Comparing Deep Networks for Predictable Polyphonic Piano Music Generation using a Symbolic Tonal Representation

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Introduction

Music generation has been a very popular topic of research since as early as the 1980s, where Recurrent neural networks (RNN) and Multi-Layer perceptrons (MLP) were mainly tested [1]. Given the complexity of music through features such as rhythm, melody, and harmony, the main challenges in music generation are integrating control and producing creative, realistic music. Purposes for music generation are currently very limited as research is focused more on music modeling [2], however overcoming these challenges will unlock new potential and open the doors for possible practical applications of music generation ranging from AI-assisted music composition to music for games.

Research in music generation has developed significantly, with most of the work done using RNNs, particularly Long Short-term memory networks (LSTM) given their effectiveness in modeling sequential data. Other network structures such as Transformer models and Recurrent Temporal Restricted Boltzmann Machines (RTRBM) have shown to generate music with more long-term structure, making up for what LSTMs generally lack. This induces the idea of layering network structures, to combine the benefits of multiple architectures. Through testing new network architectures and possible layering combinations, research in music generation aims to have more control and produce more creative, realistic music.

The focus on improving music generation through neural network structure has left other means of development lacking, a recent study has shown that by incorporating musical relationships of pitches into the input data by using a tonnetz inspired structure, the generated music appears to be more tonally stable and contain more repeated patterns [4], combining this idea with popular network structures may further develop the goal of overcoming the challenges mentioned.

The question this project aims to answer is:

Can incorporating tonal relationships allow for more predictable music generation, how does it compare between models?

Research objectives

- *Obtaining data:* The data that will be used is ADL Piano as it contains MIDI piano music from multiple genres, other data possibilities will be considered if necessary. The aim of this is to obtain the appropriate data for the task.
- *Preprocessing data:* The data will be analyzed to ensure it is in suitable condition for model training and then processed to represent the Tonnetz structure. This is the basis of the project, and the way the data is processed is expected to affect the patterns in the generated music.

- *Model adapting and training:* Popular models for music generation will be sourced and trained on the processed versions of the dataset. This allows us to investigate the consistency of the approach taken and compare the music generated by multiple models.
- *Evaluation:* A subjective and objective evaluation will be conducted to assess the model performance and find patterns in the generated music. This phase will help answer the research question and possibly inspire new tests to be carried out.
- It is expected that meaningful patterns will be found in the generated music that is based on how the data was preprocessed, to allow for more predicable music to be generated which aligns with current challenges in the field as we will have more control on the output.

The results from this project could be valuable to the following beneficiaries:

- Members of the Music Information Retrieval (MIR) society that are particularly interested in music generation and patterns in music.
- Musicians who are interested in the development of AI with regards to music, and who are possibly interested in AI-assisted products.
- Researchers that are interested in neural networks and Natural language generation as they are closely related in some cases.

Critical Context

Tonnetz

Tonnetz is a graph representation of music that encodes the harmonic relationship between notes. Its structure displays interval distances between notes where a row represents one of the 12 pitches in order of perfect fifths and a triangle of 3 notes represent a major or minor triad, minor if the triangle is upright and major if it is upside down. Triangles sharing edges are linked through parallel, relative, and leading-tone transformations as described by Neo-Riemannian operations [12].

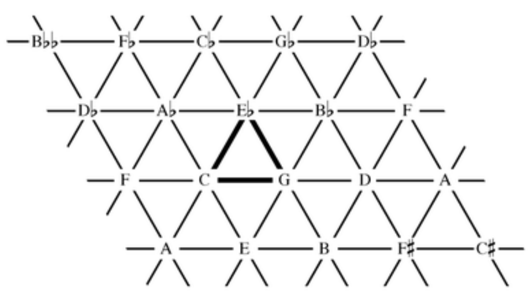


Figure 1: Tonnetz structure obtained from [6]

Symbolic tonnetz inspired MIDI data structures allow for aspects of music theory to be integrated without affecting the training process, and have produced tonally stable music, with more repeated patterns as compared to piano-roll generated models [7]. Other research conducted using a tonnetz representation focus on learning pitch, melodic or rhythmic properties of the data, in addition to testing new network architectures as seen by [16, 17], instead of testing limitations of this representation. It was noticed most of the research in music generation does not incorporate music theory into the training process.

