Using Motion Sensor and Machine Learning to Support the Assessment of Rhythmic Skills in Social Partner Dance: Bridging Teacher, Student and Machine Contexts

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in the Sydney School of Architecture, Design and Planning at The University of Sydney, Australia

Augusto Dias Pereira dos Santos
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Abstract

Social partner dance is a popular form of physical activity intended for enjoyment and pleasure. Rhythm is an essential aspect of dance, especially in relation to music; however, it can be a difficult psychomotor skill to learn. Rhythm learning is hindered because dance teachers have a short time during classes to assess and provide feedback to students, and students have limited or no access to assessment and feedback outside the classroom. Current technical solutions enable automatic assessment and feedback for dance students; however, the available technology is either expensive or cumbersome. Recent improvement and decreased price of wearable technology (e.g. smartphones, activity trackers and motion sensors) offer new opportunities for creating tools to support dance teachers and students.

The research questions of this thesis were 1) How do social partner dance teachers assess the development of rhythm skills in students? 2) How can we use motion sensors to extract rhythm-related information that enables the support of dance rhythm assessment and learning? 3) Is the extracted information valid, useful and relevant for teachers and students? This thesis proposed and investigated a technological solution that used motion sensors to extract rhythm-related information from students’ movement performance, validated its accuracy and evaluated the benefits of such information for teachers and students. This thesis used as a case study a Brazilian social partner dance style called Forró. The research questions were explored using a mixed methods approach of design based research, user-centred design and machine learning (ML) methods. User-centred research was used in two studies to understand the context of social partner dance learning from the perspective of teachers and to evaluate the proposed solution with teachers and students. An iterative design approach was employed to guide the development of the algorithms to extract features from motion sensors. The accuracy of the technical solution was validated using ML methods with
a ground truth reference of dance expert annotators using a video annotation tool to assess rhythmic skills in students performing dance steps.

The key contributions of this thesis are:

- Understanding the context of Forró dance learning from the teachers’ perspective, including the assessment and feedback of rhythm skills.

- Design of Rhythmic Dance Movement Detection (RiMoDe) v1 and v2 algorithms that extracted rhythmic and movement features from motion sensor (accelerometer and gyroscope) data; Forró Trainer, a mobile app that embedded the RiMoDe algorithm and allowed dance students to practise exercises, providing automated assessment of the development of their rhythmic skills.

- A set of performance metrics related to rhythm skills (consistency, user beats per minute, rhythm, pause, step size and weight transfer) that were validated using ML methods and the ground truth of dance experts, and achieved an average accuracy of 80%.

- Evaluation of the automatic rhythm assessment when used by dance teachers and student participants, providing insights for future development and research.

The studies presented in this thesis were explored in the context of a specific dance style; however, the findings are relevant to other learning scenarios such as different dance styles and other psychomotor skills related to rhythm.
Authorship Attribution Statement

This thesis contains material published in,


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As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

Supervisor Name: Lian Loke

Signature:

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Statement of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes. I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Augusto Dias Pereira dos Santos
I would like to dedicate this thesis to the worldwide Forró community, especially to the Sydney Forró Dance community¹, its volunteers, dance facilitators and the thousands of students that we trained and shared great life experiences together. Our love and passion for dance and our belief in the transformation that dance can bring to individual lives and to the community motivated me to pursue innovative ways of supporting dance learning.

¹http://sydneyforro.com/
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When I decided to do a PhD, my goal was to have a great life experience. Going to the other side of the globe was an adventure that should be worth more than a title. And it was.

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Chapter 1

Introduction

1.1 Context and Motivation

Social partner dance is a popular form of physical activity that is intended for enjoyment and pleasure. Many studies have demonstrated the value of social partner dancing for promoting mental and physical well-being (Kiepe et al., 2012; Lima and Vieira, 2007). Most studies have assessed the benefits of dance in populations at risk, such as the elderly or people with psychological and physical illnesses (Kiepe et al., 2012); however, several studies conducted with young adults have shown similar results (Maraz et al., 2015; Zajenkowski et al., 2015). An essential pillar for people to enjoy the benefits of social partner dance is the learning and teaching of dance.

Rhythm is an essential aspect of dance, especially its relation to music; however, it can be a difficult psychomotor skill to develop. Many people may face challenges while learning to dance because dancing is a complex activity that involves the development of cognitive and motor skills (Schmidt et al., 2005) aligned with constant auditory stimuli (Phillips-Silver and Trainor, 2007). During the learning process of dance, one of the most critical skills for students to learn is rhythm (Erkert, 2003; McCutchen, 2006). Rhythm in dance means to synchronise the dancer’s body movements with one or more components of the music. This synchronisation is a complex process that we can simplify as a series of sequential tasks that the student (or more experienced performer) must effectively accomplish. These tasks include: 1) listening to the music; 2) interpreting its patterns, i.e. deciding which part of the music to follow and
which moves to perform; and 3) expressing this decision externally, i.e. moving the body according to the music (Côté-Laurence, 2000).

Teachers commonly use a wide range of methods and exercises to help people develop the cognitive and motor skills that are required during dancing. Results of these methods vary depending on the dance style (Côté-Laurence, 2000; Flippin, 2013), the teacher’s pedagogical approach (Erkert, 2003; McCutchen, 2006) and the difficulties that individual students may face. Moreover, rhythm learning can also be challenging for some people because dance teachers have a short time during the classes to assess and provide feedback to students, and students commonly have little to no access to assessment and feedback outside the classroom or dance studio. Dance teachers commonly have to manage large numbers of students and cannot easily assess each student’s progress (e.g. in the dance studio or at home). These large numbers of students make it challenging for teachers to be aware of the individual needs of each student and to give personalised attention to them (Hsia et al., 2016). Consequently, not all students will receive the same opportunities for learning or the attention and feedback they require. Furthermore, when students practise by themselves (e.g. at home), they usually do not receive any feedback, which can discourage them from practising. In some institutions, several dance teachers share the same dance classes, which may make it difficult for the different teachers to assess the development of each of their students (Hanrahan et al., 2009). This complex environment suggests the need for supporting social partner dance education with tools that teachers can use to increase and enhance their ability to assess students’ development. For students, technology can help them practise and receive feedback independently of the teacher and be aware of their learning development. As dance learning occurs using the body and space, the technology to support dance learning must respect these constraints.

Current technical solutions enable automatic assessment and feedback for dance students; however, the available technology is either expensive or cumbersome. Recent improvements to and lower prices of wearable technology (e.g. smartphones, activity trackers and motion sensors) offer new opportunities to create tools to support dance teachers and students. As sensors are becoming less expensive, researchers are starting to investigate how these devices can support motor learning. Most research in this field, however, has focused on measuring learning (Santos, 2016) and, sometimes, automatically providing feedback regarding specific aspects of learning. Some of the
fields in which sensors have been used to support psychomotor learning include snowboarding (Spelmezan and Borchers, 2008), piano (Hadjakos et al., 2008), percussion (Kawakami and Fujinami, 2008), dance (Hinton-Lewis et al., 2016; dos Santos et al., 2018b), weightlifting (Kowsar et al., 2016) and martial arts (Kwon and Gross, 2005; Takahata et al., 2004). This thesis focuses on the use of motion sensors, with the help of machine learning (ML) algorithms, to provide automated support to the assessment of rhythmic skills in the context of social partner dance education.

The sensors that have been most commonly used to model students’ movement are accelerometers, gyroscopes and force and pressure sensors (Drobny et al., 2009; Hadjakos et al., 2008; Hinton-Lewis et al., 2016; Kowsar et al., 2016). These sensors are usually attached to specific parts of the student’s body or to items that the student is wearing such as shoes or ski gear. The main two approaches to analyse the data obtained from the sensors are to compare the student’s movements to an expert model (Hadjakos et al., 2008; Matsumura et al., 2011) or to extract features from the data that can represent the student’s performance (Hinton-Lewis et al., 2016; Senecal et al., 2018). In most of these studies, the researchers have a technical view attempting to use technology to measure performance without understanding the learning context or how technology could be used to benefit students or teachers (Hinton-Lewis et al., 2016; Faridee et al., 2018; Lee et al., 2007). In one case where the learning context was considered, the technical solution was not properly evaluated (Senecal et al., 2018).

In data-intensive educational fields, such as Intelligent Tutoring Systems, Artificial Intelligence in Education, Educational Data Mining and Learning Analytics and Knowledge, there is a stronger interest in aligning the technology solution with the learning contexts. Also in these fields, there is an increasing adoption of new sensors and devices to support the learning environment (Blikstein and Worsley, 2016; Bondareva et al., 2013). Blikstein and Worsley (2016) presented examples such as the use of speech data to assess reading proficiency and the use of Kinect sensor to study student understanding of proportions. Similarly, Bondareva et al. (2013) used eye-trackers to predict learning while using an Intelligent Tutoring Systems to learn about the human circulatory system. These new sources of data can enhance or even replace the personal computer as the main input. However, research on technological support for psychomotor learning contexts is still modest compared to tertiary and K12 education (Santos, 2016; Santos and Eddy, 2017).
CHAPTER 1. INTRODUCTION

To date, much more work needs to be done to understand how to provide automated support for the development of rhythmic skills in social partner dance learning, whilst taking into account the learning context in which teachers and students are immersed and incorporating critical dance and educational constructs. This thesis aims to contribute to the fields of dance learning, activity recognition and learning technologies, using as a case study the application of motion sensors to support a Brazilian social partner dance education called Forró.

1.2 Research Questions

This thesis addresses the following question which is at the intersection of these fields: How can motion sensors be used to extract key rhythm indicators from students’ movement and feed algorithms and machine learning models to support teachers and students in assessing the development of rhythm-related skills? From this main question, the following three research questions (RQ) were selected to be investigated:

RQ1 How do Forró dance teachers approach teaching of rhythmic skills? This question will be addressed by 1) identifying and analysing the key literature that describes the social partner dance education in terms of important dance skills, assessment strategies and types of feedback, and 2) interviewing social partner dance teachers to obtain an in-depth understanding of how they approach these three aspects, especially related to rhythmic skills.

RQ2 How can we use motions sensors on smartphones to extract rhythm indicators to enable the support of dance rhythm assessment? This is addressed by developing algorithms that use motion sensors to translate the rhythmic data captured into information that can be useful for dance students and teachers.

RQ3 Is the extracted information valid, useful and relevant for teachers and students? This question will be addressed by presenting to students and teachers the results of the automatic assessment. Students will evaluate an automated feedback report containing a series of data representations of their dance performance as collected and analysed by the algorithms proposed in this thesis. Teachers will
have the support of the automatic assessment while assessing videos of students’ performance.

This thesis aimed to address the three research questions by the following statement that summarises the approach of this thesis:

**Design and validate a technological solution, based on the use of motion sensors and the application of machine learning techniques, to automatically i) extract rhythm-related indicators from students’ movements ii) model critical rhythmic skills, and iii) support teachers and students to assess rhythm-related dance skills.**

Presented in Figure 1.1, several fields of knowledge are related to this thesis. Dance education is in the centre of the question and define the context in which technology will be used. This thesis investigates Forró dance education, a Brazilian social partner dance. Topics as the important skills required for Forró dance, assessment strategies and types of feedback are used to drive the technology development (Jarmolow and Selck, 2011; McCutchen, 2006; Vecchi, 2012). The field of learning technologies have several studies on the use of technology to support assessment and provide feedback (Blikstein and Worsley, 2016; Guerra, 2016; Papamitsiou and Economides, 2014). For that reason, this thesis used several studies on learning technology as a state-of-the-art reference on the different methods and approaches to use technology in learning contexts and model students’ performance, focusing on automated rhythm assessment and feedback. A crucial third field is activity recognition, that will provide the technical means to collect and analyse the data from students’ performance, more specifically the studies on dance movement analysis using motion sensors (Camurri et al., 2016a; Drobny et al., 2009; Kwapisz et al., 2011; Lee et al., 2007).

To provide a solution that can support both teachers and students, the system must be able to capture the students’ performance. There are many technological alternatives to achieve this; however, this thesis focused on wearable motion sensors to extract *dance movements* because it is a less obtrusive technology, and thus does not interfere in the dance class ecosystem or impair the natural interactions among students and teachers (Lieberman and Breazeal, 2007; Piana et al., 2016). Additionally, it is essential that the technology communicates to students and teachers using a vocabulary that is appropriate and compatible with their context.
This thesis uses the term dance skills to refer to skills that the students need to learn while progressing in their dance practice. Forró dance teachers and the dance literature are the primary sources of knowledge to identify the best terms that can be associated with the dance skills. Internally, the system will store the dance skills indicators as part of the student learner model (Guerra, 2016; Kay, 2001). The challenges that arose included a) identifying the appropriate dance skills to model, b) using the correct motion sensors to extract information from students c) storing this information in the student’s model and c) sharing the obtained information with the users. This is a relatively new exploration as few studies have explored learner models for dance or other psychomotor learning (Santos, 2016, 2017; Ramasamy Ramamurthy and Roy, 2018).

The data stored in the system must then be represented to teachers and students to support the assessment of rhythm-related skills. The format of this representation may vary from simple texts to complex charts. These various options pose a challenge to researchers as each option can contribute to or impede the user’s understanding of the information (Schwendimann et al., 2017). Allowing students to reflect on their activities is essential for their learning and may reduce the teachers need for intervention (Tembrioti and Tsangaridou, 2014).

1.3 Research Objectives and Methodology

The main thesis objectives (TOs) are described below and are presented in Figure 1.1, section Objectives:

TO1 Understand the teachers’ context of teaching rhythm in Forró dance. This thesis focuses on Forró, a Brazilian social partner dance; therefore, it was important to understand how Forró dance teachers approach their teaching of dance. Even though some dance concepts may be valid across different dance genres, other concepts may be specific to the targeted dance style, here Forró (El Raheb et al., 2018b). This objective addresses RQ1 by interviewing Forró dance teachers, enquiring into those skills that are important for their context as dance teachers and how they approach assessments and provide feedback to their students. The literature on dance education also offers a valuable guide on which skills are most
CHAPTER 1. INTRODUCTION

Contributions
Context
Activity Recognition
Dance Education
Learning Technologies

How can motion sensors be used to extract key rhythm indicators from students' movement and feed algorithms and machine learning models to support teachers and students in assessing the development of rhythm-related skills?

Research Questions
How do Forró dance teachers approach teaching of rhythmic skills?
How can we use motion sensors on smartphones to extract rhythm indicators to enable the support of dance rhythm assessment?
Is the extracted information valid, useful and relevant for teachers and students?

Thesis Statement
Design and validate a technological solution, based on the use of motion sensors and the application of machine learning techniques, to automatically i) extract rhythm-related information from students' movement, ii) model critical rhythmic skills, and iii) support teachers and students to assess rhythm-related dance skills.

Objectives
Understand the teachers' context of teaching rhythm in Forró dance
Design algorithms to extract rhythm related information from students' movement
Validate data extracted from motion sensors using social dance teachers' assessment
Use the automatic assessment to support teachers and students

Studies (validation / evaluation)
Study 1: Teachers' Interviews
Study 2: Pilot Study with Students
Algorithm validation
Teachers' annotations
Interview with Students

Contributions
Important aspects of Forró teaching
Rhythmic related Data Representations
RiMoDa v1 Algorithm to detect rhythm in dance students, using wearable devices
Understanding the Gap between Teachers and Algorithmic Assessment
Translating raw data into Dance Skills
Automatic Rhythm Assessment Evaluation
Video Annotation Tool

Figure 1.1: Overview of the context, objectives, studies and contributions of this thesis.
relevant to the context of dance education, as well as for assessment and feedback strategies. This thesis objective is mainly addressed in Chapter 4, although Section 2.1.1 provides a summary on how the literature identifies such skills. Although this thesis focuses on Forró dance education, the Discussion chapter (Chapter 8) presents how the results from this thesis can be translated into other dance styles or psychomotor contexts.

**TO2 Design algorithms to extract rhythm indicators from students’ movements.**
This objective is the technological foundation of this thesis and specifically addresses RQ2. The unexplored nature of this topic requires this thesis to design and develop tools that are required to research and support social partner dance teachers and students in the assessment of rhythm-related skills. From RQ1, rhythm was selected as the skill to be investigated in this thesis. The thesis describes the design and development of i) Forró Trainer: a mobile app that uses mobile sensors to collect motion data, ii) Rhythmic Dance Movement Detection (RiMoDe): a set of algorithms that translate the raw motion data into features related to rhythm skills and iii) a video annotation tool that allowed for the collection of ground truth data from social partner dance teachers. These systems are described in Chapter 5.

**TO3 Validate data extracted from motion sensors using social partner dance teachers’ assessments.** Different layers of information were generated to extract rhythm-related information. Starting from raw data, features were extracted from motion sensors that were then used to train machine learning models and finally a human-understandable data abstraction was created that could be displayed to the user (teachers or students). This objective addressed RQ3 by validating the data collected and processing this data from two perspectives: quantitative and qualitative. For the former, teachers annotated videos from students’ performances and this information was then used to statistically compare to the output from the RiMoDe algorithms. The main instruments for this validation were confusion matrices and classification metrics (e.g. accuracy, precision, F1 score). For the latter, teachers’ comments on the students’ performances were used to depict more detail on how the teachers assessed rhythm, and the teachers’ experience using the video annotation tool helped shape the rhythmic skills
vocabulary developed for this thesis. Chapter 6 contains a description of the validation methods and their results.

TO4 Use the automatic assessment to support teachers and students. It is very challenging to present information to users so that they can understand and use it. This objective also addresses RQ3. The objective here was to explore how to represent motion data to dance students so that they could reflect on their performances and learning process, and to dance teachers to enhance their assessment capabilities. Therefore, three ways of representing the movement data were presented to students: i) numbers, ii) charts and iii) text. For teachers, the students’ videos were presented together with the automatic assessment of rhythmic skills. Chapter 7 describes the approaches and results of these explorations.

This thesis used a mixed methods approach to achieve the aforementioned objectives, understanding the needs of the social partner dance learning context, proposing a technical solution and then validating the solution with dance teachers and student participants. The methodology used to guide the overall project followed a combination of design-based research methodology (Anderson and Shattuck, 2012; Fraefel, 2014; Obrenović, 2011), from learning technologies research, and user-centred design principles (Still and Crane, 2017). Machine Learning methods guided the technical enquiry (Alpaydin, 2009). More details can be found in Chapter 3. Below are described the studies carried out as part of this thesis and the methods for validation and evaluation of the thesis artefacts, presented in Figure 1.1.

Study 1 – Teachers’ Interviews. The first study aimed to gain a more grounded understanding of the context of dance teaching, specifically Forró. A series of interviews explored how Forró dance teachers approached dance teaching. The focus of the interviews was related to what were the important skills for students to learn and how teachers assessed and provided feedback to dance students, especially related to rhythm skills. The empirical contribution of this study was validated with participants quotes, triangulation with the literature and respondent validation. Results are reported in Chapter 4.

Study 2 – Pilot Study with Students. This pilot study aimed to implement and evaluate several components required to support students’ dance learning: a mobile app, an algorithm to recognise students’ movement and automated
feedback. This study explored the challenges of using technology to support dance education and better understand the users’ needs. The study validated the algorithm artefact with ML methods, evaluated the automated feedback artefact with students interviews and theory contributions with triangulation with the literature. Results are reported in Chapter 5 – Section 5.4, Chapter 6 – Section 6.1.2, and Chapter 7 – Section 7.1.

Study 3 – Improving algorithm and Skill descriptors. Following up the findings from the previous study, a new study was needed to enhance the detection system, the data collection with teachers and the terms used to describe the skills. The aim of Study 3 was to increase the number of features extracted from the movement and song data, and to use this information to describe other skills that are required for students to learn rhythm. The algorithms artefacts were validated using ML methods. It is reported on in Chapter 5 – Section 5.5 and Chapter 6 – Section 6.3. The video annotation tool, developed as part of this study, was evaluated by interviewing dance teachers and reported in Chapter 7 – Section 7.3.

Study 4 – Investigating Automatic Assessment with Dance Teachers. The last study of this thesis aimed to obtain insights into how dance teachers could use automatic assessment in their dance teaching context. The empirical contribution was evaluated by interviewing dance teachers after using the automated assessment and reported in Chapter 7 – Section 7.2.

