always require additional information to attempt an adequate interpretation, such as the known effects of a disorder in a certain client group (e.g., physical limitations or emotional problems), a particular individual's unique ways of expressing her/himself musically, and even a specific awareness of the context and issues involved in the work of improvising. Together, qualitative data from clinical observation and quantitative data from computational analysis will supply the necessary information for proper clinical assessment and evaluation.

When data exists for several clients representing the same diagnostic populations, commonalities in their musical behaviour across the sample can provide valuable hints for interpretation. Luck et al. (2006) found, for example, that severe mental retardation correlates with a staccato style of musical expression. This finding probably can be associated with a lower developmental age, where cognitive competencies such as the idea of phrasing, the creation of a melody line, or the general ability to deal with notes sequentially (all of which lead to legato rather than staccato style) are underdeveloped.

Another issue is that many aspects of musical behaviour cannot be extracted by computational methods in a trustworthy way. It is hard to teach a computer to recognise and distinguish melody, phrasing or accompaniment, for example, within a busy musical texture consisting of various overlapping aspects and events. Though research in this field is progressing quickly, computational improvisation analysis at the present time is based on a more global extraction of features.

Clearly, precision and reliability come with a price. On the other hand, traditional improvisation-analysis methods, such as the Improvisation Assessment Profile, or IAP (Bruscia, 1987) are generally unable to handle a large amount of data. They are very time-consuming and interpretative approaches with low inter-rater[1] reliability, and they are useful mostly for small-scale case studies and certain clinical applications. It is furthermore unlikely that different analysts, when employing manual analysis method, will end up with the same numeral ratings on highly abstract/interpretative musical phenomena. The consequence of this is that the analysis does not provide with reliable results. Overlapping musical features easily lead to a loss of focus and therefore reliability, in particular when employing manual methods with the computer. In the end, quantifying a highly qualitative phenomenon remains a challenging task. Whereas computational analysis methods only quantify objective facts (average pitch, for instance), one can always trust the numbers. Due to their effectiveness and precision, computational improvisation

1 Inter-rater is a basic staistical term that refers to consistency of assessments made by several independent assessors who evaluate the same event by using the same analysis method.

analysis methods will probably become more common in music-therapy research in the future, but we believe that qualitative methods will still have an important role in gaining a better understanding of the real-life implications of these findings.

Towards the standards

Computational methods develop quickly within various areas of human behaviour research, and continuously smarter and more sophisticated analysis techniques accompany them. Sometimes, however, there is a mismatch between these technology-driven measures and the actual needs of a practical profession such as music therapy. Additionally, clinical improvisation varies in popularity among cultures and nations, and there are various improvisational models with different theoretical and practical principles, first listed by Bruscia (1987). These principles may require different types of applications in terms of improvisation analysis. Free improvisation raises different challenges for analysis than other improvisation methods, which are based more closely on musical grammar, for instance.

Computational improvisation analysis is useful when it accommodates the theoretical and practical principles of an improvisational model. After successfully completing the randomized controlled trial (RCT) on depression based on improvisational music therapy (Erkkilä et al., 2011), we drew upon earlier writings, practices and our tacit knowledge to propose the model we currently call Improvisational Psychodynamic Music Therapy (IPMT). Though this work continues, we have published the outlines of the model already (Erkkilä, Ala-Ruona, Punkanen & Fachner, 2012). In IPMT, clinical improvisation is seen to represent a form of pre-conscious, nonverbal expression and interaction where thoughts and feelings that are not yet possible to verbalise or even consciously recognise are expressed in symbolic, musical form. These cerebral 'contents' are emotionally loaded and typically reflect highly personal, sometimes traumatic experiences which are otherwise repressed in everyday life. After improvising, clients often describe particularly strong sensations, images and memories that they experienced during the interaction with the instrument and the therapist. An essential part of the IPMT process is to then verbalise these (pre-conscious) experiences in a dialogue with the music therapist so as to gain a better understanding of the forces behind one's pathological behaviour. We believe that clinical improvisation stimulates the client in a therapeutically relevant way, boosts the therapeutic process, and enables a productive and appropriate expression and interaction even if the client is not yet able to verbally open up in therapy. Strong transference (and counter-transference) experiences are typical for an IPMT process and represent an essential therapeutic tool (see Bruscia, 1998b).