MIDI

MIDI is a descriptive data representation of music that is vital in the music industry as it provides information such as pitch, duration, velocity and takes up less storage as it does not contain waveform data [2]. Given its symbolic structure, it can be represented in many ways such as a 1D or 2D array, or Word2vec which constructs semantic vector spaces for polyphonic music [18]. This is advantageous as transformations allow for the use of these MIDI representations to be easily available. However, MIDI does have inconsistencies with music generation as it has trouble representing note durations and rhythmic properties such as syncopation.

Long Short-term Memory (LSTM)

A recurring neural network structure designed to learn long-term dependencies. The cell state (shown by the top horizontal line in figure 2) gives the model its long-term memory by storing information from previous events that are updated each event.

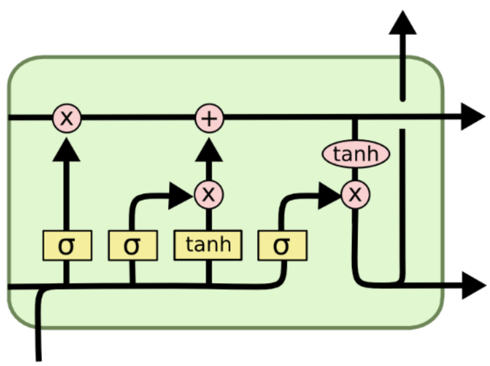


Figure 2: LSTM structure [13]

Single-layer LSTMs are generally used for monophonic music generation while more recently multi-layer LSTMs have been shown to better for polyphonic music generation. Due to its ability to model sequential data, it is arguably the most popular network structure used [19]. Comparisons of LSTMs with other network structures have shown that they fail to generalize arbitrary time lengths and produce unimaginative melodies [20]. This led to different layers of network structures being tested to combine the benefits of both architectures, an example being LSTM-RTRBM [21] which improves long-term melodies.

Convolutional neural networks (CNN)

A deep neural network structure that is usually used for image classification. CNN's learn features through adding sparsity to neuron activation using multiple filters, which are then pooled to extract characteristics of the data.

CNN performs surprisingly well even outperforming LSTMs in some cases with lower loss, faster convergence due to feature extraction, and better-quality music [23]. However, they may require temporal dependencies as it is not an autoregressive model.

Generative Adversarial Networks (GANS)

A network structure where a *"discriminator"* neural network is trained side-by-side with a *"generator"* network. A game is played between the generator and discriminator where the generator network generates new data based on the training data [2], and the discriminator network is trained to distinguish between generated and real data. GANS have been widely used with generator network architectures such as Convolutional neural networks (CNN) as seen by MidiNet [3] and LSTMs such as LSTM-GAN [4] with the use of MIDI data and have shown to be a powerful alternative to RNNs.

Transformer models

An attention-based neural network that maps data to a vector space, where they are encoded attention vectors and are used to determine parts of the data to focus on, the attention vectors are trained and decoded through the decoder component. They have recently gained popularity through their lengthy generated music and are mainly used to generate long-term structure, as seen by MuseNet which can generate around 4 minutes of music, and Music transformer [15]. [16] proposed a transformer model with a combination of GANS and have shown this structure generates higher quality music comparatively.

Recurrent Temporal Restricted Boltzmann Machines (RTRBM)

An adapted version of temporal restricted Boltzmann machines that are modeled in a temporal sequence to demonstrate chronological behaviour. RTRBMs have been used side-by-side with LSTMs and other models, mainly being advantageous due to their long-term memory. Generally, good results are obtained when RTRBMs are used, however they are computationally expensive due to the use of Markov-Chain Monte Carlo methods [17].