1.4 Thesis Contributions

The thesis contributions (TCs) are summarised below and are listed in Figure 1.1, section Contributions:

TC1 Important aspects of Forró teaching. From a series of interviews with Forró dance teachers, this thesis described the Forró teaching context. Findings were categorised into three groups: Dance Skills, Assessment Strategies and Feedback Types. A conceptual map was created as a result of the interviews analysis and helps illustrate the range of topics found during the interviews.
TC2 RiMoDe v1. An algorithm to detect rhythm in dance students, using motion sensors, is the main technical artefact of this thesis. The algorithm used simple metrics of the accelerometer waves to derive dance features. It is more efficient and more reliable than previous attempts to model rhythmic movement (Lee et al., 2007). The main insights to design this algorithm were i) the use of the song as a reference to calculate the features and ii) to define a simple but relevant dance exercise (Básico 1, Section 5.2) that generated a distinct pattern in the accelerometer waves. From its two output features, a simple two-node decision tree determined whether the student was keeping with the rhythm of the song or not (previously published in dos Santos et al., 2018b).

TC3 Rhythmic related Data Representations. Once the motion sensor’s features were validated, feedback on rhythmic skills and its derivatives was automatically generated for every student that used the mobile app. The data representations covered four aspects of rhythm learning: practice, rhythm, consistency and body motion (previously published in dos Santos et al., 2017). For each of these attributes, several metrics were derived including averages, trend and minimum and maximum, and they were categorised based on the exercise difficulty of the Básico 1 exercise (easy, medium or hard). This initial exploration highlights the challenges that future researchers will need to deal with when trying to use motion sensors to provide automated feedback. Also, the result presents insights that student participants gave while interacting with the data representations.

TC4 Understanding the gap between dance teachers and algorithmic assessment. One important contribution of this thesis was the comparison between what the machine was measuring and what a human would measure. Past studies lacked this comparison of algorithms with human knowledge when developing technology for psychomotor learning (Hadjakos et al., 2008; Hinton-Lewis et al., 2016; Kawakami and Fujinami, 2008; Lee et al., 2007; Matsumura et al., 2011). To validate, the authors used their own judgement, aligned with the literature or statistical information for the modelling experts. Dance is an abstract art and the assessment of dance performances is subjective. Using text mining in the present study, teachers’ comments on students’ performances were analysed and six main themes were found where teachers pay more attention when assessing
students’ rhythm (previously published in dos Santos et al., 2018b). The following two insights were derived from this gap: i) the aspects that escape measurement by the sensors and ii) that teachers change their assessment criteria as the students’ progress in their rhythmic skill development.

**TC5 RiMoDe v2: Detect other movements and mistakes.** Built on top of the same ideas of the first version, this algorithm used more elements of the song as a reference and more sophisticated statistical and data mining methods to extract the pattern of the waves. This algorithm generated additional features that were then used to model rhythmic skills. To derive more complex skills from the teachers’ vocabulary, the algorithm required additional features of the waves (including a gyroscope sensor).

**TC6 Translating raw motion data to rhythm-related dance skills.** The next step after extracting features from the raw data obtained from the sensors was to map the features to indicators of rhythmic skills (rhythm, step size, weight transfer and pause) annotated by the teachers. The thesis presents different ML classifiers and compares their performance in matching with the teachers’ annotations. The output of the ML algorithms were models that could reconstruct the rhythmic indicators using the features of the RiMoDe.

**TC7 Automatic Rhythm Assessment Evaluation.** This thesis presents an evaluation of the automatic rhythmic skills assessment, using the features generated by RiMoDe v1 and v2. Forró dance teachers use the automatic assessment to support their assessment while watching videos of students’ performances. The evaluation includes the perceptions of teachers while using the automatic assessment and their insights on how they would use this technology to support their current teaching strategies.

**TC8 Video annotation tool.** As a by-product of the data collection, a video annotation tool allowed teachers to easily annotate the videos of students’ performances. Other video annotations tools for dance were used as references to design this tool, together with the themes identified during the pilot study with students. A semi-structured interview with four Forró teachers helped to refine the tool to be used by this specific community. The tool also helped gain insights from the
teachers on aspects that technology can support during their teaching process (previously published in dos Santos et al., 2018a).

1.5 Thesis Structure

This section summarises each chapter of the thesis including the publication products, where applicable, obtained from each chapter.

Chapter 2 - Literature Review: Dance and Technology: starts with an overview of dance, its benefits and learning aspects, especially related to rhythm. Then, the chapter presents studies on technology applied to dance education, including related work on dance and rhythm learning technologies. Later, it reviews studies that have researched psychomotor learning technologies and the use of sensors to support education.

Chapter 3 - Research Methodology: describes the overall methodology adopted for this thesis and the details of the methodology used for each of the four studies included in the thesis. Each study is described in terms of the methods, population, instruments, procedures and RQ utilised. The chapter also presents the mixed methods approach adopted to explore how the use of technology could tackle the needs of dance teachers. Students’ movements were captured by the use of feature extraction and data mining techniques were utilised to enhance the awareness of teachers and students regarding the learning process.

Workshop paper presented at AIED 2018 (dos Santos et al., 2018c)

Chapter 4 - Understanding Forró Social Dance Education from the Teachers’ Perspective: explores the context in which this thesis was developed through the eyes of 16 Forró dance teachers. The interviews with the teachers were used as the groundwork for establishing the set of rhythmic skills involved in the dance learning process and how this process was undertaken.

Chapter 5 - Developing Algorithms and Tools to Support Dance Teaching: details the tools developed in this thesis. Algorithms were developed to extract features from smartphone motion sensors (accelerometer and gyroscope). This chapter describes the
mobile app that was developed to collect the motion data and the need to use the song as the reference to create motion features. Additionally, it presents the video annotation tool used by teachers to annotate the video episodes of student participants.

**Conference Papers:** UMAP 2017 (dos Santos et al., 2017), MOCO 2018 (dos Santos et al., 2018b), OzCHI 2018 (dos Santos et al., 2018a)

**Chapter 6 - Evaluating the Features of RiMoDe:** provides quantitative and qualitative evaluation of the information generated by the algorithms. This chapter includes a description of the assessment of rhythmic skills by social dance teachers when assessing their students’ videos. Finally, it presents data demonstrating the agreement and disagreement of the teachers during this assessment process.

**Conference Papers:** UMAP 2017 (dos Santos et al., 2017), MOCO 2018 (dos Santos et al., 2018b)

**Chapter 7 - Providing Automated Feedback and Assessment on Rhythmic Skills:** presents the final contribution of this thesis, and is an exploration where the data collected is presented to dance students and teachers to evaluate how they make sense of the automatic assessment of rhythmic skills.

**Conference Papers:** UMAP 2017 (dos Santos et al., 2017), OzCHI 2018 (dos Santos et al., 2018a);

**Chapter 8 - Discussion:** contains a discussion on the lessons learned during this thesis and how the thesis outcomes relate to the current body of research. This chapter also includes a discussion on the involvement of teachers and students during the studies and on the importance of knowing the context to design relevant technology.

**Conference Papers:** MOCO 2018 (dos Santos et al., 2018b)

**Chapter 9 - Conclusions and Future Directions:** provides an overview of the thesis and its conclusions, revisiting the RQs and providing recommendations and directions for future research in this field.
Chapter 2

Literature Review: Dance and Technology

This chapter comprises a review of research relevant to this thesis, which is at the intersection of multiple fields. The first section presents a background on dance and dance education and a discussion of the aspects that are important in the dance education context, the relevant skills for students to learn and the current strategies for assessment and feedback provision in dance classes. Then, the current technologies and algorithms used to track dance movements are discussed in the second section. The literature discussed includes critical work in the field of activity recognition, which serves as the foundation of many algorithmic approaches. The third section reviews the field of data science as applied to dance education. As this is a recent field, it also includes research work on motor learning supported by technology. The chapter concludes with a fourth section discussing open issues that this thesis aims to address through new algorithmic approaches that collect and analyse dance movement and use the information generated to support students and teachers during the dance learning process.
2.1 The Motor Learning Context: Dance

2.1.1 General Overview of Social Partner Dance

This thesis focused on addressing some of the problems found in social partner dance classes. It is important to acknowledge the terminology commonly used regarding social partner dance. However, this terminology varies across the literature. The intent here is to illustrate some of the terms used, for later defining how these terms will be used throughout the thesis. The first term used to refer to social partner dance is Ballroom Dances. The term Ballroom Dances is mostly used for a specific set of dances—Waltz, Foxtrot, Quickstep and Tango (Moore, 2012; Authors, 2016)—which are performed in formal settings (e.g. weddings, dance halls), and are related to the upper class. Later in time, this term evolved to Modern Ballroom Dances which include Latin Dances such as Cha-Cha, Salsa, Mambo, Rumba, Samba and Bolero (Allen, 2002; Gillis, 2008). The term Latin Dances refer to dances that have their origins in Latin countries or Latin communities in the US, where these dances served as a form of popular expression and were performed in simple settings, but were later adapted to the Ballroom setting. Other dance styles that can also be linked to Ballroom dances are Lindy Hop, Rock and Roll, Jive and Swing, which are also danced in a social context such as nightclubs and discos (Allen, 2002; Horwood, 2010). Recent styles of social partner dances with Latin or African origins are Cuban Salsa, Bachata, Zouk, Kizomba, Lambada, Merengue, Samba de Gafieira and Forró. All dances mentioned above are danced in pairs and in a social context as a form of entertainment and leisure. One difference between a few of the social partner dance styles is the order in which the dancers should move on the dance floor. In classic Ballroom (e.g. Waltz and Foxtrot), the pairs of dancers should move all together in a circle, around the dance floor (Jarmolow and Selck, 2011; Allen, 2002). In Salsa (New York style), Bolero and Samba de Gafieira, the pairs of dancers move in a line. In Cuban Salsa, Forró and Kizomba, there is not a specific norm for using the dance floor (O’Flaherty, 2009).

Other types of partner dances that use the same terminology but with a very specific set of rules are partner dances for competition purposes. The most popular format of competitive partner dance is called Dancesport, regulated by the World Dance
CHAPTER 2. LITERATURE REVIEW: DANCE AND TECHNOLOGY

Council. Terms like Ballroom dance, Latin dance, Samba, Salsa and Jive would represent different concepts to the ones described before. Although there are similarities between the styles of competitive partner dances and social partner dances, in some cases (e.g. Samba), the competitive format is very different from its popular origins (McMains, 2006). By contrast, the term social dances may also refer to circle, lines and folklore dances, or modern forms of group expression like Hip-Hop, Street Dance, Pop and K-Kop related to dance performances.

In this thesis, social partner dance refers to the partner dances danced in social contexts with the purpose of entertainment and leisure.

2.1.1.1 Forró, a Brazilian Social Partner Dance

From the terminology described before, Forró is a Brazilian (and Latin) social partner dance style. Other examples of Brazilian social partner dances are Zouk, Lambada, and Samba de Gafieira. Forró is an umbrella term for several styles of dance (Cacau, Miudinho, Universitário, Valsadão) and music (Toada, Xote, Coco, Xaxado, Baião, Arrasta Pé) from the Brazilian Northeast (Marcelo, 2012; de Oliveira Santos and Keays, 2017). In Forró music, zabumba (drum) is the instrument that, most of the time, keeps the strongest beat of the songs and its tempo (Fernandes, 2005). Similar to other social partner dance styles (Wright, 1996; Jarmolow and Selck, 2011), Forró dance requires two people (a leader and a follower) to perform synchronised movements, relying on the song to keep this synchrony.

Forró songs have a quaternary tempo (1 to 4 count), to which the dancers synchronise their steps in the following order (de Quadros Junior et al., 2009): the lead dancer prepares to dance by placing their body weight on the right leg; in the first beat of the music, they gradually transfer their body weight to the left leg taking one step forward; on the second beat, they transfer the weight to the right leg; and to the left leg again on beat 3, moving the left leg backwards. The fourth beat corresponds to a pause, where the movement slows down, extending the previous movement and connecting it to the next movement with less weight transfer. This creates a pattern of left-right-left-pause. The movement starts again with the weight on the left leg, following a symmetrical pattern of right-left-right-pause. Note that the follower dancer will perform this sequence.

1World Dance Council - https://www.wdcdance.com/
by mirroring the lead dancer. Dancers follow these basic patterns in many different forms, continuously and iteratively until the song stops.

Forró dance has several similarities with other styles of social partner dance, especially Latin styles. A person not experienced in social partner dances would have trouble distinguishing, for instance, Cuban Salsa and Forró. A common way to distinguish Latin social partner dances is by the different *flavours* they have. The similarities are a very close embrace between dancers, dance steps that include spins and turns, the romantic mood, fast songs (over 120 beats per minute) and the lack of order on the dance floor. Different from most social partner dances, including Latin dances such as Salsa, Forró lacks a formal vocabulary that defines its step patterns’ (routines) names (de Quadros Junior et al., 2009). This is due to the fact that Forró had a strong popular origin (Packman, 2012), where names are not relevant, and only recently, in the 2000s, did Forró style start to be incorporated into dance classes, schools and studios (Loveless, 2010) as part of their repertoire of social partner dance styles.

As Forró dance became part of dance schools and studios, teachers needed to translate a popular and cultural expression into a form of social partner dance to teach to their students.

### 2.1.2 Social Partner Dance Education

Social partner dances are mostly taught in dance schools, dance studios and in other informal settings such as bars, community centres and even cruise ships and resorts (Allen, 2002). The informal context in which social partner dances are taught is important to be highlighted when we examine the differences and similarities between teaching social partner dances and other dance styles such as ballet, modern and contemporary dance.

Some of the differences we can find in social partner dance classes as compared to classical and contemporary dances are:

- number of students in the class;
- the motivation of the students in taking the classes;
- informal educational setting (dance schools, bars, community centres, fitness centres, nightclubs) versus higher education, K12, institutes, universities and dance companies;
strictness on how the content is shared with the students;
• the technical vocabulary; and
• the structure of the learning content across different schools.

On the other hand, we can find many similarities that are related to any dance learning context:

• the skills involved (motor learning, rhythm, coordination, balance, etc.);
• the learning space (wide areas, sprung floor, mirrors, no tables, no chairs, no boards, not much pencil/paper);
• knowledge transmission mostly verbal and kinaesthetic; and
• technological support restricted to multimedia (Gruno and Gibbons, 2013; Doughty et al., 2008).

It is also important to understand the differences and similarities across dance styles when examining the literature on dance education. As the literature on social partner dance is limited when compared to formally trained dances like ballet, modern, jazz and contemporary, it becomes relevant to investigate other dance styles in the literature to complement the knowledge on dance education. Additionally, dance is considered a psychomotor skill requiring the stimulus of several sensory systems in its learning process, such as auditory, visual, tactile and kinaesthetic (Simpson, 1971). For that reason, the motor learning literature can also contribute to an understanding of the social partner dance educational context.

The literature on social partner dance is limited to books that teach a catalogue of dance steps of each particular dance, being most common books about Ballroom dances (Jarmolow and Selck, 2011; Allen, 2002; Moore, 2012; Gillis, 2008; Horwood, 2010), while there is also specific literature for more recent styles of social partner dance like Kizomba (Cristea and Ionita, 2018) and Bachata (Garcia, 2013). The scientific literature on understanding social partner dance education is very limited (Hanrahan et al., 2009; DeMers, 2013), with a few projects written in languages other than English (Varela, 2015; Vecchi, 2012). Researchers mostly use social partner dance as a means to explore other topics such as health (Kiepe et al., 2012; Lima and Vieira, 2007), social dynamics (Skinner, 2007; Flippin, 2013) and technology (Drobny et al.,
2009). The scientific literature on dance education is devoted mostly to ballet, modern, contemporary dance and formal contexts such as K-12, professional studios and university (Tembrioti and Tsangaridou, 2014; Barr, 2009; Tembrioti and Tsangaridou, 2014; Green, 2002).

The next sections will comprise a review of the aspects of dance education literature relevant to this thesis: dance skills, assessment strategies, and types of feedback.

### 2.1.2.1 Important Skills for Social Partner Dance

Several skills are needed for performing any type of dance. Some skills are common across styles and they appear consistently in the literature. These are, for example, rhythm, coordination, balance, posture, body control, spatial awareness and weight transfer (Erkert, 2003; Gibbons, 2007; Allen, 2002). For social partner dance, additional skills are relevant and relate to the relations between the two dancers. For instance, one skill relates to how dancers should be positioned in front of each other and where their arms should be placed on their partner’s. This skill can appear with different names such as frame, hold, embrace and connection (Wright, 2013; Cristea and Ionita, 2018; Garcia, 2013; Jarmolow and Selck, 2011). Turns and spins are also common in the literature, as most social partner dance styles include routines where the leader guides the follower in pivoting in her/his own axis to perform a turn (Allen, 2002). Leader and follower are the roles established in social partner dances that determine the person who will suggest the routines to be executed (the leader) and the person who will follow these suggestions (the follower). These roles have been historically gender-related as guys/man/leader and ladies/woman/follower (Garcia, 2013) but neutral terms have been increasingly adopted over time (McMains, 2015; Skinner, 2007). In this regard, another important skill required for partner dancers is to cope with the physical proximity, the roles in partner dance and the mental challenges that may arise from these requirements (Skinner, 2007; Vecchi, 2012).

As students need to learn several skills to be able to dance, teachers must be able to assess these skills to properly guide the students’ learning.

### 2.1.2.2 Assessment Strategies in Dance

Strategies used by teachers and instructors to assess students’ performance are somewhat similar across dance genres. Teachers mostly use visual observation to assess...
their students in the classroom (Jarmolow and Selck, 2011; Vecchi, 2012; DeMers, 2013; Erkert, 2003; Gibbons, 2007). Another common strategy is to perform kinaesthetic assessments by physically feeling the students’ movement (Gibbons, 2007; Vecchi, 2012). This method is particularly used in partner dance classes as the nature of the dance (in pairs) allows the teachers to take one of the roles (leader/follower) and assess the student. These two types of assessment are also in line with the literature on motor learning (Schmidt and Wrisberg, 2008). Not so common, is the use of self-assessment and peer-assessment to assess students’ progress (McCutchen, 2006; Hsia et al., 2016). In the formal context of dance classes, it is common for the teacher to objectively assess students using guidelines and rubrics (Erkert, 2003; McCutchen, 2006), which in some countries are established by national bodies (Ross, 1994). After assessing students’ skills, teachers must provide feedback so that the students know how to improve their skills and progress in their learning.

2.1.2.3 Types of Feedback in Dance

Feedback is essential to the development of students in any field (Carless et al., 2011). In social partner dance, as in other dances, the feedback should be positive and constructive (Jarmolow and Selck, 2011; O’Flaherty, 2009; Erkert, 2003; McCutchen, 2006; Wright, 1996). The feedback has the function to inform about errors, reinforce concepts, analyse students’ performance and motivate the student; and feedback can be transmitted visually, verbally or kinaesthetically (Gibbons, 2007). The teachers can provide feedback related to the result (outcome) or to the performance (which leads to the result) of the student (Krasnow and Wilmerding, 2018). The literature on motor learning agrees with the types of feedback and adds the idea of intrinsic feedback (from the student’s body) and the timing of the feedback (instant or delayed) (Schmidt and Wrisberg, 2008).

The previous subsections described different aspects of social partner dance education and how these styles of dance can be distinguished from other dance styles. As a new style of social partner dance, it is not clear how Forró teachers approach these aspects of dance education. **This thesis aims to contribute to the literature by investigating Forró dance education from the teachers’ perspective.**
CHAPTER 2. LITERATURE REVIEW: DANCE AND TECHNOLOGY

2.1.2.4 Inside a Forró Dance Class

This subsection gives an overview on the ecology of Forró dance classes. Forró dance classes, like Salsa and other social partner dance classes, vary in terms of numbers of students, from less than 10 to dozens or 100s (Flippin, 2013; Skinner, 2007). The age of students can vary from their 20s to 70s, with men and women with a variety of sexual preferences, religions, cultures and geographical backgrounds (Skinner, 2007). The motivation of these students in attending dance classes can also vary greatly from fitness and mastery to mood enhancement, intimacy and self-confidence (Maraz et al., 2015). By contrast, ballet and modern dancers find their motivation in preparing for a career and performing rather than social contact and fitness (Nieminen, 1998).

Forró classes are commonly led by one or more instructors that can be supported by multiple assistants. The instructor background may also vary from having formal dance education or training in universities or dance institutes; to no formal instruction and just dance experience from dance schools (Vecchi, 2012). A Forró class commonly follows a standard routine by starting with a warm-up dance or exercise, followed by pair matching. Then, the instructor demonstrates the steps of the day, students copy and change partners. The instructor then gives more details or new steps, and the process repeats itself over and over until the end of the class (Flippin, 2013). After the class, students may have an opportunity to practise what they learned during free time or after-class practice.