Improvising in IPMT is always based on the free, unstructured and spontaneous production of sounds, and improvisations are never alike in musical features or feature combinations. Sometimes, potentially meaningful shifts during the process are so subtle that only careful analysis will reveal them. In addition, a long-term music therapy process may comprise numerous improvisations, so a different set of specific analytical tools will be needed in order to reveal the overall evolution of the client expression. This kind of improvisation analysis helps music therapists to better understand this clinical tool and its function and implications for different diagnostic groups and individuals. Perhaps the most important potential of IPMT is to generate new insights into how clinical themes (e.g., aspects of pathology or recovery) affect improvisation; this knowledge might then be turned around to improve IPMT practice as well.

Our aim is to make our model, or approach, both useful and transferable nationally as well as internationally, to develop training around it, and to continue research activities by introducing new clinical target groups. To label IPMT a treatment model is, of course, rather ambitious at this stage – according to Bruscia (1998a), who has creditably defined music therapy in general, a model is the highest concept in a hierarchy also consisting of the technique, method and approach. Time will tell whether IPMT is unique enough to deserve this status, so for now we will think of it as an approach, one that in fact owes much to existing improvisational models and definitions as well. Our aim has always been to include all aspects of a treatment model in our plans, and to make IPMT as consistent as possible. A full-blown treatment model requires coherent theory, clear clinical procedures, a training system and outcome research, all of which presently exist with IPMT, even though more elaboration is required.

If a large enough group of clinicians and scholars takes up the gauntlet and participates in the development of clinical applications and research regarding IPMT, it might be possible to standardise the approach relatively quickly. Because computational improvisation analysis is fundamental to IPMT, this approach would allow for a better understanding of the implications of clinical improvisation for therapeutic work as well. Large samples representing different diagnostic populations, possibly based on international, multi-site studies, would contribute significantly to the preparation of the relevant standards.

Conclusion

In this chapter we have looked at the possible impacts of modern technology on music therapy clinical practice and research, focussing primarily on clinical improvisation. Certainly the computational analysis of clinical improvisations demands compromise and flexibility from the clinician, who, first of all, must sometimes accept the fact that his or her favourite instrument or clinical setting is not ideal (or even possible) from a data-collection point of view. Sometimes, one has to accept poorer sound quality as well, in the interests of obtaining a more optimal analysis. The clinician also has to acquire a basic knowledge of different digital-music data formats and the transfer of this data between applications. Thankfully, technology is now omnipresent and generally based on shared standards and functionality; it is also more affordable all the time, which allows for unprecedented improvements. For example, a mid-range digital piano is now fully able to compete with or supersede a traditional acoustic piano in terms of purchase price and service costs, convenience and sometimes even sound quality.

Computational improvisation analysis, such as MTTB, provides a precise and highly objective picture of the musical features of the process. Still, a human being is needed to interpret the results. In addition, purely musical analysis is seldom a sufficient basis upon which to construct relevant clinical interpretations. Additional data, such as the therapist's journals, video recordings, existing knowledge of the client's condition, and so forth, are also needed for successful interpretations during assessment and evaluation. It might be possible to connect MTTB analysis to other visualisation methods, such as traditional musical notation. For example, MIDI-based musical representation can be automatically converted into musical notation. Traditional notation, in turn, might expose certain musical phenomena, such as rhythmic patterns and melodic phrases, which are not possible to detect through MTTB, which produces a rather coarser representation of musical events.

Though computational analysis as such is a speedy process that allows one to deal with a huge amount of data at once, the clinical work that follows is not. A real challenge in terms of improving modern analysis possibilities is perhaps not the technology in question but the availability of coherent (and sufficiently large) samples to be analysed. Consensus is therefore needed regarding clinical models and procedures, so that this data can be acquired. Happily, IPMT, which combines all of the core elements of a treatment model, matches well with a computational improvisation analysis method. This is because in IPMT the musical expression and interaction are seen as an important source of information concerning the aspects of illness and recovery. An important element of the IPMT is also to put attention to, and to investigate the relationship between identifiable musical features and their symbolic meanings. This challenging task greatly benefits from the computational methods, which allow dealing with big amount of data in a systematic manner. It will not be long before we know much more about the clinically relevant implications of musical behaviour in improvisational music therapy.

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