Evaluating generated music

Evaluating generative models is a big challenge in music, as it is inherently subjective. Descriptive musical metrics have been tested to evaluate the generated music, however there is no rigorous metric to evaluate it [14], unlike other classification tasks where accuracy is the main metric used to evaluate the model's performance.

Due to this, multiple methods have been developed to assess generated music, objective tests which include general model metrics such as loss or mean squared error and descriptive music statistics that are usually defined beforehand and vary based on what is being assessed, some examples are the number of unique pitches used or polyphonic rate [15]. In addition to objective metrics, listening tests where participants are asked about the generated music is strongly recommended.

Approaches

Literature Search and Survey

The literature obtained was sourced from Google scholar and conferences held by the International Society of Music Information Retrieval (ISMIR) to establish a suitable research question and valid approach. An ongoing literature search and survey will be conducted while writing the project to assist as seen necessary.

Software and machine

The main program that will be used is python as it contains all the necessary MIDI manipulation (pretty_MIDI), machine learning (Pytorch and TensorFlow), and visualization tools (Matplotlib and Seaborn) to run all tasks of the project, libraries will be installed beforehand along with the specified requirements to train the chosen models.

The project will be done on a local computer with main specifications 16GB RAM and NVIDIA GeForce GTX 1080 graphics card that will run all the model training. Cloud services will be decided on beforehand to allow for distributed learning in case model training times take longer than expected.

Data collection and preprocessing

The symbolic data that will be used is ADL Piano MIDI [8] as it is highly due to its reliability and variety of available genres. The dataset is a subset of the Lakh MIDI dataset, however ADL Piano MIDI has been filtered to remove duplicates and keep pieces that only have piano as an instrument, the final dataset contains 11,086 unique piano pieces from various genres. It is likely the whole dataset will not be used for training due to its size, and training times can take very long, therefore subsets of the data with balanced genre distributions will be sufficient for training. Similar datasets have also been sourced in case ADL Piano MIDI becomes unavailable, they are GianMIDI-Piano and Piano-MIDI.

The MIDI data will be processed using the necessary libraries to prepare it to be used for model training, some musical features such as velocity are lost in this stage due to limitations, however this does not greatly affect the project as the focus revolves around melody and harmony.

Once initial models have been trained, the data will be reprocessed to a tonnetz structure inspired [3] shown in figure 2. Before converting the MIDI data to this structure, pieces will be transposed to the same key signature to preserve the roles of pitch, which are determined by the intervals separating them [9].

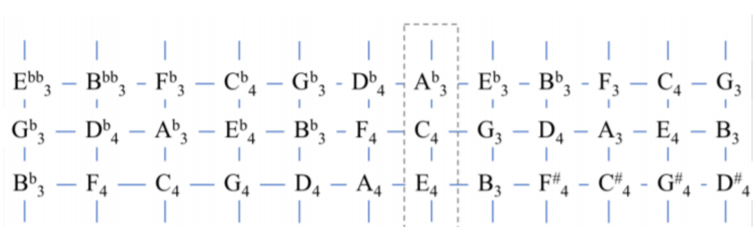


Figure 3: Tonnetz matrix done by Chuan and Herremans, n.d.

Comparing multiple models that are trained on the same data but transposed to different keys will play a major role in answering the defined research question.

Model selection and adjustment

Constructing network architectures from scratch can take a long time, therefore prebuilt models that have been made for MIDI polyphonic music generation will be used, these are also more reliable as they have been tested and proven to work. Multiple models will be compared since prebuilt architectures will be used, this will provide insight on the consistency of using a tonnetz data representation and an idea of which network architectures generally perform better, the results from these models will be evaluated carefully and are expected to help answer the chosen research question through the evaluation.