The aforementioned literature helps in generating understanding about the context of dance education and Forró dance. Yet, there is not much previous work that exploring Forró teachers’ point of view regarding important skills for social partner dance, their assessment strategies, and the ways they commonly provide feedback. Insights and information specifically about Forró will be provided in Section 4 since it was tackled as a goal of this thesis. This knowledge is essential if we want to design technological solutions to support dance education; otherwise, we may come up with solutions that are not appropriate to the context or that do not address its problems. It is important to highlight that this section compared Forró education with other practices, demonstrating how the technological solutions proposed by this thesis are also relevant to other dance educational contexts.

2.1.3 How Rhythm and Dance Are Connected

This subsection explores different aspects of rhythm, as this is the main skill covered in this thesis. Rhythm can be found in every aspect of our daily life. Rhythm can be found in nature, for example, in the cycles of day and night, ocean waves, heartbeats, breathing patterns and the gait of animals (Goodridge, 1999). Rhythm is also found in technology-rich contexts such as in car engines, escalators, aircraft propellers and use of social media (Mislove et al., 2010). Humans have developed human-made rhythms using their bodies (clapping, walking) and instruments (drums, sticks) (Goodridge, 1999; Dean et al., 2009).

The development of dance and music is inseparable in many cultures (Dean et al., 2009). Both forms of art share a common denominator – time – and use it to create rhythmic and expressive patterns. In music (Apel and Daniel, 1961), rhythm is everything pertaining to the duration (long-short) of musical sounds. A similar concept is tempo, the rate of speed of a composition or section, as indicated by tempo marks or by metronome indications. The term beat is also critical to musical rhythm and defines the temporal unit of a composition. Rhythm is formed by a sequence of different patterns produced by beats – stresses and/or pulses that are arranged in a musical composition.

Dance often builds on the patterns in music to set its rhythm. Some studies have attempted the opposite, making the music follow dance movements (Guedes, 2005). There are many definitions of what rhythm means in dancing (Guedes, 2005). In aesthetic terms, ‘Dancing is the art of expressing emotion by means of rhythmic bodily movements’ (Jaques-Dalcroze, 1921, Chapter XI). In general terms, rhythm consists of the time duration of intended bodily movements with stress and/or accentuation that follow a pattern. This thesis uses the definitions from the dance literature to define: rhythm, the patterned repetition of the movement of the body in space and time; and tempo, as to the speed of the music (Erkert, 2003; McCutchen, 2006).

2.1.3.1 The Role of Rhythm in Dance Learning

Rhythm is usually taught in dance classes as part of a broader topic called musicality (Erkert, 2003; Côté-Laurence, 2000). Musicality is an abstract topic and, for that reason, each teacher approaches it differently. Overall, musicality refers to the quality of the dancer’s movement and its connection with the various elements of the music (when there is music). For example, rhythmic expression includes the flow of arms...
and legs following the music; the bodily interaction with time, space and gravity; the extent to which weight and energy are used to express movements; and the use of the ground to land, push or absorb the impact of the body (Erkert, 2003).

Teachers scaffold the development of rhythmic skills using different strategies, sometimes developing (somewhat) standard exercises (Côté-Laurence, 2000). These exercises not only focus on the temporal aspects of rhythm but also on the accuracy of the motor response, feeling the music, building a phrase (sequence of movements), breathing or even “playing” with the song (Côté-Laurence, 2000). Also, teachers’ feedback is central to the development of rhythmic skills. Teachers may focus on the technique: quality of body position/movement/alignment and face direction; or on the rhythm itself: the precision of movements according to time, accent and duration of the movement (Côté-Laurence, 2000). In short, rhythm in dance education involves the development of quite complex motor skills that allow the body to move in synchronicity with particular elements of the music, which is fundamental for higher-order forms of dancing expression.

2.2 Technological Support for Dance and Rhythm Learning

Researchers in human-computer interaction (HCI) have used motion sensors to model and support dance education and rhythm learning. Emerging sensing technologies are allowing researchers to also investigate learning in a wide range of motor learning scenarios (Santos, 2016; Santos and Eddy, 2017). In one study related to rhythm, the researchers placed accelerometers on the wrists and waists of students to understand the learning process of playing a samba percussion instrument (Matsumura et al., 2011; Kawakami and Fujinami, 2008). They used the data collected from students’ movement as a form of feedback to promote students’ awareness. Students that visualised their movement compared with the instructor’s movement learnt better than students that received only a score for their performance evaluation.

In the same field of learning musical instruments, a system was created to help piano students diagnose hand coordination problems (Hadjakos et al., 2008). Using accelerometers attached to hands, wrists and arms of the students, the system translated the data into textual feedback and visual cues, comparing the teacher’s and students’
performances. The system was able to provide valuable feedback, but the visualisations were difficult to be understood by musicians. In both previous cases, percussion and piano, the researchers did not investigate the current approach of the teacher for providing feedback to music students. At the same time, they reported that students had difficulty with or could not interpret the feedback provided by the proposed system. As it will be seen further in this thesis, the information presented to people follows a similar approach: selected movement features, validated by dance teachers, are presented in a way that are easier to interpret when compared to the raw data.

This nascent interest in capitalising on accelerometer data for modelling rhythm in musical instrument-playing has also been explored in dancing. In one of the pioneering studies in the area, Lee et al. (2007) used several accelerometers attached to participants to model rhythm in human motion. The authors used frequency analysis and a voting scheme to determine the rhythm of the movement, described as a combination of beat intervals, pattern lengths and the number of beats. The method was evaluated using data recorded from movements performed with the hands. In this scenario, the algorithm reported partially inaccurate results. Later, they tried to detect the rhythm of a professional dancing Cha-cha-chá. The method was useful for identifying some critical features of the movements, such as pattern length, but was not helpful for assessing the dance movement rhythm. Importantly, the correlation between the system’s output and the experts’ mental model was suggested for future work. This thesis plans to address this gap by comparing the sensor features with the rationale followed by dance teachers to assess students.

In one study, Camurri et al. (2016a) developed a system to support the learning of movement qualities in dance. The system used IMU sensors to extract features (Jerk and Kinetic Energy) that were used to evaluate the movements of dancers in terms of Dynamic Symmetry. This metric could then be used to control the parameter of an auditory feedback provided to students when performing a specific exercise to practise Dynamic Symmetry. The authors did not test the system with students but suggested an evaluation of the system by experts as future work. The paper was part of a larger project called WhoLoDancE (Camurri et al., 2016b). In another study within this same project (Piana et al., 2016), the authors suggested the creation of a multi-modal repository for the analysis of expressive movement qualities in dance. They recorded 90 minutes of four dance experts performing movements with specific characteristics: fluidity, impulsivity, and rigidity. The data included a number of sources
used to track the movements of the dancers, like IMU sensors, Motion Capture and video/audio recording. They highlight the importance of studying the expressive quality in dance performance and how technology can support this process. This approach can also be used to enhance dance teaching/learning, although the authors acknowledge the difficulty of using their recording system in other scenarios. Once more, the authors suggested the evaluation and validation of their data recordings by human experts. **These previous two papers motivate the approach of this thesis in adopting a scalable modality of technology to record movement (e.g. using the sensors embedded in most mobile phones). This thesis also goes beyond this by comparing evaluations of algorithmic solutions by experts.**

In another study, Drobny et al. (2009) used a transducer attached to students’ shoes to help them in learning rhythm while dancing. The sensor data was automatically analysed and the system then triggered acoustic feedback to inform students if they were dancing out of the rhythm. The study reported that some students liked this system as it helped them to stay on the correct beat. Nevertheless, this approach was only able to identify mistakes that happened on the strong beats of the song. Also, other aspects related to the learning of rhythmic skill were not evaluated. **A question remains in regards to which other rhythmic skills can be monitored by using sensors.**

Using an Indian dance style as a case study, Faridee et al. (2018) used four accelerometer sensors to model the 10 steps of a dance routine. The sensors were placed on the limbs of the dancers. The authors compared the use of the 46 features modelled using Random Forest algorithm with the use of a Convolutional Neural Network (CNN) architecture with self-evolving features. They annotated the data by manually splitting the data based on the time that each of the 10 steps occurred. The proposed CNN architecture improved the model accuracy by 7% when compared to the features and Random Forest approach. They defend the idea that CNN is able to save time compared to manually creating features. This thesis precisely uses hand-crafted features to improve the readability of the machine learning (ML) models by humans, as deep-learning algorithms create black-box models that are impossible to interpret (Doshi-Velez and Kim, 2017).

This thesis aims to address the gap identified in the literature presented above. **A critical question is: how closely does a fully automated approach to evaluating dance performance resemble evaluation made by dance experts?** More work needs to be done in order to gain an understanding of the differences between an algorithmic
approach and teachers’ evaluations. This can facilitate the generation of more robust algorithmic and modelling approaches with better chances of success in providing effective support and feedback to students working on building up their psychomotor skills for dancing. Also, a critical challenge to address is understanding how the information was collected and the features created by algorithms can be presented to people to create opportunities for reflection and support the dance learning context.

2.2.1 Pedagogical use of technologies in dance education

This section aims to discuss how technologies are used pedagogically in dance education. A very common approach to using technology as a pedagogical instrument is the use of videos and CD-ROMs to deliver content and enhance the classroom artefacts (Smith-Autard, 2003; Leijen et al., 2009; Birringer, 2002). In a similar approach, Karkou et al. (2008) built a web-based learning environment (WebDANCE) to deliver content to students in an open learning environment, having the teacher as a facilitator. The tool included a comprehensive material on Karsilamas (Greece) and Valentine Morris (England) dances including text, image, audio, video, 3D animations and interactive activities such as slide shows, quizzes, match photos to words, play music or video, and record rhythm. The learning objectives of this tool’s content was to develop dance skills, make compositions and performances, offer knowledge about the cultural, historical and social context of the dance, and develop appreciative skills. The tool was evaluated by dance experts and teachers and students in two pilots. The tool received a positive evaluation in both user interface and pedagogical quality. Teachers reported that their learning objectives could be assisted by the tool, that there was a balance between simple, interactive and in-person activities and that the tool encourages students in learning dance.

Technology can be used not only to deliver content but also to mediate the interactions between dance students. Having this in mind, Hsia et al. (2016) developed a web tool for students to post their video and receive peer-feedback besides having a flipped classroom style. The authors compared three approaches of peer-feedback on videos: (a) peer comment, (b) peer rating and (c) peer comment + rating. A study with 100 students showed that students that received both peer comment + rating performed better than students that received just rating or comment. Students that received just rating performed better than students that received just comment. Although, there was
no difference in students’ motivation and self-efficacy across the different feedback approaches.

Videos have also been used in an annotation tool to promote reflection in students. Cherry et al. (2003) created a tool where dance composition students could annotate videos recording their voices. Annotations from different authors could be linked to each other to create relationships. The authors claim that the tool can enhance critical evaluation skills and that instructor reported that the tools encouraged students to be more critical when giving peer-feedback in class.

Other digital online tools can also be used to enrich the dance pedagogy. Parrish (2016) used her own experience to report several technologies that could be used for dance students to rethink, customise and take charge of their learning. She mentioned the use of massive online open courses (MOOC), video conferencing tool, social media and mobile apps. According to her, to achieve high-quality instruction using online tools requires:

• a clear and responsive instructor;

• encouragement, particularly initially when students may feel challenged and disconnected to an unfamiliar learning style;

• relevancy to both immediate and long term goals of the student;

• careful planning of the design interface;

• layered communication methods;

• and activities that are collaborative and discovery-based.

Her research shows that, in most cases, technology has been used only to mediate knowledge transmission.

More advanced use of technology was developed by Yang et al. (2013), where they use motion capture (MoCap) to capture the teachers’ dance movement and transformed these into separate dance lessons. When the student interacted with the system, the system was able to detect the student performance and recommend the next lesson step. This research used state-of-the-art concepts for storing the learner model and create adaptive rules to match the lessons to the student current knowledge. Authors evaluated the system with a control group that did not receive tailored lessons. There was a
significant difference between the groups favouring the use of the system with tailored lessons. Although their research proposed a smart system to guide students learning, the hardware cost and constraints might not be suitable in most learning contexts.

This thesis aims to cover the gaps presented in this section by using technology not to mediate the transmission of knowledge but to automatically assess students rhythmic skills. The proposed technology can be used in various scenarios as it uses devices already present in most peoples lives and contexts.

2.2.2 Comparison of Different Studies

This section compares several studies according to the features that are relevant to this thesis. The focus of the comparison is papers that address the challenge of supporting dance and rhythm learning with the use of motion sensors. However, widen the scope of comparison, the section also includes other papers related to dance learning support using similar technologies. Table 2.1 summarises the papers used in this comparison and the features chosen to connect previous work, which are:

- **Purpose**: the purpose of the researchers when designing the solutions;

- **Learning Support**: the learning support the solution provides for teachers and/or students;

- **Modelling Body Parts**: where the sensors are positioned or which parts of the body are tracked;

- **Evaluation Method**: how the authors evaluated the proposed solutions;

- **Technology**: which type of sensors and algorithms were used;

- **Raw x Features**: did the authors pre-process the sensor data or create features, or did they use the raw sensor data?
<table>
<thead>
<tr>
<th>Paper</th>
<th>Purpose</th>
<th>Learning Support</th>
<th>Body Parts</th>
<th>Evaluation</th>
<th>Technology</th>
<th>Raw x Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lee et al. (2007)</td>
<td>Detect rhythmic movements</td>
<td>Not mentioned</td>
<td>Fingers, Hands, Waist</td>
<td>No formal evaluation</td>
<td>Accelerometer + Fourier and spatial analysis</td>
<td>Features</td>
</tr>
<tr>
<td>Hadjakos et al. (2008)</td>
<td>Visualise arm movement</td>
<td>Raw Sensor Charts + Allow Annotation</td>
<td>Hand, Wrist, Upper Arm</td>
<td>Questionnaire with students</td>
<td>MIDI + Gyroscope + Accelerometer + Visualisation</td>
<td>Raw</td>
</tr>
<tr>
<td>Drobny et al. (2009)</td>
<td>Detect steps and give instant feedback on the music that is playing</td>
<td>Acoustic feedback while practising</td>
<td>Foots Ball, Heel</td>
<td>Questionnaire with students</td>
<td>Force sensors</td>
<td>Raw</td>
</tr>
<tr>
<td>Matsumura et al. (2011)</td>
<td>Compare lumbar and arm movement</td>
<td>Not mentioned</td>
<td>Arm, Lumbar</td>
<td>Statistical (ACF)</td>
<td>Accelerometer + ACF</td>
<td>Raw</td>
</tr>
<tr>
<td>Paper</td>
<td>Purpose</td>
<td>Learning Support</td>
<td>Modelling Body Parts</td>
<td>Evaluation</td>
<td>Technology</td>
<td>Raw x Features</td>
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<tr>
<td>Thiel et al. (2014)</td>
<td>Use accelerometers to measure ballet routines</td>
<td>FW: Feedback to the dancer</td>
<td>Ankle, Knee, Sacrum</td>
<td>Statistical (RMS)</td>
<td>4 accelerometers + RMS</td>
<td>Statistical features</td>
</tr>
<tr>
<td>Saxena et al. (2014)</td>
<td>Conceptual tool</td>
<td>Distance learning</td>
<td>Whole Body</td>
<td>No</td>
<td>Electro active polymer + AR + Kinect</td>
<td>N/A</td>
</tr>
<tr>
<td>Kikhia et al. (2014)</td>
<td>model LMA categories</td>
<td>No</td>
<td>Chest, Wrist, Thigh</td>
<td>ML Classifiers (Accuracy)</td>
<td>3 accelerometers + activity recognition features</td>
<td>Raw</td>
</tr>
<tr>
<td>Kitsikidis et al. (2015)</td>
<td>Game-based learning</td>
<td>Textual Feedback + tailored activity</td>
<td>Whole Body</td>
<td>Comparison between # repetitions X score</td>
<td>Kinect + DTW + Screen</td>
<td>Raw</td>
</tr>
<tr>
<td>Camurri et al. (2016a)</td>
<td>Detect and teach Dynamic Symmetry</td>
<td>FW: Sonification exergame</td>
<td>Wrists</td>
<td>No</td>
<td>2 Inertial measurement units</td>
<td>Features</td>
</tr>
<tr>
<td>Hinton-Lewis et al. (2016)</td>
<td>self-assessment practice, accelerometer to measure angles of ballet routines</td>
<td>FW: Inform ballet coaches</td>
<td>Lumbar Spine, Thoracic Spine</td>
<td>Comparison between mean and sd of different movement</td>
<td>2 accelerometers</td>
<td>Statistical features</td>
</tr>
<tr>
<td>Paper</td>
<td>Purpose</td>
<td>Learning Support</td>
<td>Modelling Body Parts</td>
<td>Evaluation</td>
<td>Technology</td>
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<tr>
<td>Hsia et al. (2016)</td>
<td>peer-feedback</td>
<td>Online Video Peer-feedback</td>
<td>N/A</td>
<td>ANCOVA</td>
<td>video</td>
<td>N/A</td>
</tr>
<tr>
<td>Kim et al. (2017)</td>
<td>classify K-pop dances</td>
<td>No</td>
<td>Whole body</td>
<td>ML classifiers (accuracy)</td>
<td>Kinect</td>
<td>Features (Angle between joints)</td>
</tr>
<tr>
<td>Senecal et al. (2018)</td>
<td>classify Salsa dancers’ level</td>
<td>No</td>
<td>Whole body</td>
<td>Statistical</td>
<td>MoCap</td>
<td>Statistical features</td>
</tr>
<tr>
<td>Faridee et al. (2018) &amp; Md Faridee et al. (2019)</td>
<td>classify Indian dance steps</td>
<td>No</td>
<td>Wrists and Ankles</td>
<td>ML classifiers (accuracy, precision, recall)</td>
<td>4 accelerometers + Deep learning</td>
<td>Raw x Features</td>
</tr>
</tbody>
</table>

ACF: Auto-Correlation Function; RMS: Root Mean Square; AR: Augmented Reality; DTW: Dynamic Time-Warping; ML: Machine Learning; IMU: Inertial Measurement Unit; MoCap: Motion Capture; N/A: Not Applicable; FW: Future Work
2.2.2.1 Purpose

Most studies’ aim is to model body movement. Some seek to use this model to describe with numbers (mean and standard deviation) the difference between ballet movements (Thiel et al., 2014) and movements across gender and body parts (Hinton-Lewis et al., 2016). Other studies have attempted to classify different dance routines from dance styles (Kim et al., 2017; Senecal et al., 2018; Faridee et al., 2018). Another study (Lee et al., 2007) describes the movement-creating features related to rhythm, like beat interval and length. Other studies specifically focus on how to support learning for musical instruments (Hadjakos et al., 2008; Kawakami and Fujinami, 2008; Matsumura et al., 2011), dance (Drobny et al., 2009; Kitsikidis et al., 2015; Hsia et al., 2016; Lin et al., 2018), other dance practices (Camurri et al., 2016a), or distance learning (Saxena et al., 2014; Hadjakos et al., 2008). Some studies are concerned with which body parts result in better modelling of dance movements (Kikhia et al., 2014; Thiel et al., 2014). Similar strategies are also required for the field of activity recognition (Gupta and Dallas, 2014; Kwapisz et al., 2011), which models human movement like walking, running and standing. This thesis’ main purpose is to design a solution that is able to support dance learning.

2.2.2.2 Learning Support

All studies that focus on support learning use a strategy to give feedback to learners. Some use the raw data presented as line charts (Hadjakos et al., 2008), others compare students’ and teachers’ raw data giving a score (Kawakami and Fujinami, 2008) or compare students’ and experts’ movements to give textual feedback and tailor exercises for the students’ current learning stage (Kitsikidis et al., 2015). In one study (Drobny et al., 2009), researchers gave acoustic feedback by comparing the synchronisation score of students’ sensor data and music. Other studies suggest the use of their solutions for learning purposes as future work (Thiel et al., 2014; Hinton-Lewis et al., 2016; Kim et al., 2017; Senecal et al., 2018) or as a concept (Saxena et al., 2014; Camurri et al., 2016a). This thesis uses a combination of several of the approaches above like presenting to students raw data from the sensors, rhythmic features, comparisons of students’ performance with the song and textual feedback.
2.2.2.3 Modelling Body Parts

The place in which the sensors are located will vary depending on the context of the solutions. In some cases, the position is not trivial and researchers need to test different positions to identify the best one(s) (Matsumura et al., 2011; Kikhia et al., 2014; Thiel et al., 2014; Hinton-Lewis et al., 2016). For practical reasons, the wrist is used to model arm/hand movements (Hadjakos et al., 2008; Kawakami and Fujinami, 2008; Camurri et al., 2016a; Faridee et al., 2018) and the waist (or lumbar) is used to model the trunk (Lee et al., 2007; Hinton-Lewis et al., 2016). Some studies model the whole body (Kitsikidis et al., 2015; Camurri et al., 2016b; Senecal et al., 2018; Kim et al., 2017), although this makes the data processing more difficult and expensive and harder to interpret or generate feedback. For the sake of user convenience, in this thesis, the sensors (smartphones) are placed inside the students’ pockets (front or back), which represents the same functionality as modelling the waist, see Section 5.4.

2.2.2.4 Evaluation Method

The existing studies can be placed into three categories of evaluation: quantitative (statistical, machine learning), qualitative (questionnaires, interviews) or no evaluation.

Some papers use more consolidated quantitative evaluations like ANCOVA (Hsia et al., 2016; Lin et al., 2018) comparing data from students having different strategies of peer-feedback while using an online tool, t-test (Kawakami and Fujinami, 2008) to compare students improvement when receiving automated feedback, Cochran’s Q test to compare students’ level of proficiency in rhythm comparing accelerometer place on lumbar and arm (Matsumura et al., 2011) and accuracy of machine learning models when modelling participants movement from accelerometer and Kinect data (Kikhia et al., 2014; Md Faridee et al., 2019; Kim et al., 2017). Other researchers use simpler methods like visual comparisons of students’ score using an online tool compared to expert’s movement (Kitsikidis et al., 2015) or mean/standard deviation of accelerometer data to compare different dance movements and motion features (Hinton-Lewis et al., 2016; Senecal et al., 2018). For qualitative methods, Likert-type questionnaires have been used (Hadjakos et al., 2008; Drobny et al., 2009) and interviews (Drobny et al., 2009). Other papers offer conceptual solutions with no evaluation (Lee et al., 2007; Saxena et al., 2014; Camurri et al., 2016a). This thesis uses a mixed method approach evaluating the proposed solutions with quantitative and qualitative methods.
2.2.2.5 Technology

As the focus of this thesis is the use of motion sensors, most researchers use IMUs (Inertial Measurement Units) or accelerometer devices. (Lee et al., 2007; Hadjakos et al., 2008; Kawakami and Fujinami, 2008; Matsumura et al., 2011; Thiel et al., 2014; Kikhia et al., 2014; Camurri et al., 2016a; Hinton-Lewis et al., 2016; Faridee et al., 2018). In one case (Drobny et al., 2009), force sensors were used in the sole of the students’ shoes. A very simple approach is to use video recorded from students’ performances (Hsia et al., 2016). In the case of whole-body tracking, the most common methods are Kinect (Kitsikidis et al., 2015; Kim et al., 2017) or Motion Capture systems (Piana et al., 2016; Senecal et al., 2018). In an attempt to adopt widely used devices that are affordable and convenient for users, this thesis makes use of smartphones as they have embedded accelerometer and gyroscope sensors.

2.2.2.6 Raw x Features

It is not a trivial task to analyse raw sensor data and transform it into meaningful information. Most researchers do simple transformation when using the raw sensor wave to create their solutions. Hadjakos et al. (2008) simply overlapped the student’s raw sensor data with the expert in a line chart, using as a time reference the notes played on the piano. Matsumura et al. (2011) transformed the raw wave using autocorrelation function (ACF) to compare the ACF properties from instructor’s data with students’ data. Kitsikidis et al. (2015) used dynamic time warping (DTW) to compare the similarity between learners and experts’ movement and present the comparison using as scores. Kim et al. (2017) calculated the angles between joints from the skeleton data, reducing the dimensionality using a combination of principal component analysis and linear discriminant analysis. Another approach is to use simple statistical metrics as the mean and standard deviation from the motion data (Thiel et al., 2014; Hinton-Lewis et al., 2016) to compare the performance of dancer from different levels. A next step to evolve the quality of information obtained by motion sensors was developed by Kikhia et al. (2014), who used features well established in the field of activity recognition (Gupta and Dallas, 2014; Kwapisz et al., 2011) to model the Laban Effort Framework. Lee et al. (2007) attempted to use sophisticated analysis with spatial and spectral algorithms and a voting system to choose the best information, but they could
not achieve good results. Faridee et al. (2018) processed the raw wave used CNN to directly classify in dance episodes. A more appropriate solution was suggested (Camurri et al., 2016a) by interpreting the wave according to the requirements and constraints of the context. Senecal et al. (2018) also use the context to create music-related motion features, using the median of each feature to compare beginners, intermediate and advanced dancer. One of the main contributions of this thesis, RiMoDe (Section 5.4), incorporates the rationale behind several of the above approach to design its solutions, such as builds upon features from activity recognition to develop algorithms, together with information from the dance learning context.

2.3 Related Learning Technologies Regarding Psychomotor Learning and Sensors

There is a growing body of work demonstrating the potential of learning technology systems to support psychomotor learning (Santos, 2016). There are a myriad of psychomotor learning cases that could be supported by technology. Some attempts to model psychomotor learning have included human activities such as the martial arts (Takahata et al., 2004; Kwon and Gross, 2005; Bloomfield and Badler, 2008; Corbí and Santos, 2018), musical instrument playing (Van Der Linden et al., 2011; Hadjakos et al., 2008; Matsumura et al., 2011; Tsuji and Nishitaka, 2006; Hochenbaum and Kapur, 2012), sports (Baca and Kornfeind, 2006; Spelmezan and Borchers, 2008; Portillo-Rodriguez et al., 2008; James et al., 2011; Ghasemzadeh et al., 2009; Hassan et al., 2017), handwriting (Amma et al., 2014) and cooking (Stein and McKenna, 2013). Demonstrating how far technological support for psychomotor learning can go, researchers have been able to capture traces from the participants’ muscle movements even without the participants’ mental awareness, with the purpose of building a running assistant (Hassan et al., 2017). Using an electrical muscle stimulation (EMS) device and force sensors installed inside the participants’ shoes, the authors electrically stimulated the users’ calves if they were not landing on their feet at the correct angle. Participants should land using their toes, and not their heels, to avoid injuries. In a control study, participants were divided into two groups: a) learning the proper landing angle by watching slow motion videos, and b) using EMS real-time feedback. The second group outperformed the first regarding a decrease in average heel strikes even
without receiving any instructions. The participants would retain their muscle memory even after the EMS device was removed. This thesis’ algorithms allow for technologies such as EMS to be used in scenarios other than dance by developing algorithms which can detect whether the user is doing the correct movement such as following the correct rhythm and doing the correct step size.

Another common strategy to teach users to practise sports is the use of vibrotactile feedback (van Breda et al., 2017). In one attempt (Spelmezan, 2012), researchers used vibrotactile feedback to teach snowboard amateurs how to properly place their weight and turn their body. The real-time system used pressure sensors to measure the weight distribution on the feet and direction of the turn. During the ride, vibration motors placed on one thigh would indicate to the user to change their weight and motors placed on the shoulders would indicate to which side the user needs to turn their body. Riders could perceive and obtain the benefits of the system during simple and easy exercises but not during difficult exercises. The use of vibrotactile feedback to support sports practice lacks scientific evidence as most studies cannot achieve good results (van Breda et al., 2017). In this thesis, the strategy chosen was to provide automated feedback to students immediately after their dance practice. This would allow students to practise the dance exercises as in an authentic scenario, without constraints being imposed by the support technology used.

Even though there are many attempts to support psychomotor learning with technology, they are still far from achieving the advances that learning technologies have achieved for learning contexts like tertiary education and K-12. In these contexts, systems are able to model students and students’ behaviour, predict performance, increase reflection and awareness, predict dropouts and retention and give recommendations of resources (Papamitsiou and Economides, 2014). They can also build cognitive and meta-cognitive models, support open-ended learning and large-scale deployments (Paviotti et al., 2012). This thesis intends to bridge the gap between these learning technologies and psychomotor contexts by automatically assessing dance skills relevant for social partner dance education and presenting these assessments to teachers and students to support their teaching and learning practices.

There has also been an increased interest in research to include new sources of student data to enhance student models and learning technologies (Salmeron-Majadas et al., 2015; Bondareva et al., 2013). For instance, learning models can now include affective aspects of learning (Blanchard et al., 2009; Craig et al., 2004). To include
these new aspects, we need to combine multiple sources of data (e.g. logs, sensors, cameras, electroencephalography) into one system. Electrodermal activity (EDA) sensors have also been frequently used, together with heart rate (HR) sensors, to measure students’ stress and excitement levels. In one study (Chikersal et al., 2017), authors attempted to measure collective intelligence by means of facial expression, EDA and HR sensors. Evaluating their hypotheses with 60 dyads, they found that collective intelligence (CI) has a positive correlation with the synchrony of facial expressions. EDA and HR showed no impact in CI but group satisfaction had a positive correlation with EDA. The synchrony between students’ EDA measures was shown to be related to an improvement in students’ emotional states (Gashi et al., 2018).

Multimodal approaches have also looked at combining different sources of data to understand learning, usually from different devices (computer, tabletop, tablets, objects) and learning theories to create holistic technological solutions for learning (Blikstein and Worsley, 2016). In the case of psychomotor learning, students may be manipulating other devices and using the computer as an auxiliary tool or not using computers at all. Learning can occur in many other scenarios, such as contexts where students interact with other people, space and time (Martinez-Maldonado et al., 2018). This thesis follows the same rationale, allowing teachers and learners to perform their activities in their natural context while improving their awareness of learning processes.

2.4 Chapter Summary

This chapter presented an overview of important fields that are related to this thesis. First, Section 2.1 described important aspects of dance education, especially regarding important skills for dance, assessment strategies and types of feedback. Section 2.2 presented a review of current attempts to support dance learning with the use of technology. The detail on each body of work is presented and related to how this thesis addresses some of the gaps found on the literature. Finally, Section 2.3 connects the thesis with other learning technologies related to other psychomotor contexts or that use sensors to support traditional education (tertiary, K-12). Below, a list of the open issues found in the literature is presented, indicating how this thesis addresses these issues and pointing to the related chapters.
• Investigate Forró dance education. Lack of information on social partner dance education, especially regarding how Forró dance teachers approach assessment and feedback and which dance skills they see as important. Chapter 4 presents the result of interviews with several Forró dance teachers.

• Model additional rhythmic skills. Previous studies used sensors to model rhythm as an isolated skill. This thesis presents several rhythmic skills that together can help students and teachers in assessing rhythm. Chapter 5 describes the algorithms proposed to achieve rhythmic modelling.

• Validation with dance teachers. Previous studies lacks the involvement of dance teachers when validating technology. This thesis validates the proposed technology with teachers using quantitative and qualitative methods. Respectively, Chapters 6 and 7 present the results of the teachers’ validations.

• Expand automated feedback. Only a few projects have used the data collected to provide feedback to students. This thesis presents several ways of representing the motion data and evaluates it with dance student participants. Chapter 7 presents the data representation and evaluation results.
Chapter 3

Research Methodology

This chapter presents the research design of this thesis. A mixed method design approach was applied with the aim of examining the different research questions (RQ) listed in Chapter 1. The RQs were addressed via a series of studies that explored the potential use of sensing technology in a social partner dance learning context. Qualitative methods were used to understand the needs and challenges that teachers and students commonly face and how a proposed solution could help them. Quantitative methods were used to evaluate the reliability of the proposed technologies and to measure students’ performance. Each of the four studies are described in terms of the particular methodology and protocols used, and the participants involved in each study. The studies listed here were approved by the University of Sydney Human Research Ethics Committee under project numbers 2013/811, 2017/787 and 2017/807.

3.1 Research Approach

The purpose of this thesis was to: Design and validate a technological solution, based on the use of motion sensors and the application of machine learning techniques, to i) automatically extract rhythm-related information from students’ movements, ii) model critical rhythmic skills, and iii) support teachers to assess and students to learn rhythm-related dance features. To achieve this purpose, the methodology used to guide the overall project followed a combination of design-based
research (DBR) methodology (Anderson and Shattuck, 2012; Fraefel, 2014; Obrenović, 2011), from learning technologies research, and user-centred design (UCD) principles (Still and Crane, 2017). Machine learning (ML) methods guided the technical enquiry (Alpaydin, 2009). For DBR, this thesis followed the definition and principles of Anderson and Shattuck (2012), who defined DBR as a methodology that seeks to transfer the education research outcomes. In this thesis, the automated rhythm assessment was used to improve practice, while building theory and improving both practice and research. The principles of DBR are listed in Table 3.1. DBR uses a mixed methods approach that intervenes in real situations with the collaboration of researchers and practitioners. DBR makes use of multiple iterations that allow researchers to create, test and refine designs with a constant evolution. The studies included in this thesis were performed in sequence; therefore, each study benefited from the results of the previous one. DBR iterations were cycled over phases of design, implementation and analysis, repeating as required (Fraefel, 2014). This thesis used Obrenović’s 2011 concept for the outcomes of a DBR methodology, i.e. problem analysis that leads to domain theories.

To complement the use of DBR as an overarching research method, this thesis applied UCD principles to guide the involvement of stakeholders during the research process. The philosophy of UCD is that the design should put the user’s needs and wants first (Still and Crane, 2017). The studies included in this thesis involved several members of the dance community to ensure that the technical solution was aligned with their needs. In the real world, this philosophy must also be aligned with other constraints such as budget, time, team and user knowledge. UCD principles (Table 3.1) aim to involve the user early, often, and in their context, keeping it simple, and understanding users and giving them control, designing with emotions and triangulating different sources to verify the outcomes. As the learning space of dance is wide, and involves cognitive and motor skills, the involvement of users was inherently emotional. At the same time, results from the studies were crosschecked with different sources to increase their value. UCD is a continuous cycle with phases of discover, design and deliver, repeating as required (Still and Crane, 2017).
Table 3.1: Summary of DBR and UCD. The elements of the methodologies used as a reference for this thesis are marked in **bold** and those weakly used are in *italics*.

<table>
<thead>
<tr>
<th>Methodology</th>
<th>DBR (Anderson and Shattuck, 2012)</th>
<th>UCD (Still and Crane, 2017)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Principles</strong></td>
<td>Being Situated in a Real Educational Context&lt;br&gt;Focusing on the Design and Testing of a Significant Intervention&lt;br&gt;Using Mixed Methods&lt;br&gt;Involving Multiple Iterations&lt;br&gt;Involving a Collaborative Partnership Between Researchers and Practitioners&lt;br&gt;Evolution of Design Principles&lt;br&gt;Practical Impact on Practice</td>
<td>I. Involve users early&lt;br&gt;II. Involve users often&lt;br&gt;III. Design for use in context (the product will be used in the real world, so design accordingly)&lt;br&gt;IV. Keep it simple&lt;br&gt;V. Be polite&lt;br&gt;VI. Know your users&lt;br&gt;VII. Give users control&lt;br&gt;VIII. Remember and design for emotion people feel as much as they think&lt;br&gt;IX. Trust but verify triangulation is the key&lt;br&gt;X. Discover before designing and delivering, and know that discovery never ends, even after delivery</td>
</tr>
<tr>
<td><strong>Cycle</strong></td>
<td>Design - Implementation - Analysis</td>
<td>Discover - Design - Deliver</td>
</tr>
<tr>
<td><strong>Outcome</strong></td>
<td>Design Procedure - Methodology&lt;br&gt;<strong>Problem Analysis</strong> - Theory&lt;br&gt;Design Solution - Framework&lt;br&gt;Design Principles, System, etc...</td>
<td>User research&lt;br&gt;Product prototyping&lt;br&gt;User testing</td>
</tr>
</tbody>
</table>
Although DBR involves iterative technological development, ML methods strengthen the quantitative parts of the studies. The design of the technical experiments followed best practices and use cross-validation to avoid model over-fitting; used measures of quality such as accuracy, recall and F1 score; stratified training/test datasets to better average the results regarding imbalanced classes; used confusion matrices to report the model results; used a baseline model for comparison; used McNemars test (Dietterich, 1998; Keller et al., 2006) to compare the models with the baseline model; tested multiple ML algorithms and compared the features designed in this thesis with state-of-the-art features. These best practices attempt to ensure that the experiment procedures have been carefully designed and that the results have statistical validity.

Figure 3.1 presents a high-level schema of the research design iterations. The five research activities are represented in the form of columns starting with the literature review, and followed by the four studies. The research design includes a theory track and technology track that corresponds to developments in the domain, Forró and dance, and the technological developments in each study, respectively. Each cell of the figure contains an iteration symbol on the background showing the contribution description, which corresponds to one DBR cycle of Design - Implementation - Analysis used in the study. Each study executed a full DBR iteration cycle.

The following sections of this chapter describe each study, methods, protocol and participants’ information. The results of these studies are described in the remaining chapters of this thesis. Figure 3.2 provides a summary of each study and its relation to the findings, algorithms, tools and contributions of this thesis.

Study 1 carried out interviews with dance teachers providing an empirical contribution from a deeper understanding of teachers’ practices, which is reported in Chapter 4. This supports the design of RiMoDe v1, an algorithm that extract rhythm features from the students’ movement, and the Forró Trainer, a mobile app that collected motion data while students practised dance exercises.

Study 2 developed and tested an algorithm that extract rhythm indicators from motion sensors providing artefact, theoretical and dataset contributions. Results are reported in Chapters 5, 6 and 7 and this study helped inform RiMoDe v2, an algorithm that extracted new rhythm features from motion data, and the video annotation tool, a tool that supported teachers in assessing rhythmic skills from students’ video-recorded performances. The mobile app Forró Trainer, described in Section 5.3, was used in both Study 2 and study 3.
CHAPTER 3. RESEARCH METHODOLOGY

RESEARCH DESIGN

- Literature Review
  - Skills: Rhythm
  - Teaching Aspects: Assessment and Feedback

Theory Track
- Technology Track
  - Tech.: Wearables
  - Algorithms: Movement and Rhythm Detection
  - Video Annotation

Study 1
- Understanding Forró social dance education from the teachers’ perspective

Study 2
- Understanding Teachers’ Vocabulary on Rhythm Assessment
- Motion Sensors’ Features Validation
- Automatic Assessment Evaluation with Students

Study 3
- Validating Teachers Rhythm Assessment Vocabulary
- Validation of New Motion Sensors’ Features
- Video Annotation Tool to Support Dance Teaching

Study 4
- Investigating Automatic Assessment with Dance Teachers

Research Questions
- RQ1 - How do Forró dance teachers approach teaching of rhythmic skills?
- RQ2 - How can we use motion sensors to extract rhythm-related information that enables the support of dance rhythm assessment and learning?
- RQ3 - Is the extracted information valid, useful and relevant for teachers and students?

Figure 3.1: Diagram of the research design

Iteration: Design - Implementation - Analysis  No Iteration
<table>
<thead>
<tr>
<th><strong>Inform / Source</strong></th>
<th><strong>User Studies</strong></th>
<th><strong>Findings</strong></th>
<th><strong>Algorithms / Tools</strong></th>
<th><strong>Contributions</strong></th>
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<tbody>
<tr>
<td><strong>Studies</strong></td>
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<tr>
<td>Study 1</td>
<td>Interview with dance teachers</td>
<td>Dance Context</td>
<td>RIMoDe v1</td>
<td>Empirical: Forró Teachers’ Context</td>
</tr>
<tr>
<td>Study 2</td>
<td>with Students App., Feedback</td>
<td>Dance Learner Model</td>
<td>RIMoDe v2</td>
<td>Artefact: RIMoDe Theory; 6 Themes</td>
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<tr>
<td></td>
<td>with Teachers Video Annotation</td>
<td>Student BPM, Consistency, # of Practices</td>
<td>Forró Trainer</td>
<td>Dataset: 94 sessions</td>
</tr>
<tr>
<td>Study 3</td>
<td>w/ Students and Teachers Data → Machine Learning</td>
<td>Machine Learning</td>
<td>Video Annotation Tool</td>
<td>Artefact: RIMoDe v2</td>
</tr>
<tr>
<td>Study 4</td>
<td>w/ Teachers Teachers’ Insights</td>
<td>Teachers’ Insights</td>
<td>Video + Automatic Assessment Probe for Teachers</td>
<td>Empirical: Design Recommendations</td>
</tr>
<tr>
<td></td>
<td>with Teachers Video Annotation Tool</td>
<td>Students’ Perceptions</td>
<td>Assessment and Feedback</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Difficult Data Sense Making</td>
<td>RIMoDe v2</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Six Themes</td>
<td>Forró Trainer</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Gap between Teachers</td>
<td>BPM, Consistency</td>
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<tr>
<td></td>
<td></td>
<td>and Algorithm</td>
<td>Rhythm, Step Size, Pause, Weight Transfer</td>
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</table>

Figure 3.2: Overview of the studies, algorithms, tools, findings and contributions of the thesis. Different colours are assigned to each study and are used to represent findings, algorithms, tools and contributions.
Study 3 improved the algorithms to extract rhythm indicators by using more details from the song and motion sensor data providing artefact, empirical and dataset contributions. It is reported on in Chapters 5 and 6, and helped inform the tools used for collecting data during Study 4.