Given the timeframe, it is expected 2 network architectures will be a sufficient comparison. Models were ranked based on interest and were selected if the code and a related research paper using the model were available. In addition to this, extra models were found in case unseen circumstances do not allow the chosen ones to be used, or more time is available allowing for other models to be compared.

The first model chosen is bi-axial LSTM [10], a two-layered LSTM architecture that captures melodic and harmonic relationships between notes. Results from the relating paper show that the loss of this model settles down after approximately 2 hours of training, however the longer training time is reflected in the music it generates [10]. The second model chosen for the comparison is MidiNet [11], a CNN-GAN architecture that develops more interesting music when compared to other models according to the related research paper. These models were selected as they are good representations of popular network structures that work well as shown in the related research papers. Other network architectures that may be explored if time allows it include transformer models and RTRBM as they have recently grown in popularity and generally produce music with a more long-term structure.

Once the models generate satisfactory music, they will be adapted to take the tonnetz inspired MIDI data as input, and new models will be trained using this data. It is expected to take a few days to install the requirements for the chosen models and train them, which should leave time for the planned experimentation to be carried out.

Results and evaluation

The evaluation process involves subjective and objective assessments of the generated music through listening tests, and metrics relating to the neural network and music produced.

Objective tests carried out regarding model performance include general metrics such as loss, while descriptive music metrics will be created to outline properties of the generated music such as the number of notes, polyphonic rate, and pitch interval range. Descriptive music metrics will be explicitly defined in the report along with details on how they are calculated before the evaluation process begins.

Subjective assessments will involve online listening tests. An online listening test and survey will be created and conducted to obtain opinions on the music generated and will be the base for evaluating the model's ability to generate music. Questions about the participants like their musical background will be asked in addition to their opinions on the generated music, personal questions will be avoided. A limitation of this method is that online surveys can be unreliable as it lacks validity, however the extra information should prove to be useful and can be discarded if seen necessary.

The results obtained from the objective and subjective tests will provide the necessary information required for the next step. The results will be compared using techniques such as dimensionality reduction (e.g PCA, t-SNE) to display similarity in descriptive metrics of generated music, as well as exploratory analysis for the survey results. Comparing the results obtained between models should help find patterns that will allow for generative music predictions to be made.

Report

The report will be written during each stage of the project with key points of the project logged as well as issues faced and how they were overcome. A set period before the deadline will be dedicated to completing the report, this will allow for sufficient feedback from the supervisor and enough time to address the points. Extra time is allocated to parts of the project that have a chance of taking longer than expected, this considers unexpected issues that may occur and allows for enough time to overcome them while not falling behind schedule.