Study 4 tested with dance teachers the automated rhythmic assessment having empirical contributions and its results are reported in Chapter 7.

A total of 19 dance teachers were included in the thesis. Table 3.2 provides a summary of the teachers’ participation in each study. T7, T12 and T15 acted as lead users because they participated in all four studies. Their gradual exposure to the solutions proposed in this thesis gave them a different experience, and insights compared to the other teachers. For the students, a total of 21 participants were recruited to take part in Study 2 (10 participants) and Study 3 (16 participants), with 5 participated being involved in both studies.

Table 3.2: Summary of teachers’ participation in each study.

<table>
<thead>
<tr>
<th></th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>T6</th>
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<th>T13</th>
<th>T14</th>
<th>T15</th>
<th>T16</th>
<th>T17</th>
<th>T18</th>
<th>T19</th>
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</table>

3.2 Study 1: Teachers’ Interviews

3.2.1 Objectives and research questions

The first study aimed to gain a more grounded understanding of the context of dance teaching, specifically Forró. While most of the dance teaching literature has focused on K-12, tertiary and other dance practices (Côté-Laurence, 2000; Erkert, 2003; Karkou et al., 2017; Kassing and Jay, 2003; McCutchen, 2006), limited research has looked at social partner dance, with even less at Forró. The interviews explored how Forró dance teachers approached dance teaching. The focus of the interviews was related to what were the important skills for students to learn and how teachers assessed and provided feedback to dance students, especially related to rhythm skills. Teachers were also invited to comment on the difficulties regarding beginner students and the different
strategies to support them. The research questions for this study, that expand on RQ1, were the following:

- **RQ1.1** - What are the skills required for Forró students to learn to dance?
- **RQ1.2** - How do Forró dance teachers assess students’ rhythm skill development?
- **RQ1.3** - What are the types of feedback that Forró dance teachers commonly use?

### 3.2.2 Participants

Dance teachers were recruited via snowball sampling beginning from a contact list of Forró dance teachers. A total of 16 teachers (T1-T16) were recruited, eight males and eight females, whose teaching experience varied from 5 to 40 years, with an average of 15.4 years (±10.4). Four of them had less than 10 years’ experience, whereas 12 had more than 10 years’ experience. Two of the teachers worked part-time as dance teachers, whereas the others worked exclusively teaching dance. Their average age was 35 years (±9.3). Nine of them were teaching in Brazil and the others were teaching in five different countries (details are not revealed to preserve the participants’ anonymity).

### 3.2.3 Procedure

A list of questions guided the participants in semi-structured interviews to explore the research questions (RQ1.1, RQ1.2 and RQ1.3). The interviews took place over the internet in Skype or Messenger sessions. All interviews were recorded, automatically transcribed using Google Cloud Speech-to-Text API\(^1\), manually edited and later identified researcher and interviewee segments. The interviews were carried out in Portuguese or English, depending on the participant’s preference. The interview questions are listed in the Appendix, Section A.1. The data analysis followed a grounded theory approach (Lazar et al., 2017a) to prioritise the voice and practices of the participants in the generation of analytical themes, compared to imposing an existing coding system. Interviews were transcribed and processed with open coding of the teachers’

\(^1\)https://cloud.google.com/speech-to-text/
answers using the RQs to guide the creation of emerging categories. During axial cod-
ing, categories were connected to establish relationships between them. The resultant
categories and their connections formed a conceptual map (Elo and Kyngäs, 2008;
Lazar et al., 2017b). To strengthen the results, concepts were triangulated with the lit-
erature, examples were elicited from interviewee statements (e.g. interview quotation
below) and a member check was performed. A member check, or respondent valida-
tion, occurs when the findings of an empirical study are validated with its participants
(Lincoln et al., 1985; Maxwell, 2012). The results of this first study are described in
Chapter 4, Section 4.1, and were used to inform which skills to focus the thesis on, the
learning aspects that could be supported by technology and the methods to be used to
evaluate the technology with teachers and students.

One example of the data analysis process, following previous studies (Côté-Laurence,
2000; Lazar et al., 2017a; Santos et al., 2016) is described below:

a) Research question: RQ1.1 - What are the skills required for Forró students to
learn to dance?

b) Interview quotation: “Very essential in the beginning is to deal with the rhythm,
because it will help in tune the pair, to be together when they are dancing. This
will give much more security to the student.”

c) Key point: Rhythm is essential for beginner students, help to tune the pair and
give more security to the student.

d) Code: Rhythm is essential for students.

e) Categories: DANCE FOUNDATIONS, rhythm.

f) Axial coding: dance foundations → rhythm.

g) Group concepts into categories: Dance Foundation: rhythm, body awareness,
weight transfer, etc.

h) Formation of theory: Teachers said that rhythm is an important and difficult skill
for some beginner students to learn.

Table 3.3 below shows an example on how codes were grouped into categories. More
examples regarding the coding process are available at the Appendix C.
Table 3.3: Sample of creating the category ‘Connection with the partner’ from open coding

<table>
<thead>
<tr>
<th>T#</th>
<th>Interview quotation</th>
<th>Open code</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>I think those who are starting to learn how to dance should concentrate a lot on finding a good position to embrace the other person something that is comfortable for them. I pay attention if they are hurting each other.</td>
<td>Know how to embrace is an important dance skill</td>
<td>Connection with the partner</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Being comfortable is important for partner dance</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Students should not hurt each other</td>
<td></td>
</tr>
<tr>
<td>T4</td>
<td>Also the ability of the couple to interact, dance to each other, looking into each other’s eyes.</td>
<td>Eye contact is important for dance</td>
<td></td>
</tr>
<tr>
<td>T8</td>
<td>A lot of people have difficulty getting closer to each other.</td>
<td>Dance together is difficult to students</td>
<td></td>
</tr>
<tr>
<td>T16</td>
<td>Something the closeness involved with the dance styles that physical closeness they can find difficult, emotionally difficult.</td>
<td>Emotional connection is difficult for students</td>
<td></td>
</tr>
</tbody>
</table>

The member check of Study 1 occurred during a follow-up interview, performed with participants of Study 4. Teachers answered the following questions when evaluating the conceptual map:

- Which aspects of the map apply to your context?
- Do you disagree with any of these aspects?
- Would you add other aspects that are not included in the map?
- Is there something you don’t understand?

The results of these interviews were analysed using the same procedure described before, i.e. transcription - coding - axial coding, with the exception of constructing the conceptual map, which was not used in this part of the study. The report also included quotes from the teachers response and triangulation with the literature.
3.3 Study 2: Pilot Study with Students

3.3.1 Objectives and research questions

The pilot study aimed to implement and evaluate several components required to support students’ dance learning: a mobile app, an algorithm to recognise students’ movement and automated feedback. This study explored the challenges of using technology to support dance education and better understand the users’ needs. For this first attempt, the focus was rhythm, which is reported to be an essential skill for students to learn, according to one teacher from Study 1. The research questions that guided this study, expanding on RQ1, RQ2 and RQ3, were the following:

- RQ2.1 - How do we translate motion data to rhythm information?
- RQ2.2 - What is the accuracy of the RiMoDe v1 algorithm?
- RQ1.4 - What is the vocabulary used by teachers when assessing students’ rhythm skills?
- RQ3.1 - How do students make sense of the automatic assessment data?

3.3.2 Participants

A total of 10 participants (five males and five females) were recruited from the University of Sydney to join a free individual private dance course consisting of three classes of 30 minutes. All of them were IT graduates or PhD students. Their ages ranged from 18 to 54 years, with five in the range of 25-44 years. Three participants reported more than six years of dancing experience (not professionally), Four had less than one year of experience and three had no experience at all. Six participants did not dance regularly and only five of the participants had experience with Forró.

Six dance teachers (T4, T5, T7, T12, T15 and T17) were recruited to assess the videos (see next subsection). They were three males and three females, whose teaching experience varied from 7 to 12 years, at an average of 9.7 years ($\pm 2.2$). All of them were teaching in Brazil. Their ages ranged from 26 to 33 years with an average of 28.5 years ($\pm 3.1$). Three of the teachers reported working exclusively teaching dance and three worked part-time as dance teachers. None of the teachers knew the students in the videos.
3.3.3 Procedure

The experiment was performed in a laboratory. In each class, the participant was video recorded individually while performing a Forró dance exercise, called Básico 1. The participants used a mobile app to track and record their movements. An average of six recordings were obtained per participant in each dance class, split into two blocks: three before and three after the class. A total of $96 \times 1$-minute sessions were recorded. Each participant participated in at least six sessions and at most 19 sessions, as some participants withdrew during the middle of the study. For each session, information collected included mobile app data (sensor data) and the video recording. In each block of recordings, the participant was asked to perform the same dance exercise following different songs. The duration of the exercise recording was 1 minute; therefore, several units of 1-minute recordings per dance class were obtained. After the end of the course, participants were invited to evaluate a report created, for each of them, with the data collected, see Section 3.3.3.3. The participants’ videos were sent to the Forró teachers to assess the students’ performances. This assessment was used as a ground truth to compare with the output of the algorithm proposed in the study.

3.3.3.1 Video analysis – establishing the human-based ground truth

The aim of the video analysis was to validate the accuracy of the algorithm for identifying the student rhythm and unveil the tacit assessment process of dance teachers. Teachers annotated the videos remotely using an online tool to watch the videos and annotate them in a separate online spreadsheet, without any intervention or observations from the researchers. To reduce the assessment process load for the teacher, each video was assigned to only three of them and each teacher assessed only 48 of the 96 videos.

<table>
<thead>
<tr>
<th>Teacher</th>
<th>T7</th>
<th>T4</th>
<th>T5</th>
<th>T15</th>
<th>T12</th>
<th>T17</th>
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<tbody>
<tr>
<td>Video Group</td>
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</table>
The video allocation, for each teacher, followed an allocation schema that evenly distributed the videos for the teacher and ensured that all teachers assessed each participant at least once, see Table 3.4. The videos were ordered by each participant’s number and then by date/time. Then, each video was assigned a group number from one to six (the number of teachers), repeating this numbering over and over, until the last video. After, each teacher was asked to assess three of these groups. When assessing a video, the teacher was asked to respond to the following questions:

Q1 In this video, is the person in the right rhythm? (Yes/ No).

Q2 How much on the rhythm is the person? Too much slower/Slower/Correct (on the rhythm)/Faster/Too much faster

Q3 What is the speed of the song? Very slow/Slow/Medium/Fast/Very Fast

Q4 How hard is it to identify the tempo of this song? Very easy/Easy/Medium/Hard/Very hard

Q5 Please include here your comments about the quality of the student’s movement. By quality, we mean posture, arm position, legs, feet, joint movements, etc. Be as detailed as possible. Thank you.

Questions 1 to 4 allowed us to establish a quantitative common ground for the assessment of the students’ skills across teachers. The last question was intended to elicit qualitative explanations about the assessments.

3.3.3.2 Algorithm evaluation

Using ML methodology for evaluation (accuracy, precision, recall and F1 score) (Alpaydin, 2009), the teachers’ annotations were compared against the output from the algorithm. Confusion matrices and performance metrics were produced to evaluate the quality of the RiMoDe algorithm and guide the quantitative discussion. The results of this evaluation are reported in Section 6.1.2.

The comments made by teachers during the video assessment were used to guide the qualitative analysis. First, the comments were classified using text mining and were then grouped into themes of skills that the teachers observed observing when assessing the performances of the students. The result is presented as part of Chapter 6 – Section 6.1.2 and further discussed as part of Chapter 8 – Section 8.3.
CHAPTER 3. RESEARCH METHODOLOGY

3.3.3.3 Student Participants’ reflection

After the three lessons, each student participant was asked to provide feedback on a report created with the data collected during the study. The report presented several types of data representation including statistical information, charts and textual feedback. More details and results are presented in Section 7.1.2. Nine of the participants participated in a final interview. A total of 15 aspects were evaluated using a 5-point Likert scale questionnaire regarding the clarity and usefulness of each data representation. A questionnaire that evaluated multimodal feedback for traditional education assessments (Phillips et al., 2016) was used as a reference to create the questions. For the Forró Trainer app evaluation, the System Usability Scale (Brooke et al., 1996) and other usability questionnaires found in the literature (Nielsen, 1995) were used, which were adapted to our needs. A full description of the interview script used is available online² and in the Appendix, Section A.2.

3.4 Study 3: Improving Algorithm and Skill Descriptors

3.4.1 Objectives and research questions

Following up the findings from the previous study, a new study was needed to enhance the detection system, the data collection with teachers and the terms used to describe the skills. The aim of Study 3 was to increase the number of features extracted from the movement and song data, and to use this information to describe other skills that are required for students to learn rhythm. The accuracy of these features in modelling the new skill set was evaluated using teacher annotations. This study also included a step where teachers helped define what vocabulary better represented the new skills detected. The research questions addressed in this study, expanding on RQ1, RQ2 and RQ3, were the following:

- RQ2.3 - How do we improve the extraction of features from the translated motion data to rhythm information?

- RQ2.4 - What is the accuracy of the new features of the RiMoDe (v2) algorithm?

²https://goo.gl/x03Yuj
• RQ1.5 - Which vocabulary do teachers use to represent the new rhythm skills detected by the algorithm?

• RQ3.2 - How do teachers perceive the use of technology to support their dance teaching?

3.4.2 Participants

We recruited 16 participants (ten males and six females) to join a free individual private dance course consisting of three classes. Their ages ranged from 18 to 54 years, with an average of 31 years (± 6), with five participants in the range 25-34 years. Two participants did not dance at all, seven participants reported as being beginners, two were confident dancing simple steps, whereas five reported feeling confident dancing quite a variety of dance steps/style. Nine participants did not practise dance regularly and only eight of the participants had experience with Forró.

Four dance teachers (T6, T7, T12 and T15) were invited to assess the videos (see next subsection). All of them were Brazilians, two males and two females, whose teaching experience varied from 7 to 12 years, with an average of 10 years (±2.4). All of them were teaching in Brazil. Their age range was from 26 to 28 years, with an average of 27 years (±0.8). Three of the teachers reported that they worked exclusively teaching dance and one worked part-time as a dance teacher. The teachers did not know the students in the videos.

3.4.3 Procedure

In each class, the participants were video recorded while performing the Básico 1 exercise while wearing a smartphone to track and record their movement. They performed the movements individually (the same as for Study 2) while being video recorded. The participants underwent 10 recordings per class, split into two blocks: five before the class and five after the class. Each recording was 1 minute long. In each block of recordings, the participant was asked to perform the same dance exercise using five different songs that had different paces. The pace of each song gradually increased from the first to the last. This design ensured that the participants were exposed to various levels of difficulty, thus enriching the data collected. After the end of the course,
the participants’ videos were sent to the dance teachers who assessed the students’ performances.

A total of 480 videos (16 participants $\times$ 3 classes $\times$ 10 exercises) were recorded and tracked with the Forró Trainer app. All sessions were pre-annotated by the researcher during the classes using one of the following labels: correct, rhythm problem, pause problem, weight transfer problem and other problem. A total of 70 videos were selected to be assessed by the teachers following the same proportion as the pre-annotated labels, 14 for each label. Teachers annotated the videos remotely using an online video annotation tool, purposely built for this study, without any intervention or observations from the researchers.

In comparison with Study 2, this study included a stricter protocol for data collection and annotation. The students were recorded under the exact same conditions. They all performed the exercises using the same songs, with the smartphone in their left pocket. In this study, the mobile app contained a feature that allowed the motion data to be synchronised with the timing of the song. This allowed for richer data analysis and feature extraction, see Section 5.5. The tool that was built for the video annotation increased the quality of the annotation by making it easier for teachers to annotate the data and allowing teachers to specify the time position of the annotation and to include comments, see Section 5.6.

**Interview about the Video Annotation Tool.** This study included a semi-structured interview with the dance teachers while using a video annotation tool. The purpose of this interview was to allow teachers to explore the prototype of the video annotation tool and discuss the vocabulary to be used during the annotation process. This step of the study helped to answer RQ1.5. The teachers were asked to comment on how they expected the interface to work and if they could understand the dance terms used in each of the buttons. Next, they were asked to assess four videos to test the prototype. After the test, the teachers could add new comments on how they found the process and what they would like to change in the prototype. We modified the prototype based on the feedback comments obtained from the teachers to create the final version of the video annotation tool.

**Assessment of students’ dance through video annotation.** To relieve the assessment process load for the teacher, a batch of 30 videos was allocated to all teachers to assess so that inter-rater agreement could be generated, and later a batch of 10 different videos was allocated to each of the four teachers. This generated a total of 70 videos
assessed by the dance teachers. When assessing each video, the teacher was asked to flag and comment on the following aspects of each student’s dance:

- Rhythm/tempo: Slower, Correct, Faster
- Pause: Wrong Beat, Correct, No Pause
- Weight transfer: Too Few, Correct, Too Much
- Step size: Too Small, Normal, Too Large
- Other mistakes: Dance Jumping, Stepping Strong, Hip Twist
- Comments section. ‘Write here additional comments about this video if necessary’.

Semi-structured interview. The use of the video annotation tool unveiled important aspects of the teachers’ process of assessing students, answering RQ3.2. We interviewed the teachers after the previous step to obtain insights into their experience using an online method to assess students. The interview questionnaire contained four groups of questions regarding the tool, which were related to 1) how they would use the tool to track student learning and provide feedback, 2) the usability of the tool, 3) the interface design and 4) the use of the tool compared to using a spreadsheet to annotate (as used in Study 2). The questions were based on other usability questionnaires found in the literature (Brooke et al., 1996; Davis, 1989; Nielsen, 1995; Venkatesh and Zhang, 2010) that were adapted to our scenario, see Section A.3.

3.4.3.1 Algorithm evaluation

Using ML classification algorithms (Ravi et al., 2005; Kwapisz et al., 2011), teachers’ annotations were used as labels and modelled using RiMoDe v2 and statistical features. Different from the previous study, in this study classification algorithms were used with a combination of different parameters (inputs) to evaluate which features were more relevant during the classification.

Seven different types of classification methods were used to evaluate the features: Neural Network, kNN, Tree, Support Vector Machine (SVM) Leaner, Random Forest, Naive Bayer and Logistic Regressions. A Baseline model was used as a baseline and
corresponded to the most frequent class. We used a stratified 5-fold cross-validation. Stratified means that each fold contains roughly the same proportions of each class (Demšar et al., 2013).

To evaluate the importance of the features in modelling each skill, the following feature selection metrics were used (Demšar et al., 2013): gain ratio, Gini, $X^2$ and reliefF.

To evaluate how powerful the features were for modelling each skill we used the following modelling performance metrics (Demšar et al., 2013): area under ROC, accuracy, F1 score, precision and recall (explained in Section 6.3).

For the semi-structured interview analysis, this study followed the same strategy as that described in Study 1, Section 3.2, with the exception of constructing the conceptual map, which was not used in this study.

### 3.5 Study 4: Investigating Automatic Assessment with Dance Teachers

#### 3.5.1 Objectives and research questions

The last study of this thesis aimed to obtain insights into how dance teachers could use automatic assessment in their dance teaching context. The research questions for this study expanded RQ3 and included the following:

- RQ3.3 - How do teachers use the automatic assessment to assess students’ video performance?

- RQ3.4 - How would teachers use the automatic assessment in their context as dance teachers?

#### 3.5.2 Participants

Eight Forró teachers took part in this study, four of them had participated in Study 3 (T6, T7, T12 and T15) and had been exposed to the four metrics used in the automatic assessment. The other four teachers had not seen the metrics before (T8, T14, T18 and T19). They included four males and four females, whose teaching experience varied from 7 to 24 years, with an average of 11.4 years ($\pm 5.9$). Five of them were teaching
in Brazil and three were teaching in other countries. Their age range was from 25 to 47 years, with an average of 30.2 years (±7.6). Seven of the teachers reported to be working exclusively teaching dance, with the other one working part-time as a dance teacher.

### 3.5.3 Procedure

A total of 10 videos were taken from the dataset recorded in Study 3, each containing a student performing the Básico 1 exercise for 1 minute. Several of the teachers were asked to watch and assess the first five videos without any assistance and the last five videos with the support of information generated using the automatic assessment. The videos were selected based on the automatic assessment using the second version of the algorithm (Study 3), base on the following criteria:

- Case 1 – Good performance
- Case 2 – Step size problem
- Case 3 – Weight transfer problem
- Case 4 – Pause problem
- Case 5 – Rhythm problem
- Case 6 – Pause problem
- Case 7 – Weight transfer problem
- Case 8 – Step size problem
- Case 9 – Good performance
- Case 10 – Rhythm problem

Semi-structured interviews were conducted with teachers base on the following protocol (more detail is found in the Appendix, Section A.4):

1. The teacher assessed five students using just the videos and answered the following questions for each video:
   - What is the diagnosis for this student?
   - What feedback would you give to this student?
   - How easy/hard was it to assess this student? Comment on this please.

2. The teacher assessed five students using videos that contained information generated using the automatic assessment of each student’s performance and for each video they answered the same three questions as above.

3. The teacher was asked to share their experience using the automatic assessment during the video assessment.
4. The teacher was asked to formulate hypothetical scenarios where they would see benefit from using the automatic assessment.

The method used to summarise the interviews was the same as that described in Study 1, Section 3.2, i.e. transcription – coding – axial coding – conceptual map. The report also included quotes from the teachers’ responses and triangulation with the literature.

### 3.6 Methodological Changes

This thesis began with the aim to develop a technological solution to support rhythm learning in social partner dance using motion sensors. The initial focus was to develop algorithms and systems that could measure and evaluate rhythm skills that had statistical validity. However, during the execution of the pilot study with student(Study 2) and from the analysis of its results, new perspectives emerged. thus, it was necessary to explore more deeply the dance community and how they approached the assessment and feedback of rhythmic skills. Specifically, which terms they used when referring to rhythm assessment and which other skills were related to rhythm. With these new perspectives, we adopted UCD approaches to ensure that the technology was developed to support human experiences and needs in their context of use. The main change was to target the new studies to Forró dance teachers and include their involvement in the design and evaluation of the proposed technology. Their involvement made the technology more connected to their context, using the same vocabulary as they used and, most importantly, representing the same mental concepts (semantic meaning) as they expected.

### 3.7 Research Transparency Statement: My Experience as a Dance Teacher and its Role in this Thesis

As a principle of qualitative research, this section attempts to acknowledge the frame of reference that was embedded in the researcher’s eyes, allowing the reader of this thesis to understand how the reasoning process was conditioned (Ben-Ari and Enosh, 2011; Mortari, 2015). My experience as a dance teacher guided many decisions of this thesis
project and it is important for transparency to explain to the reader the predisposition that my role as a dance teacher affected my role as a researcher. In the first year of my PhD (2015), as a hobby, I started to give free Forró dance classes in a community centre in Sydney, Australia. It is a dance that I have been practising since 2010 and together with other physical and teaching practices, it was not hard to transfer my dance knowledge to other people. The project became very popular, within a few weeks I had 20 to 40 students that grew to more than 100 in the first year.

The dance classes project allowed me to gain a first-person perspective on the challenges associated with a dance facilitator, to understand the different types of difficulties that the students can have and to come into contact with several professionals from the dance community, especially Forró. Being inside the Forró dance community, I had unique access to that world, the practice and the participants. Access to tacit knowledge and experience as a dance teacher conditioned how I understand and perceive this phenomenon of interest. The easy access and communication with other Forró teachers allowed me to include them in this research project as well as being accepted as one of them. My exposure to teaching practices and to dance students helped me to gain insights on ideas to use technology to help dance learning, shape the research methodologies and prototype solutions that were more appropriate to the Forró dance learning context. For instance, while prototyping the mobile app with dance colleagues and students, I realised 1) the need to embed a song inside the Forró Trainer app so that the song could be used as a reference for rhythm and 2) using the app inside the classroom was embarrassing for some students, as they needed to practise the exercises alone. A reminder of the social and emotional aspects of learning and the context in which it takes place.

While determining which Forró dance skills could be assessed with technology, rhythm was the first one that I thought of. Many of my students, especially beginners, had problems with acquiring rhythm skills. There was a clear division of two types of difficulties that students faced regarding rhythm. First, students that were not able to interpret the rhythmic pattern of the song and reproduce this pattern inside their mind. These students would not be able to reproduce the patterns by speaking out loud or clapping their hands. It was not a coordination problem, but rather a problem interpreting the rhythm pattern. Second, students that had mastered the previous step, from experience or formal learning, but were unable to translate this pattern to a bodily movement pattern that matched the song’s rhythm. therefore, students could interpret
the song pattern, some of them would be able to clap the rhythm; however, they did not have the coordination to reproduce these patterns with their legs. By observing several students, I could understand that the coordination problem occurred because 1) when using the legs for dancing, students’ muscle memory associate the movement with what they already know, which is walking; thus, students produce wide steps and use their heels, spoiling their posture and slowing down their movement; and 2) while using their legs they need to do a movement similar to walking backwards, which is not a natural movement for most people and some students were afraid of hitting something when doing the backwards movement.

Although my experience as a dance teacher provides a rich contribution to this research project, it may also bring personal bias. The main strategy used in this thesis to mitigate personal bias was the triangulation of different data sources (Patton, 1999). The data sources used were the literature, Forró dance teachers, students and participants. For RQ1, I assumed that rhythm was an important, and sometimes difficult, skill for students to learn and that teachers had little time to assess and provide feedback for the students during the class. The bias of these assumptions was mitigated by triangulating this information in the literature and by interviewing several dance teachers. In answering RQ2, the motion data collected had to be annotated to train the ML models. With my experience as a dance teacher, I could have annotated the data myself. To remove potential bias, teachers were recruited instead to annotate the videos for Studies 2 and 3. At the end of this thesis, teachers were recruited to evaluate the automatic assessment. Four teachers have been working with me since the beginning of the PhD project. To enrich the data collected in Study 4, another four Forró teachers were recruited, thus reducing the bias that the first four teachers might have had in participating in the study.

### 3.8 Chapter Summary

This chapter described the overall methodology used in the thesis. Because of the lack of work in this field, this thesis required the use of a methodology that could be adaptable. DBR was suitable because of its iterative process. UCD principles guided the user studies. This chapter also presented a description of each of the four studies included in this thesis. In summary, the aim of Study 1 was to understand the teacher’s
context and which skills were relevant to dance education. The aims of Study 2 and Study 3 were to design and re-design the technology to support teachers and students while also validating their outcomes. Study 4 evaluated how the metrics of an automated assessment could be useful in the current teaching practices of the dance teachers.
Chapter 4

Understanding Forró Social Dance Education from the Teachers’ Perspective

This chapter presents an enquiry into the teaching of Forró social dance. It is important to understand the context of Forró dance teachers so we can draw a more complete picture of other aspects related to the assessment of rhythm skills in Forró students. These aspects are presented in the list below and complement RQ1. By widening our enquiry related to rhythm assessment, this thesis will connect the use of technology to the practice of Forró teaching and to understand other skills that are important for the development of rhythm in dance students. The following sections compile an extensive interview process reporting on several perspectives of Forró dance teachers. The focus of these interviews was to generate an understanding of the skills that students must learn, appropriate feedback strategies and how teachers assess the development of their students. Teaching strategies are also a significant topic to be covered; however, these are not in the scope of this investigation as the focus is on the assessment of rhythm skill development in dance students. The research question (RQ) of this thesis and the complementary RQs of this study are listed below:

- RQ1 - How do Forró dance teachers approach teaching of rhythmic skills?
  - RQ1.1 - What are the skills required for Forró students to learn to dance?
  - RQ1.2 - How do Forró dance teachers assess students rhythm skill development?
– RQ1.3 - What are the types of feedback that Forró dance teachers commonly use?

4.1 Study 1: Teachers’ Interviews - Data Analysis

The aim of this study was to understand the context of dance teaching from the perspective of Forró dance teachers. By mapping the teachers’ knowledge regarding the research question, a more informed and appropriate technical solution could be developed to support their practice. Although some literature exists regarding other dance practices that have investigated similar questions such as the role of rhythm in dancing (Côté-Laurence, 2000); dance teaching, assessment and feedback in formal education (Erkert, 2003; Kassing and Jay, 2003; McCutchen, 2006) and dance education and feedback in other contexts (Karkou et al., 2017; Quinn et al., 2017), there is no literature covering the practices of Forró dance teachers. For that reason, it was important to understand how this community deals with dance teaching, specifically rhythm, assessment and feedback.

To address the RQs proposed above, this study interviewed 16 Forró dance teachers. The interviews were semi-structured with questions that guided the conversation with the dance teachers. The complete list of questions is reported in the interview script in the Appendix, Section A.1. The interview process took an average of 1 hour per participant. The interview questions evolved after each interview session. New topics emerged during the interviews, which were relevant to the research question, and were added as questions for the following interviews. For instance, T5 mentioned the need to adapt the feedback depending on the age of the students and their interests. This question was then added to the interview script. For the first interviewees, a follow-up interview was required to cover these emerging aspects, which had not been covered during the first interview. More details of the methodology, participants and the procedure of this study can be found in Section 3.2 – Study 1: Teachers’ Interviews. The questions were intended to elicit a broad understanding of what teachers consider important when teaching students to dance, the skills that students need to develop and the teaching strategies regarding assessment and feedback. In the subsequent analysis, a closer examination of rhythm was highlighted.
The categories created from the open coding were compiled in a conceptual map and can guide the reader in following the next sections. The conceptual map is presented in Figure 4.1. The items under ‘Member Check Phase’ will be explained in greater detail in Section 4.1.4. The next sections describe the interviews with teachers (T1–T16) based on the procedure described above.

Figure 4.1: Conceptual map containing a summary of the teachers’ interviews.
4.1.1 What are the skills required for students to learn to dance?

Understanding the skills involved in a dance class was the most important part of the teachers’ interviews. It was critical to understand which skills were relevant from the teachers’ perspective and target at least one of these to investigate how technology could aid in the assessment of such a skill. As mentioned in Section 3.7, there was already a predisposition to believe that rhythm was a fundamental skill for students to learn and that rhythm could be a good starting point to use technology.

Teachers named many skills, with the list being consistent across most interviewees. In some cases, different teachers would use different words to represent one skill or would use the same word with various meanings, as explained below. The very basic skills that appeared in most interviews and that should be the first things for students to learn were rhythm, coordination, balance and weight transfer. For some teachers, coordination and balance were components of what they called rhythm. The same occurred for weight transfer, which could be a part of coordination. Each of the skills listed by the teachers are defined and discussed below.

**Rhythm.** Rhythm is the skill that allows the students’ body to move in synchronicity with particular elements of the music. In Forró, dancers use mainly the drum’s (Zabumba) beat and tempo to guide the rhythm of their movements. All teachers mentioned that rhythm is an important and difficult skill for some beginner students to learn. For the teachers, rhythm can be something as simple as having the movements synchronised with the strong beats of the song (having the same tempo), or can a more elaborate concept that some teachers referred to as musicality or connection with the music. Musicality means the ability of students to move and play with the different elements and instruments of the song. This includes not only the beat but also the melody and tone of the songs, and to connect some or all of these elements using the body. Some teachers (T3, T5, T9 and T10) thought that to naturally embody the elements of the songs was one of the most difficult skills for the students to master. T8 mentioned that the difficulties faced by students regarding interpreting the rhythm were related to their exposure to music. Another teacher, T14, said that musicians would have rhythm abilities but had problems with expressing the rhythm with their body. T8 said, “Students who have never had contact with music, who never even listen to music, usually will have a horrible difficulty to get the beat and the tempo” and T14 commented,
I have had many students who were musicians, who play one, two or three instruments divinely well and they could not dance. They have rhythm, but the rhythm is in their hands, in the head, it is not in the whole body, it is not coordinated with the legs and the arms.

One way that teachers develop these skills in the students is by first training them individually before partnering them with other students. T15 explained that they ask the students to dance separately, following the music, in front of the mirror so that the students can train independently, perform the movement individually and see what they are doing, which provides an opportunity for direct feedback from the mirror. Overall, teachers agree that students must mentally interpret the song and later express the rhythm using their body. Therefore, rhythm relates to other dance skills such as weight transfer, coordination and balance. Additionally, teachers may use rhythm to represent different levels of connection with the music or the word musicality for that purpose. For beginner students, having rhythm means to be in sync with the strong beat of the song, having the same tempo as the song. As the students advance, rhythm represents a more complex skill that, in some cases, is replaced by the word musicality, which is the ability of the student to sync their movement with more subtle elements of the song.

**Coordination.** Coordination relates to the ability to use the body and its different parts to perform movements synchronised with the song and its different parts. It also relates to the ability to coordinate thoughts (intentions) and body movements, and to coordinate one body movement with that of their partners. For instance, T1 related coordination to the control of thoughts, intentions and movements,

To say that a student has learned how to dance, it means he’s more able to control his axis, to control internally what his body is willing to do and what he’s trying to do, to coordinate what he’s trying to do with his body with what he’s thinking and to know that what he’s pretending to do with his body is exactly what he’s doing with his body.

T1’s description contributes to the idea that dance involves a process that starts in the music, reaches the dancer, the dancer needs to interpret the music, elaborate a movement that matches the music and express this movement with their body. T14 contributed with an explanation on coordination saying,
Today I consider clearly [regarding importance] that it is first the motor coordination and balance and then the rhythm, in that order. Then you have to have motor coordination, you have to develop reasonable motor coordination between the arm and leg, open at the same time and close the same time. Then mirror that with someone else and distribute the roles.

As T14 described, teachers have a tacit rank on which skills are more important. In T14’s case, this is coordination, balance and then rhythm. T6 reported ordering the importance of skills into coordination, balance, time, space and fluency. As T4 said, coordination is a skill that is also required for dancers when dancing with someone else. The student must be able to synchronise their movement with the music and themselves, as well as coordinating these with their dance partners.

**Balance.** Teachers related balance with students’ ability to control their body axis and maintain a steady and straight posture. T9 mentioned,

> Just like the younger girls, the boys, are too soft or sometimes do not have the firmness of the axis, the axis is not formed. So often they get out of balance, and they take the other person out of balance too.

The student’s axis is formed by their spine, posture and body position. Their balance is not only related to the student themselves but also on how their balance, or lack of balance, relates to and affects their partners. T14 went deeper and explained that, in a partner dance, the axis is shared between the dancers, where alone you would have a 90-degree axis by yourself. To find this axis, dancers must use the other’s body to counterbalance their own weight. T14 also mentioned, “*Spinning influences balance, because of spinning the student loses his balance, goes into rotation, and then he loses his rhythm by acceleration, not because he has no rhythm but because he has no balance*”. This demonstrates the influence of balance in affecting the ability of students to maintain their synchrony with the rhythm of the song. Good balance reinforces a good connection between the student, the song and their partner.

**Weight transfer.** Weight transfer is directly related to the previous skills. It is the ability to move the weight of the body from one leg to the other, following the rhythm of the song. It requires rhythm, balance and coordination. For T1, this was the main skill required for mastering dance. T1 said,

> I believe that one of the most important concepts in dance is the transfer of weight. Transfer of weight is a good starting of the communication, of the
dance, in which you notice if your partner is listening to the same thing you’re listening, if you are connected or not.

T1 demonstrates that weight transfer is also important to create a connection between dance partners. A few teachers reported weight transfer as one of the main difficulties of beginner students (T2, T4 and T15). T2 said,

The biggest difficulty I encounter is to make the student understands that he can not transfer too much the weight, that he can not leave the weight on the back [leg] to step forward without any weight, or leave the weight in front and step back without any weight. Until [the student] understands this dynamic they will have difficulty.

However, it is not clear what the causal relationship is among weight transfer, rhythm, balance and coordination, and how teachers can distinguish these influences when assessing the students. T4 illustrated, “What happens next is even though [the student] understands [the rhythm], [the student] does not have the necessary weight transfer or the motor coordination for dancing”. T6 and T14 did not include weight transfer in their list of skills, which suggests that some teachers use coordination, balance and rhythm to represent what other teachers define as weight transfer.

**Spatial awareness.** This ability relates to how dancers interact with their surroundings, environment, space and people. Several teachers mentioned that students must learn how to respect the space and not to hit or bump into their partner or other dancers (T1, T3, T8 and T14). T8 also mentioned that the use of the space refers to understanding how much space the partner can use and also how dancers must adapt to partners who are of different heights or sizes. Related to the quality of the dance, T15 said that students should not dance on the same spot, “In Forró the displacement between the couple is very important, is a dance that has a lot of changing positions. This exchange is important for dance to flow more naturally and prettier”. For T6, the use of space was included as their second most important topic, “The students must coordinate and balance the movements they makes within time and space. That would be the rhythm and the space that is permissible for him”. In a more technical term, T14 said, “Our methodology contains exercises to stimulates spatial laterality and proprioception\(^1\), that is the notion of the body itself in relation to the space”. Spatial awareness also

\(^1\)Reference to proprioception (Schmidt and Wrisberg, 2008)
relates to the student’s awareness of their own body. T15 mentioned that students, especially beginners, have difficulties with adjusting the size of their steps. By undertaking large steps, students transfer too much weight, which will make it hard for them to perform the dance movement. When students learn to take smaller steps, they can better control their movement, weight transfer, displacement on the floor and body rhythm.

Posture, energy and creativity. These three aspects are connected because for different teachers they may represent similar concepts. Physically, posture may refer to having a straight body posture as a dancer, chest open, head and trunk in a straight line (T3, T10 and T16). Posture may also refer to how the student uses their body to dance, which some teachers may refer to as the energy that the dancer uses or the quality of their movement (T15 and T19). This quality may describe whether the students are performing the movement using the appropriate technique. For instance, students may have floppy arms, depressed posture, not reacting to the qualities of music or, alternatively, they can properly interpret the music with their body in a lively manner and have good muscle tone. T3 explained, “It is how you can use the energy of one movement to another. It is how you can recycle the energy of your movement to create a different quality of movement”. The energy may also refer to the student saving energy while doing the movement (T6 and T9), thus avoiding expending energy for no reason or benefit. The music plays an important role for the teachers to identify the ability of students in interpreting its nuances, which will determine the student’s creativity, improvisation and styling (T7, T8, T9, T11 and T16). T8 said, “I really like a very creative dance. The person may not have a good technique, but at least he can make someone else laugh and have a good experience, a good time. I think that’s the most important thing”. As the previous skills influence and are influenced by rhythm, the skills listed here appeared later on in the students learning process and required more proficiency in basic skills such as rhythm, coordination and balance. When students possess musicality, as described previously, they will be able to play with different elements of the song, using the energy of their body to shift between these elements. Their ability to use and play with this energy is related to their creativity.

Connection with the partner. In Forró, as in other partner dances, there are two roles, the leader and the follower. The leader suggests the steps to be danced and the follower should respond to these triggers and execute the corresponding movement. Teachers reported many skills that are involved in the connection between the two
dancers that allow these roles to be properly played out. The first set of skills are related to the physical connection. Dancers should use their entire bodies to establish a clear medium of communication, which involves the embrace, arms, body, legs and hands (T15). A few teachers mentioned that for students to be comfortable in the dance, they must be aware of how much force and pressure they use to guide this leader–follower connection, having a clear leading and not hurting their partner (T15, T9 and T1). This connection will mediate their ability to coordinate their movement between themselves and with the song (T2). Additionally, T15 mentioned the importance that the music and its rhythm have on allowing the dancers to connect to each other. T15 said, “I can see the evolution of the student when they are able to put in harmony their body, their partner and the music” The second set of skills relates to their emotional connection. Their connection should go beyond the physical, where they interact with their partners looking in their eyes, admiring each other and dancing to each other (T4). As this connection becomes deeper, they gain trust and are more open to each other, and from this quality they gain more musicality (T3). T16 said, “Connection is the ability to be physically close but also emotionally connected to your partner and be able to really read that other’s body”. T16 commented on the difficulty for beginner students to acquire this skill, “My students would definitely not be that comfortable initially holding each other in the embrace”. The dancers should be aware of their partner’s physical and emotional conditions, including physical and skill limitations (T3). These aforementioned skills influence how well the dancers will be connected. When students improve their rhythm, weight transfer and coordination skills they are also going to improve their connection with their partners and their overall enjoyment of the dance.