Project meetings

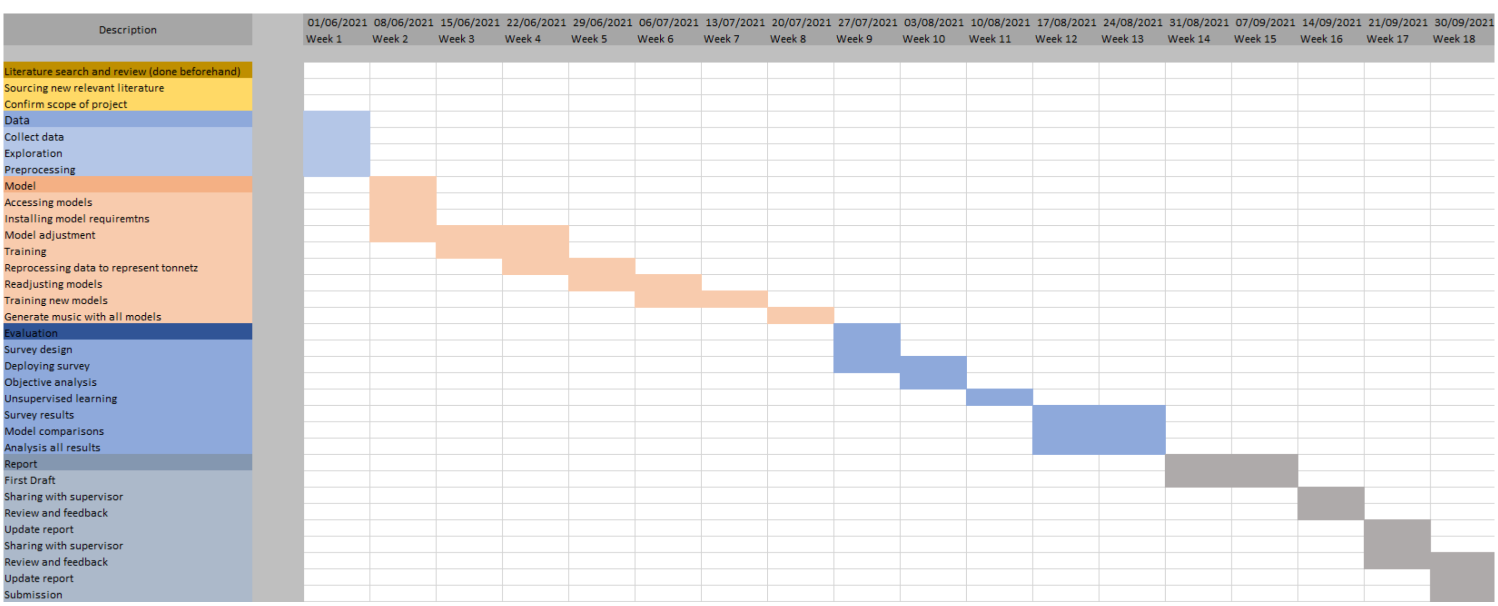
Weekly meetings will be scheduled with the project supervisor to discuss progress made and get feedback and advice. If weekly meetings cannot be arranged due to certain circumstances extra effort will be put in to ensure there is at least 1 meeting every 2 weeks.

Risks

Description	Likelihood (1-3)	Consequence (1-5)	Impact (L x C)	Mitigation
Original dataset cannot be obtained	1	3	3	Use backup datasets
Difficulty in adapting model	2	4	8	Other models that use MIDI can be used
Model training taking a long time	3	3	9	Adjust model or use cloud services
Models cannot be retrieved	2	5	10	Build off different model
Unable to conduct listening test	1	4	4	Compare objective results
Not enough results from listening test	1	4	4	Compare objective resutlts
Loss of motivation	1	4	4	Discuss with supervisor
Code accidentally lost or deleted	2	5	10	Code regularly pushed on version control software e.g., GitHub

Workplan

Phase	Description	Outcome
Literature search and review	• Sourcing new relevant literature • Confirm scope of project	Updated Approach
Data collection and pre-processing	• Collect data • Exploration to make sure the dataset format is understood • Data processing	Data ready for model training
Model adapting and training	• Accessing models • Installing requirements • Model adjustment • Training • Reprocessing data to represent Tonnetz • Readjusting models • Training new models • Generate music with all models	Music generated from all models, allowing for evaluation phase to proceed
Evaluation	• Survey design • Deploying survey • Objective analysis • Unsupervised learning • Survey results • Model comparison • Analysis of all results	Provides necessary information to answer research questions and can focus on report writing or testing new models if time allows
Report writing	• Cycle of drafting, getting feedback from supervisor and addressing points until submission	Submit final report



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Research Ethics Review Form: BSc, MSc and MA Projects

Computer Science Research Ethics Committee (CSREC)

http://www.city.ac.uk/department-computer-science/research-ethics

Undergraduate and postgraduate students undertaking their final project in the Department of Computer Science are required to consider the ethics of their project work and to ensure that it complies with research ethics guidelines. In some cases, a project will need approval from an ethics committee before it can proceed. Usually, but not always, this will be because the student is involving other people ("participants") in the project.

In order to ensure that appropriate consideration is given to ethical issues, all students must complete this form and attach it to their project proposal document. There are two parts:

PART A: Ethics Checklist. All students must complete this part. The checklist identifies whether the project requires ethical approval and, if so, where to apply for approval.