**Psychological skills.** Teachers have, as a part of their implicit curriculum, skills that work the minds of the students. Preparing psychologically for learning to dance is just as important as the physical training. Teachers want students to learn how to relax, and to have confidence and trust in themselves and their dancing. For instance, teachers reported different strategies for teaching students how to relax. The way they speak to the students, making jokes, sharing mistakes, putting themselves on the same level as students, through exercises, playful activities, sounds and lights will slowly put the students in a relaxed state that will, eventually, allow them to open themselves, and feel free and not afraid of making mistakes (T4, T6, T8, T9, T10, T12, T15 and T18). This may help students gain self-confidence, which can speed up their learning (Mainwaring
and Krasnow, 2010). T9 explained: “The technique to teach students should include tasks that promote self-confidence and moments of relaxation. For you to teach a person to dance, you have to make her confident with herself. Teaching that trust is hard work”. T18 reported that their classes have as the main driver the relaxation and building of trust within the students themselves, and among the students and the teacher. Only after this environment is established does the teacher start introducing the dance concepts. T18 explained,

If students learn in a very strict environment, with a lot of technique, they can get quite tense. Relaxation is more chilled out, joy. We teach through relaxation. Then they can get into the rhythm, musicality and energy. When you have fun you generate confidence, they are close to each other. This is a very important point. I first use the relaxation, the confidence, the joy. Then you get into the technical part that, which is also important. When the students have confidence and relaxation they are open to absorbing the technique.

It is important, for teachers or researchers trying to support dance education, to be aware of the subtleties of dance learning. If teachers are aware of the difference between, for instance, students’ rhythm difficulties and their lack of confidence, teachers can approach the students using different methods. Similarly, when using technology to support dance learning, researchers and developers can, for instance, create a more relaxed environment for students to learn, allowing them to practise by themselves with gadgets. Additionally, technology can provide information to teachers regarding students’ technical skills, so that teachers can focus more on the subtleties not measured by the sensors.

This subsection presented several skills reported by the teachers and connected those to the learning of rhythm. Some skills affected the rhythm ability of the students, including coordination, balance, weight transfer, spatial awareness and psychological skills. If the student has problems with coordination or weight transfer, this will affect their ability to perform the movements inside the rhythm of the song. Other skills are affected by their rhythm skills, such as their connection to the partner, and their own posture, energy and creativity. If the student does not have rhythm, they will not be able to properly connect with their partner or creatively develop their dance using the song.
Additionally, some skills are interpreted differently by different teachers. Some teachers consider weight transfer as part of the rhythm (T6 and T14), whereas for other teachers musicality is part of the rhythm (T3 and T9). Understanding these differences is important when communicating to students and teachers the results of their performance assessment.

The technical skills described in this subsection help us to better understand which skills are fundamental for students to learn, and which skills are developed further throughout the learning process. Rhythm is confirmed to be an important skill, especially for beginner students, followed by coordination, balance, weight transfer and spatial awareness. Rhythm is defined as having movements in synchrony with the beats or other elements of the song.

4.1.2 How do Forró dance teachers assess the rhythm skill development of students?

Dance skills related to Forró learning span across physical, mental and emotional requirements; therefore, teachers need to use various methods to assess students. The most used resource, which all teachers reported as having used, was the observation of students inside the classroom. T8 explained a way of undertaking this observation, “We make a comparison. They are constantly compared to each other. If everyone can do what is asked of them in class and only one student can’t, then we see what difficulties these persons have”. Another very common method is when teachers dance with the students, using their body as the media of evaluation and information. T6 said, “I’m always watching all the students. I go around the class and join the practice, dancing girls and dancing with the boys to see how their leading is doing”. A few teachers and schools use periodic assessments (every 3 or 6 months), with some using standard methodologies and rubrics to guide the assessment and technology to record and transmit the results (T4, T6, T14 and T15). A few teachers mentioned that they also use verbal communication to assess the students’ development (T1 and T19), such as when students report their experience when dancing at parties and festivals. T19 said, “The student’s conversations with the teacher and the student’s feedback about their own dance is also a follow-up method for the teacher to assess the student’s learning”. Outside the classroom is where the social dance context differs considerably from traditional education. Teachers keep assessing students’ developments in
workshops, parties and festivals as “the moment of truth”, as stated by T1, where the students show their consolidated knowledge. Some teachers continue their assessment beyond face-to-face using videos, social media, e-mail and instant messenger (T1, T6, T8, T14 and T15), thus tracking the students’ dance skills and experiences. For example, one teacher (T6) organised events for the students to perform at, as a way to boost their skills and assess their development.

In most assessment methods, using their eyes, their body or writing, teachers do it individually and use their memory to track students’ development. Teachers have a limited range when assessing students. On the one hand, this simplifies the technology requirement as it must assess one student at a time if we compare it to the teachers’ capacity. On the other hand, it would be a change of paradigm for teachers if we use technology to expose them, using the data collected from the students, to aggregated information from students and information plotted over time. Understanding how teachers assess students can help to better situate the use of technology inside the teachers’ workflow. Once the teacher has information regarding the students’ skills and can track their development, teachers can better inform students on how they are performing and how they can improve.

4.1.3 What are the types of feedback that Forró dance teachers commonly use?

Teachers have several ways of sharing with their students how they are performing and what they can do to improve. The main way to deliver this feedback is verbally. Teachers provide their feedback directly to the student(s), sharing the information with them individually or with the whole group. T9 said,

Most of the time you have to address the person individually and provide little hints. Being very kind and with affection. When feedback is provided at a group level the aim commonly is for everyone to understand that the problem of one student is also in everyone else.

Alternatively, teachers can use indirect methods, for example, asking the student to perform an exercise, asking them to perform a self-assessment or asking students to do a peer-assessment. Teachers use indirect methods especially with beginner students so as not to demotivate them by pointing out their problems. T1 explained, “We can
use activities and exercises that sometimes reach students in an indirect way. They are not aware that, for instance, they are studying body awareness, but the activities and exercises have this purpose”. Teachers mentioned they commonly talk about positive and negative aspects of the students’ performances or use a sandwich approach (positive + negative + positive). Most teachers mentioned that they also physically move the student so they can understand the movement from the kinaesthetic sense. Teachers reported using their own body as a way to provide feedback, by demonstrating the movement or breaking the movement into parts. T1 summarised these different feedback strategies as follows: “These are mainly the three ways that I have to show the students what I’m expecting from them: explaining, doing and manipulating their bodies”. T6 commented as follows:

There are things you do not need to talk about, you just let them feel and perceive. Because there are several ways the student can understand the same thing. When I teach in a college classroom, I write on the board, write, draw, to facilitate their understanding. Some people learn more by listening, others seeing and others by feeling. I try to always walk through these methods to be able to make the student understand in different ways the same thing.

A few teachers used videos (T2, T6, T14, T15 and T16) to show to the students how they are moving. The students are then able to see with their own eyes what the teachers are referring to in their verbal feedback. Two teachers mentioned the use of written feedback (T6 and T15). The written feedback is commonly mediated using technologies such as e-mail and instant messenger.

The teachers’ interviews results present several feedback strategies that can help technology designers support dance education by providing students and teachers the information in the appropriate format and with the appropriate content. In addition, and relevant to this thesis, the teachers’ reports helped to understand when, in the classroom or outside the classroom, the technology could be used. The solution proposed in the thesis can support teachers and students inside the classroom, but its main objective was to allow students to practise and receive feedback outside the classroom. In addition, teachers can have access to students’ data, understand their needs and provide more accurate feedback during classroom time.
4.1.4 Member check: Concept map validation with teachers

The scope of the interviews from Study 1 was very wide, which could potentially prevent teachers from remembering, during the interview, all the skills, assessment and feedback strategies that they use in their teaching context. To strengthen the results of the interview analysis, a member check was undertaken. A member check, or respondent validation, is when the findings of an empirical study are validated with its participants (Lincoln et al., 1985; Maxwell, 2012). The member check occurred during a follow-up interview and was performed with the participants of Study 4 (T6, T7, T8, T12, T14, T15, T18 and T19). The interview used a conceptual map during the member check, which summarised all the teacher interviews, thus allowing the teachers to easily recall which skills, assessment methods and feedback strategies applied to their context and what was missing. Teachers answered the following questions when evaluating the conceptual map, produced as a summary of the interview analysis:

- Which aspects of the map apply to your context?
- Do you disagree with any of these aspects?
- Would you add other aspects that are not included in the map?
- Is there something you do not understand?

Overall, teachers had a high agreement with the summary presented to them. Figure 4.1 presents the final conceptual map and concepts that were added (plus signal) and changed (pencil) during the member check phase, or that a few teachers had concerns about (exclamation mark). As the dance teachers come from different educational backgrounds, it was difficult to find terms that would represent the same information for all of them. For that reason, some concepts contained multiple terms. For example, some teachers could not understand what methodology/rubrics represented, especially those teachers that do not use them. For some teachers, the word technique could represent skills including rhythm and balance or the ability to perform specific dance steps. Some teachers did not know what sandwich meant at first but reported to use it after having the concept explained to them. T19 considered that ‘exercise’ is not a form of feedback but a teaching strategy. However, several teachers use exercises as an indirect way to provide intrinsic feedback to their students. The analyses of the
interviews performed during the member check were merged with the coding of Study 1 results and reported as part of the previous subsections.

For the remainder of this thesis, the definitions below will be used. However, these definitions will be enriched as the thesis analyses the results of the next studies.

- **Rhythm**: skill where the student is able to perform a movement at the same beat rate as the song (not faster, not slower).

- **Weight transfer**: skill where the student is able to transfer the weight from one leg to another using the proper amount of weight (not too much, not too little).

- **Assessment**: teacher’s or technology’s ability to diagnose whether the student has a specific skill or not.

- **Feedback**: provide information to students or teachers that can improve their learning or teaching.

### 4.2 Chapter Summary

This chapter presented the analysis of the interviews performed during Study 1 and the follow-up member check. During the interviews, teachers explained the different skills required for students to learn Forró dance, the methods they used for assessing these skills and their strategies to provide feedback. Several concepts resulting from the analysis were summarised in a conceptual map. The key findings of the analysis that are relevant for this thesis include:

- Teachers have different concepts of rhythm, depending on their background, individual practice and the stage of development of students. The skill range of rhythm is from the student just having the same tempo as the song to being able to shift their body synchrony among several elements of the song;

- Rhythm can be defined in a network of related terms, including synchrony, musicality, coordination, balance, weight transfer and spatial awareness;

- One strategy for teaching rhythm is asking students to perform dance movements individually;
• Other advanced concepts of partner dancing that require or affect rhythm include posture, energy, creativity, connection with the partner and psychological skills;

• Assessment methods: teachers require several methods of assessment to capture the complexity of the students’ learning development. Teachers mostly assess students individually because of their limited conditions;

• Feedback strategies: teachers mostly use verbal feedback, although they do have several other strategies to complement the verbal feedback, including indirect means.

The following chapters of this thesis will focus on modelling rhythmic skills with the use of technology. Related rhythmic skills will be added as the algorithms are improved. Because of limited time, only a few skills were modelled and evaluated. Chapter 5 describes the technology and algorithms that extracted the rhythm features from the sensor data. The list of skills presented in this chapter, and their relations, will help to interpret the qualitative results of Study 2, presented in Section 6.1.3.1, where these skills are related to how teachers assess rhythm. For Study 3, the main skills described here will help to decide which additional skills related to rhythm could be measured by the motion sensors, presented in Section 5.5. The feedback strategies reported by teachers in this study inspire the provision of automated feedback described in Section 7.1. In Study 4, reported in Section 7.2, the assessment methods described in this chapter will be revisited and related to how technology could help teachers with an automated assessment.
Chapter 5

Developing Algorithms and Tools to Support Dance Teaching

This chapter presents the set of tools required to develop and evaluated a technology that uses motion sensors to model rhythmic skills. As presented in the previous chapter, such technology could be used to help teachers to assess Forró dance students and help students to receive automated feedback. The chapter presents the algorithms that were developed to extract features from the smartphone motion sensors (accelerometer and gyroscope). It also describes the mobile app developed to collect motion data and indicators and the requirement of using the song as the reference to create motion features. Additionally, it presents the video annotation tool used by teachers to annotate the video episodes of students. In sum, this chapter aims to address RQ2, which can be described by the following complementary research questions:

- RQ2: How can we use motion sensors to extract rhythm related information that enables the support of dance rhythm assessment and learning?
  - RQ2.1 - How do we translate motion data to rhythm information?
  - RQ2.3 - How do we improve the extraction of features from the translated motion data to rhythm information?

The first section presents the rationale for using motion sensors in the context of Forró dance education. The second section describes the Forró dance exercise that this thesis focuses on. The third section presents Forró Trainer, a mobile app developed to collect motion data while students practised their rhythm and dance exercises. The
fourth section presents RiMoDe, an algorithm that converts the student’s movement into rhythmic information. The fifth section describes RiMoDe v2, a set of additional algorithms that extract new features from the data collected by the sensors. The last section explains the video annotation tool that was developed for this thesis and used by dance teachers to annotate videos and comment on students’ performances. Teachers’ annotations were needed to label the collected data and were later used to train the machine learning (ML) models and evaluate the proposed features.

Figure 5.1 presents the tools that were developed, how they are related and where teachers and students interact with them. The Forró Trainer app embedded RiMoDe v1, so students could see immediate feedback after practising. The motion data are stored in a database that associates the raw data (accelerometer and gyroscope) with student id, time and song id. This motion data was used to develop and test the algorithms of RiMoDe v1 and v2. The output of these algorithms feed the dance features database, where the information is stored for further processing. These features were used in Study 2, Section 7.1, to evaluate how this information could help students obtain insights regarding their learning progress.

In parallel to the motion data, videos were recorded while students were performing the dance exercises as part of the studies. Some of these videos were annotated and commented on by teachers. First, teachers used a spreadsheet to annotate the videos. Later, they used a web-based video annotation tool. These annotations were stored in
the annotation database. The dance features were then used to model the skills, annotated by the teacher, via ML algorithms (classifiers). The output of such classification creates skill models that automatically annotate students’ performances. In Study 4, to be presented in Section 7.2, the automated rhythmic assessment was presented to dance teachers to support their assessment of students’ video recorded performances. The study evaluated how dance teachers would use an automatic rhythm assessment in their current practice.

5.1 Dance Motion Data

In any learning context where a teacher is assessing their students, they basically require two pieces of information: a reference (guide or rubric) and the student’s performance (Hsia et al., 2016). In rhythm learning, this is no different. The teacher looks for how well the student is synchronised with the beat of the song. Then, the teacher uses the song as a reference and compares it to the student’s body movements (Erkert, 2003). The rationale behind the algorithms proposed in this thesis also relies on this information.

The first piece of information is the song, which is used as a reference for assessing the rhythm skills of the student. The teacher mainly uses the strong beat of the song to match with the student’s movements. In Forró, the cycle length of the song’s strong beat determines the tempo of the song. A typical measure for tempo is beats per minute (BPM), which is widely used in music and social dance (Apel and Daniel, 1961; Jarmolow and Selck, 2011; Wright, 2013). This thesis also uses BPM to measure the song’s tempo and the student’s rhythm. Forró songs have a quaternary tempo (4 beats per bar). With the BPM information, it is possible to derive other information such as the cycle length of the strong beat (Formula 5.1). The strong beat is also the element of the music that students should use to guide their dance steps. The strong beat cycle length can be represented in seconds by the following formula:

\[
\text{Strong Beat Cycle Length (s)} = 60 \div \left( \frac{\text{BPM}}{4} \right) \tag{5.1}
\]

\(^1\)The strong beat of a song is a stress in the music that determined the song’s rhythm. This element is the moment that the student must start their movement. Most of the time, the strong beat matches the beginning of each bar in the songs score. See section 5.5.1.2.
The second piece of information is the student’s performance. This should be captured by technology so it can be processed, analysed and compared with the song’s tempo. There are a few technologies that can be used to track the student’s body movement such as inertial measurement unit (IMU) sensors, motion capture, video/audio recording and pressure sensors. Because one of the objectives of this thesis was to develop a technology that can be easily integrated into current teaching practices without the need for expensive and obtrusive equipment, accelerometer and gyroscope sensors included in IMU sensors, offer a good potential to capture movement information from dance students. In this thesis, data from these sensors is obtained from off-the-shelf smartphones to measure students’ movement performance as it is a device that is pervasive in our society nowadays.

Accelerometers have been used in many learning scenarios to track people’s movements. In dance, they have been used to track the rhythmic movements of hands (Lee et al., 2007), ballet movements (Hinton-Lewis et al., 2016), Indian dance steps (Faridee et al., 2018) and the dynamic symmetry of contemporary dancers (Camurri et al., 2016a). The field of activity recognition has traditionally relied on these types of repetitive patterns to detect physical activities (Gupta and Dallas, 2014). These patterns can then be modelled using ML algorithms and used to automatically detect correct or incorrect performances by the students.

The smartphone’s accelerometer API returns, for each request, the amount of acceleration in each one of the axes (x, y and z) measured in metres per second squared (m/s²) and a timestamp (current time of the observation) measured in milliseconds. The effect of gravity (9.81 m/s²) is included in the axis values depending on the orientation of the smartphone. Figure 5.2 shows the direction of each axis using the smartphone itself as a reference. The smartphone requires a parameter of frequency, which defines how many times per second the API will read the accelerometer information.

![Figure 5.2: Axis orientation of the smartphone](image-url)
Figure 5.3: Time series of motion data from a participant while performing a dance exercise. Red dots show peaks detected using our approach.

The nominal frequency set for the accelerometer reading is 100Hz. Laboratory tests have shown that slow or old smartphones cannot reach a reading frequency between 80 and 99 Hz and do not produce enough information to precisely extract the students’ movements. An example of what the accelerometer data looks like is presented in Figure 5.3. The green broken line represents the raw data collected by the accelerometer and the blue continuous line represents the filtered data. At the centre of the chart, the numbers represent the beats of the song, that were automatically synchronised with the accelerometer data. The footprints show what the wave means in terms of the student’s expected movements (e.g. stepping back or forward) The red dots the peaks detected, which will be explained in the following section. Further explanation of the graphed data is given in Section 5.4. After the accelerometer data are obtained, it must be converted into useful information to be used by dance teachers and/or students.

5.2 Choosing a Forró Dance Movement: Básico 1

As mentioned in Chapter 4, teachers often give their students different exercises to practise dance movements or to learn dance skills. This thesis was interested in capturing movements that could be used as exercises for an automated assessment system.
Some Forró dance movements have repetitive patterns that can potentially be modelled using accelerometer sensor data. A common and important movement in Forró is the Básico 1. This is the first movement, also used as an exercise, taught in Forró dance classes and includes many fundamental skills, such as rhythm, balance and coordination that are used throughout the entire process of learning Forró dance. The Básico 1 movement was chosen as the movement to be modelled and used by participants in the studies reported in this thesis. This movement has similar rhythm patterns and movements to many other social partner dances (Wright, 2013; Jarmolow and Selck, 2011). Forró songs have a quaternary tempo (1–4) to which the dancers need to synchronise their steps. In the Básico 1 movement, the student must perform a movement in the period of 8 beats of the song, which match the following movement patterns (Figure 5.4):

1. Move left foot forward
2. Change weight to right foot
3. Move left foot to the original position
4. Pause (a slowing down of the speed of the movement, to prepare for the next movement)
5. Move right foot backwards
6. Change weight to left foot
7. Move right foot to the original position
8. Pause
9. Repeat from step 1.

Figure 5.4: Dance notation for the Básico 1 Forró movement. The purple (darker colour) footprint represents the foot where the weight should be on the corresponding beat of the music.
Then, the same sequence must be repeated over and over again. This exercise was chosen because it has a repetitive pattern commonly used by beginner students, and thus can be easily exploited by a detection algorithm. This exercise was used together with the algorithm embedded in the mobile app to allow students to practise dance skills and receive feedback.

5.3 The Forró Trainer Mobile App

The Forró Trainer app provides exercises to improve rhythm keeping by practising several Forró dance movements. It includes songs with different levels of difficulty, so that students can progressively improve their skills. Design decisions were made to create a basic prototype of a tool that students could interact with to practice rhythm exercises. The development of the tool was based on ad-hoc usability tests with dance teachers’ and students and industry best practices. This knowledge contributed to making the following design decisions, identified in Figure 5.5:

a) use a song as a reference to measure student’s rhythm ability;
b) provide multiple songs inside the Forró Trainer app;
c) use bread crumbs to help with the Forró Trainer app navigation;
d) have multiple exercises that assess different abilities;
e) include instructions on how to do the exercises; and
f) include a countdown before the song starts.

This Forró Trainer app was tested on seven participants during Study 2, to be described in Section 7.1, and received an 89 System Usability Score, showing that the system is easy to use.

As identified during teachers’ interviews, Chapter 4, teachers use different approaches to teach rhythm to address the difficulties associated with different students. The mobile app also includes multiple exercises for students to practice rhythmic skills. The movement pattern described in Section 5.2 apply to the following app exercises:

- Weight transfer: the student must stand up, legs slightly apart, and follow the beats of the song, transferring the weight of their body from one foot to the other.
Figure 5.5 shows sample screenshots of the Forró Trainer app. The first image (left to right) shows a menu that contains the activity list and instructions. The menus in the second and third images allow the student to select the activity and the difficulty level of the songs. The Forró Trainer app has four difficulty levels and 13 songs: Percussion – two songs, Slow pace – four songs, Medium pace – three songs and Fast pace – four songs. Artists gave their consent to have their songs used for the purpose of this research. An exercise is therefore a combination of an activity, a difficulty level and a song (not shown). Next, the Forró Trainer app shows the instructions of the selected activity and the start button.