PART B: Ethics Proportionate Review Form. Students who have answered "no" to all questions in A1, A2 and A3 and "yes" to question 4 in A4 in the ethics checklist must complete this part. The project supervisor has delegated authority to provide approval in such cases that are considered to involve MINIMAL risk. The approval may be ***provisional*** – *identifying the planned research as* likely to involve MINIMAL RISK. In such cases you must additionally seek ***full approval*** from the supervisor as the project progresses and details are established. ***Full approval*** must be acquired in writing, before beginning the planned research.

A.1 If you answer YES to any of the questions in this block, you must apply to an appropriate external ethics committee for approval and log this approval as an External Application through Research Ethics Online - https://ethics.city.ac.uk/		*Delete as appropriate*
1.1	Does your research require approval from the National Research Ethics Service (NRES)?	**NO**
1.2	Will you recruit participants who fall under the auspices of the Mental Capacity Act?	**NO**
1.3	Will you recruit any participants who are currently under the auspices of the Criminal Justice System, for example, but not limited to, people on remand, prisoners and those on probation?	**NO**
A.2 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee, you must apply for approval from the Senate Research Ethics Committee (SREC) through Research Ethics Online - https://ethics.city.ac.uk/		*Delete as appropriate*

2.1	Does your research involve participants who are unable to give informed consent?	**NO**
2.2	Is there a risk that your research might lead to disclosures from participants concerning their involvement in illegal activities?	**NO**
2.3	Is there a risk that obscene and or illegal material may need to be accessed for your research study (including online content and other material)?	**NO**
2.4	Does your project involve participants disclosing information about special category or sensitive subjects?	**NO**
2.5	Does your research involve you travelling to another country outside of the UK, where the Foreign & Commonwealth Office has issued a travel warning that affects the area in which you will study?	**NO**
2.6	Does your research involve invasive or intrusive procedures?	**NO**
2.7	Does your research involve animals?	**NO**
2.8	Does your research involve the administration of drugs, placebos or other substances to study participants?	**NO**
A.3 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee or the SREC, you must apply for approval from the Computer Science Research Ethics Committee (CSREC) through Research Ethics Online - https://ethics.city.ac.uk/ **Depending on the level of risk associated with your application, it may be referred to the Senate Research Ethics Committee.**		*Delete as appropriate*
3.1	Does your research involve participants who are under the age of 18?	**NO**
3.2	Does your research involve adults who are vulnerable because of their social, psychological or medical circumstances (vulnerable adults)?	**NO**
3.3	Are participants recruited because they are staff or students of City, University of London?	**NO**
3.4	Does your research involve intentional deception of participants?	**NO**
3.5	Does your research involve participants taking part without their informed consent?	**NO**
3.5	Is the risk posed to participants greater than that in normal working life?	**NO**
3.7	Is the risk posed to you, the researcher(s), greater than that in normal working life?	**NO**

A.4 If you answer YES to the following question and your answers to all other questions in sections A1, A2 and A3 are NO, then your project is deemed to be of MINIMAL RISK. **If this is the case, then you can apply for approval through your supervisor under PROPORTIONATE REVIEW. You do so by completing PART B of this form.** **If you have answered NO to all questions on this form, then your project does not require ethical approval. You should submit and retain this form as evidence of this.**		*Delete as appropriate*
4	Does your project involve human participants or their identifiable personal data?	**YES**

PART B: Ethics Proportionate Review Form

If you answered YES to question 4 and NO to all other questions in sections A1, A2 and A3 in PART A of this form, then you may use PART B of this form to submit an application for a proportionate ethics review of your project. Your project supervisor has delegated authority to review and approve this application under proportionate review. You must receive final approval from your supervisor in writing before beginning the planned research.

However, if you cannot provide all the required attachments (see B.3) with your project proposal (e.g. because you have not yet written the consent forms, interview schedules etc), the approval from your supervisor will be ***provisional***. You **must** submit the missing items to your supervisor for approval prior to commencing these parts of your project. Once again, you must receive written confirmation from your supervisor that any provisional approval has been superseded by with ***full approval*** of the planned activity as detailed in the full documents. **Failure to follow this procedure and demonstrate that final approval has been achieved may result in you failing the project module.**

Your supervisor may ask you to submit a full ethics application through Research Ethics Online, for instance if they are unable to approve your application, if the level of risks associated with your project change, or if you need an approval letter from the CSREC for an external organisation.

B.1 The following questions must be answered fully. All grey instructions must be removed.		*Delete as appropriate*
1.1.	Will you ensure that participants taking part in your project are fully informed about the purpose of the research?	**YES**
1.2	Will you ensure that participants taking part in your project are fully informed about the procedures affecting them or affecting any information collected about them, including information about how the data will be used, to whom it will be disclosed, and how long it will be kept?	**YES**
1.3	When people agree to participate in your project, will it be made clear to them that they may withdraw (i.e. not participate) at any time without any penalty?	**YES**
1.4	Will consent be obtained from the participants in your project? Consent from participants will be necessary if you plan to involve them in your project or if you plan to use identifiable personal data from existing records. “Identifiable personal data” means data relating to a living person who might be identifiable if the record includes their name, username, student id, DNA, fingerprint, address, etc.	**NO**
1.5	Have you made arrangements to ensure that material and/or private information obtained from or about the participating individuals will remain confidential?	**Yes**

	Details: Any personal information such as IP addresses obtained through the survey tool will be deleted, in addition to this information will be stored on a password protected computer and backed up in a safe location	

B.2 If the answer to the following question (B2) is YES, you must provide details		*Delete as appropriate*
2	Will the research be conducted in the participant's home or other non-University location?	**NO**

B.3 Attachments **ALL of the following documents MUST be provided to supervisors if applicable.** **All must be considered prior to final approval by supervisors.** **A written record of final approval must be provided and retained.**	***YES***	***NO***	***Not Applicable***
Details on how safety will be assured in any non-University location, including risk assessment if required (see B2)			**Not applicable**
Details of arrangements to ensure that material and/or private information obtained from or about the participating individuals will remain confidential (see B1.5)			**Not applicable**
Full protocol for any workshops or interviews**			**Not applicable**
Participant information sheet(s)**		**No**	
Consent form(s)**			**Not applicable**
Questionnaire(s)**		**No**	
Topic guide(s) for interviews and focus groups**			**Not applicable**
Permission from external organisations or Head of Department**			**Not applicable**

***If these items are not available at the time of submitting your project proposal, then **provisional approval** can still be given, under the condition that you must submit the final versions of all items to your supervisor for approval at a later date. **All** such items **must** be seen and approved by your supervisor before the activity for which they are needed begins. Written evidence of **final approval** of your planned activity must be acquired from your supervisor before you commence.*

Changes

If your plans change and any aspects of your research that are documented in the approval process change as a consequence, then any approval acquired is invalid. If issues addressed in Part A (the checklist) are affected, then you must complete the approval process again and establish the kind of approval that is required. If issues addressed in Part B are affected, then you must forward updated documentation to your supervisor and have received written confirmation of approval of the revised activity before proceeding.

Templates for Consent and Information

You must use the templates provided by the University as the basis for your participant information sheets and consent forms. You **must** adapt them according to the needs of your project before you submit them for consideration.

Participant Information Sheets, Consent Forms and Protocols must be consistent. Please ensure that this is the case prior to seeking approval. Failure to do so will slow down the approval process.

We strongly recommend using Qualtrics to produce digital information sheets and consent forms.

Further Information

http://www.city.ac.uk/department-computer-science/research-ethics

https://www.city.ac.uk/research/ethics/how-to-apply/participant-recruitment

https://www.city.ac.uk/research/ethics