To use this app, students launched the exercise they wished to perform and placed the smartphone in one of their pockets. As the music started, they commenced dancing. While the students do their movements, the accelerometer recorded their motion. After
Figure 5.6: RiMoDe. Data flow from the accelerometer to the decision about the student’s performance.

the exercise has finished, the student can see their performance results calculated using the RiMoDe v1 algorithm. The student can use this tool after (or during) a dance class course, where he/she received instructions on how to perform basic partner dance movements.

The mobile app recorded, for each exercise session, the exercise setup (exercise name, song name, song difficulty and song BPM), motion data (accelerometer and gyroscope) and the song playback positions. The song playback positions were used to synchronise the motion data’s features with the song’s features. The data were sent to the database server, which stored all the sessions performed by the researcher and participants. The data were then used to develop, test and evaluate the algorithms proposed in this thesis, as it presented in the following sections.

5.4 The RiMoDe v1 Algorithm – Transforming Raw Data into Features

This section describes in detail how the RiMoDe v1 algorithm works. RiMoDe v1 has two main components, as shown in Figure 5.6:

- RiMoDe 1.1: converts the accelerometer data into the student’s movement rhythm (expressed in BPM) and its consistency (expressed as a percentage);

- RiMoDe 1.2: uses the output data from RiMoDe 1.1 and the song BPM to classify whether the student’s rhythm was the same as the tempo of the song or not.

The first component of the algorithm, RiMoDe 1.1, provides a novel approach for transforming accelerometer data into rhythm information. It is different to previous solutions (Demey et al., 2008; Kuhn et al., 2011; Lee et al., 2007) in that it is simple and effective for identifying movement skills in social partner dance movements and for
Figure 5.7: **RiMoDe 1.1.** Data flow from the accelerometer, passing through a gravity removal, low-pass filter, peak detection and rhythm calculation.

using the song as a reference to create motion features. Lee et al. (2007) used a voting scheme across different algorithms to determine the rhythm of any body movement, without presenting an evaluation of the approach. Other researchers (Demey et al., 2008; Kuhn et al., 2011) presented a rhythmic detection solution, using Fast Fourier Transform, that successfully measured the body rhythm, but only worked for simple movements that matched the same or half tempo of the song. The movements in social partner dance and in Forró dance feature complex patterns that require a customised solution.

A schematic representation of RiMoDe 1.1 is pictured in Figure 5.7 and the description of the algorithms’ steps is as follows:

1. The first step was to **remove the gravity** component from all three accelerometer axes, using the formula suggested by the hardware manufacturer\(^2\). This step was especially important in our approach, to allow students to use their smartphones in several orientations. Our preliminary laboratory tests showed that disregarding the orientation of the phone on the student’s body (in the pocket, on the hand or in a strap), the algorithm worked the same.

2. Next, a **low-pass filter** removed the noise to enable a smoother pattern detection and a clearer visualisation of the sensor data.

3. The next step was to **find the peaks** in the wave, which represented accentuated movements in students’ motions, using the local maxima strategy. The song’s

\(^2\)https://developer.android.com/guide/topics/sensors/sensors_motion.html#sensors-motion-accel
BPM were used to define the moving windows size of the local maxima algorithm. Even though Forró songs are structured in 4 beats per bar, the Forró dance movements are composed of an 8-beat pack. An 8-beat pack is defined as two × 1 strong beat cycle length which is the window size for finding the peaks. The peak detected represented one accentuated movement in each 8-beat cycle. This pattern of one strong accent in a dance movement occurs in several Forró steps. To evaluate this strategy, the algorithm used a 1-minute session of the Básico 1 step exercise (Section 5.2). The axis that recorded this strong accent in the movement was, most of the time, the z-axis (see Figure 5.2 as a reference). Because the smartphone can be used in different orientations, even upside down, the algorithm ran a search for peaks over all three axes, in their natural reading and in their inverted version (changing the signal). Thus, there are six waves to be analysed: x, y, z, -x, -y and -z. Figure 5.3 shows a sample of the z-axis of a participant doing the Básico 1 movement using the smartphone in the front left pocket of their pants. In this sample, a strong accent movement was detected when their left leg moved backwards.

4. Next, the algorithm calculated the distance between each consecutive peak, called the time between peaks (TBP), measured in milliseconds. This feature is commonly used in activity recognition algorithms (Gupta and Dallas, 2014). The rationale here was simple, if the TBP was the same throughout all consecutive peaks and this time distance matched the 2 × strong beat cycle length (Formula 5.3), then the student was moving in the same rhythm as the song. Each wave had a list of all TBP differences.

5. Outliers of each list were removed at the beginning to avoid noise. For instance, students usually required some time to listen to the song before beginning their movements, and these accelerometer readings should not be considered. In addition, when students made a mistake during the exercise but recovered the rhythm, the mistake (outlier) was not considered in the calculation.

6. The last step was to calculate the coefficient of variance (CoV = standard deviation/mean) for each wave, measured in percentage. The CoV helps to identify whether the student maintained a regular rhythm (TBP) throughout the entire 1-minute exercise. The wave that returned the top CoV was selected to represent
Figure 5.8: **RiMoDe 1.2.** Data flow from the output of the first step (RiMoDe 1.1) and the thresholds that define good/bad.

The student’s consistency score. The average TBP of the top wave provided us with the student’s rhythm, called here the User BPM. The average TBP ($TBP$) was measured in milliseconds. To translate this value into a more informative measure, the number was converted back to BPM, using Formula 5.4 below. The value 1000 in the equation converts the values of TBP from milliseconds to seconds. The value 60 at the beginning of the formula is to convert from seconds to minutes while $MP$ (movement pattern, Formula 5.2) is eight and converts from user steps to song beats (8-beat cycle). For example, in a song with 142 BPM, the expected TBP for the student’s movement cycle length is 3.38 seconds (Formula 5.4 isolating TBP). If the song has a 142 BPM tempo and the student’s movements translate to a 135 BPM tempo, the student’s movements that were detected are slower than the song.

\[ MP \text{ (Movement Pattern Signature in beats) } = 8 \]  
\[ TBP \text{ Window Size } = 2 \times \text{ Strong Beat Cycle Length} \]  
\[ \text{Student's BPM } = \left(60 \div \left(\frac{TBP}{1000}\right)\right) \times MP \]  

The next component of the algorithm, RiMoDe 1.2, used the output from the first component and determined whether the student was in rhythm, or not. Figure 5.8 shows the decision tree used in this step, with the respective thresholds. The song BPM is compared with the user BPM to determine the ratio BPM. The song was used only to compare the overall BPM of the students with the BPM of the song. At this level of analysis, there was no need for real-time synchronisation with the raw accelerometer.
data and the song’s beats. The ideal was for the student to have a ratio BPM close to 1, which meant that the student had the same, or a very similar, BPM as that of the song used as the reference. The next step of the decision tree was to check the consistency metric. A high consistency meant that the student maintained the rhythm regularly throughout the entire song/exercise.

The first version of RiMoDe (v1) was validated using the teachers’ annotations to compare with the output from the algorithms. A quantitative evaluation validated the power of representation that the output from the RiMoDe v1 had in modelling the teachers’ assessments of the students’ rhythm. This will be presented in Section 6.1.2. A qualitative comparison was performed to identify which other skills teachers assessed when evaluating the rhythm of students. This is presented in Section 6.1.3.1. The result of this comparison helped to inform which other aspects of rhythm were important and that could be incorporated in the next version of RiMoDe.

5.4.1 Limitations

A disadvantage of this filter was that it shifted the data forward in time due to its iterative process of smoothing the wave with neighbouring values. However, this did not affect the algorithm accuracy. In Figure 5.3, the reader can visualise that the filtered data were slightly shifted to the right in relation to the raw data. For example, between the first 8 and 1, there is a peak on the raw wave that is shifted to the right having its peak on the first 1. Although this detailed information was not required for this study, it should be considered in future deployments once there is a need to give more precise information to students and teachers regarding the movement and beats of a song.

Also, in RiMoDe v1 the motion data was not synchronised with the song’s time, therefore, it was impossible to assess whether the student was on the same beat of the song or not. The student could have the same BPM as the song and, at the same time, not have their movement synchronised with the strong beat of the song. For teachers, the student must have their movements synchronised with the beats of the song, not only have their movement with the same speed as the song. More precisely, teachers want students to match their movement to a specific beat of the song. Forró songs are structure in 4 beats per bar, where beats 1 and 3 have a stress (strong beat). Teachers differentiate if the students are synchronised with beat 1 or 3 as this will impact how much the student can explore other features of the song such as song’s breaks and the
lyrics. Similarly, this information was not required to evaluate RiMoDe v1 but should be added in further developments of the feature extracting algorithms.

5.5 RiMoDe v2 – Expanding Features Extraction

RiMoDe v2 was developed based on the lessons learnt from the RiMoDe v1. Although RiMoDe v1 was a successful first attempt to model students’ rhythm (to be presented in Section 6.1), a few weaknesses were discovered once Study 2 was finished. First, the RiMoDe v1 algorithm only detected one peak for each 8-beat segment. This peak corresponded to one of the six movements performed by the student while doing the Básico 1. The movement with the most acceleration intensity would vary across students but, in most cases, it was step 1 of the Básico 1. The intended improvement was to detect all six steps made by the student during the Básico 1 and create a signature of the movement that could potentially more precisely assess the students’ skills. Second, as mentioned before, the pilot mobile app implementation did not synchronise the accelerometer data with the timing of the songs. The assumption was that by synchronising the motion data with the timing of the song, the algorithm would be able to extract features that carried this synchronisation information. Following the DBR methodology, presented in Section 3.1, the lessons learnt in the first iteration helped to improve the system architecture, the number of data sources and to create new feature extraction algorithms.

A description of each data source is provided in the subsections below, together with the rationale used to derive each feature extracted during the second implementation of RiMoDe (v2), summarised in Table 5.1. The overall rationale is to use the Forró dance context as an inspiration to derive features. This means i) use the Básico 1 movement pattern, which determines six steps in the movement, and ii) the Básico 1 movement cycle length of eight beats related to the song tempo.

5.5.1 Extracting features from the songs

The song is a valuable source of information to be used as a reference when people are dancing. There are several elements of the song that can be used by the dancer to guide their dance movements, including tone, pitch, intensity, duration, beat and tone colour (Apel and Daniel, 1961). These elements can be extracted from the song using
music information retrieval algorithms (Böck et al., 2016; Lartillot and Toiviainen, 2007). Teachers can use the information from one or several songs to create exercises for their class or tailor them for each student’s needs. Similarly, automated systems can use the information extracted from songs and compare this with the motion data detected from motion sensors. This information can enable learning systems to detect and assess the performance of dance students base on predefined models and/or user-defined parameters.
<table>
<thead>
<tr>
<th>Feature</th>
<th>Details</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>6-Move Score</td>
<td>Search for six peaks/valleys in each wave section (Fig. 5.9c)</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>K-Move Score</td>
<td>Coefficient of variability</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>K-Move #cluster</td>
<td>Best number of clusters</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>K-Move closeness</td>
<td>Average closeness of the clusters</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>K-Move sd-beats</td>
<td>Average standard deviation of the beat component of each cluster</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>K-Move centred {1,7}</td>
<td>K-Move Score having the clusters centred in 1 or 7</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>songBPM</td>
<td>BPM manually derive from the song audio file</td>
<td>Song Profile</td>
</tr>
<tr>
<td>userBPM</td>
<td>User BPM (RiMoDe v1)</td>
<td>Accelerometer</td>
</tr>
<tr>
<td>1-Move Score</td>
<td>User consistency (RiMoDe v1)</td>
<td>Accelerometer</td>
</tr>
<tr>
<td>bpmRatio</td>
<td>Ratio between userBPM and songBPM (RiMoDe v1)</td>
<td>Accelerometer + Song Profile</td>
</tr>
<tr>
<td>MinAcc</td>
<td>Minimum value of the accelerometer wave</td>
<td>Accelerometer</td>
</tr>
<tr>
<td>MaxAcc</td>
<td>Maximum value of the accelerometer wave</td>
<td>Accelerometer</td>
</tr>
<tr>
<td>MeanGyro</td>
<td>Average value of the gyroscope wave (Z-component)</td>
<td>Gyroscope</td>
</tr>
<tr>
<td>SdGyro</td>
<td>Standard deviation of vertical the gyroscope wave (Z-component)</td>
<td>Gyroscope</td>
</tr>
<tr>
<td>yFinalVerticalScore</td>
<td>Vertical accelerometer component compensated with Gyroscope data</td>
<td>Accelerometer + gyroscope data</td>
</tr>
</tbody>
</table>
5.5.1.1 Beats per minute (BPM)

An important element of dance is the music. The BPM feature extracts from the song its beat rate. This feature can be extracted by automated tools or by manual annotation. It is possible to compare the beat rate of the song to the beat rate of the student’s movements, and use this comparison to inform students about whether their moments are in time, too slow or too fast. In this thesis, the BPM was automatically extracted from the song using the Madmom algorithm (Böck et al., 2016).

5.5.1.2 Strong beat

In Forró, the strong beat of the song is the moment that the student must start their movement. Most of the time, the strong beat matches the beginning of each bar in the song’s score. This feature identifies from the song when each strong beat occurs. We need only two pieces of information to compute all the strong beats of the song, which are the occurrence of the first strong beat and the period of time (in seconds) that the strong beat is repeated. This information can be used to assess whether students are synchronised with the song’s beat and derive other metrics as presented in the next subsection.

5.5.2 Improving the features of the accelerometer

The new accelerometer features were designed based on the quantitative and qualitative findings and data from Study 2. These include a) understanding more details of the Básico 1 movement that were captured by the motion data, b) matching the motion data and song data to extract features, c) using information related to vertical motion and d) using data from the gyroscope sensor. The synchronisation of motion and song data is achieved using the internal clock of the smartphone. Since the song is played from the smartphone, both motion sensors and music player share the smartphone internal clock. The following subsections describe in detail the algorithms and hypotheses on how they are related to the Básico 1 characteristics. These hypotheses will be later tested in Chapter 6.
5.5.2.1 RiMoDe v2 (K-score)

Using the lessons learned during the development and evaluation of RiMoDe v1, this feature used the Básico 1 movement pattern to go into greater detail for the consistency extraction. The Básico 1 movement requires the student to perform six movements during each 8-beat cycle of the song (Section 5.2). This can be formulated as a pattern recognition problem, where the algorithm analyses the data obtained from the sensors in search of a pattern that contains six consecutive observations that equally repeats across the data stream. Additionally, it uses the song’s features (i.e. strong beats) as an additional source of data to compare the student’s movement with the song’s pattern. This feature aimed to segment the student’s movement, using the strong beat cycle length as the window size, and analysed whether each segment was similar to the other segments, or if the segment data varied. This can be formulated as a clustering problem, with the steps to extract this feature illustrated in Figure 5.9 and described below:

1. The first step performed was to **identify the peaks and valleys** in the accelerometer data. The local maxima formula was used to find the peaks/valleys having the window sizes defined by the song’s beat interval length (Section 5.5.1.1). This window size was eight times smaller than the window size used for the 1-move consistency (RiMoDe v1). The peaks/valleys represent moments of the movement where the student was changing the acceleration polarity (Fig. 5.9b).

2. Next, **the motion wave was divided into segments** with a window size of 8 beats (Fig. 5.9c). Depending on the song, this window size will be different. If the dance was performed correctly, these intervals should contain six points (three peaks and three valleys), which represent six movements (Fig. 5.9d). These points are two-dimensional (time and acceleration).

3. Then, the time value of each point in the segment **was converted** to a time value that was relative to the start of the segment. The time dimension was converted to beats so that the resultant information was the same disregarding the song, and could be compared with sessions from different songs. For example, the song *Beijo Bom - Trio Dona Zefa* has the first strong beat in the 1.3 seconds position and has a strong beat cycle length of 1.6 seconds where each beat is separated by 0.4 seconds. A peak that is detected at 3.23 seconds from the start of the song
will be converted to 4.82 beats, to indicate that it occurred 4.82 beats after the start of the 1st segment \(((3.23 - 1.3)/0.4 = 4.82\)). Figure 5.9d to 5.9i show the data having time dimensions varying from 1 to 8 beats.

By converting the values to a relative position, it is possible to compare the points of different segments.

4. Once this was completed, every point from every segment had a time value between 0 and 8. We then plotted all the points together. If the student’s movements were consistent, then the points corresponding to the same movement step should be close together in this space (Fig. 5.9d).

5. At this stage, even though similar points were generally close together, the two-dimensional space could not capture the continuous nature of the data. For example, a point on beat 8 should be close to a point on beat 1, but in this space they will be far apart. To avoid this issue, we mapped the points in a three-dimensional space. Specifically, we mapped the points onto a three-dimensional cylinder, where the original acceleration value corresponded with the point’s height, and the time value corresponded with the radial angle on the cylinder (Fig. 5.9e). Thus, points with the same acceleration that were closer to beat 0 or 8 occupied the same region in the new three-dimensional space.

6. In this new cylindrical space, we applied the \textbf{K-means clustering} algorithm to split the points into groups (Fig. 5.9f and 5.9g).

7. We calculated the CoV of each group (excluding outliers) and computed the average CoV (Fig. 5.9h).

In some cases, the students had 5-pattern movements or 4-pattern movements. To select which \textit{n-pattern} better described the students’ movements, we performed steps 6 and 7 with different \textit{K} numbers. We used \textit{K as an additional feature} to classify the performances of the students.

From this process, we extracted several features, all of which averaged across the clusters:

- Cluster score: CoV of the beat’s dimension (removing outliers)
- Cluster closeness (between-cluster sum of squares ÷ total sum of squares.)
• Standard deviation of the differences between the beat’s dimensions and the closest beat

• Number of clusters ($K$ of K-means)
Figure 5.9: Workflow of RiMoDe v2. a) Filtered accelerometer waves (X, Y, Z). b) Peaks/valleys identified. c) Using the strong beat of the song to slice the wave. d) Overlapping the wave slices in one 1–8-beat space. e) Creating a circular space to keep the time relation between beats 8 and 1. f) Using K-means to find the clusters. g) Clusters in the linear space. h) Retrieving the score of each cluster. i) An example of a low score attempt.
5.5.2.2 6-move score

This feature followed a similar strategy as that of the K-score, without the creation of a cyclical space to find the best cluster. Instead, the algorithm searched for six peaks/valleys in each window (of 8-beat size). The peaks/valleys were selected based on how close/apart they were from each other. They must be at least 1/6 of the window size apart from each other. The other steps to calculate the final value of the 6-move score were the same as that for the K-score, where the average CoV of the six groups of peaks/valleys was calculated. The hypothesis was that the 6-move score would be associated with good students, who performed the Básico 1 using the six movements, which is the correct form for performing this exercise.

5.5.2.3 4-moves consistency

Obtaining more information can help us derive features that are related to the mistake patterns that students might have. If the student does not properly transfer their weight at stages 1, 3, 5 and 7 of the Básico 1 movement, the movement will appear to have a 4-stage pattern. We can search in the sensor data for a 4-move pattern to identify whether the student was performing the Básico 1 without doing the pause. This feature was calculated by fixing the K value of K-means in 4, at the 6th step of RiMoDe v2 (K-score).

5.5.2.4 Move x beat interval

In this feature, we compared the movements of the student, extracted from the accelerometer/gyroscope data, with the beats of the song. Generally, most body moves in dance movements should match the beats of the song. Thus, this feature gave us a good estimate as to whether the student was synchronised with the song and, if not, where in the song the student was making their mistakes.

5.5.2.5 Vertical fluctuation

The y-axis of the accelerometer provided us with information on how much the student fluctuated vertically when performing the movement. If the student hit the ground too hard with their foot, this would also affect the y-axis; therefore, we could identify how
much weight the student place on their feet. Ideally, Forró dance students should have a stable height when dancing and land smoothly on the floor with their feet.

5.5.3 Gyroscope

This version of the algorithm just used information from the gyroscope as a correction factor. Gyroscopes track angular velocity, for example, a movement that changes the x-axis of the sensors by $90^\circ$ in 2 seconds. Similar to accelerometers, gyroscopes can also track dance movements, but these are related to spin and turns, which are commonly executed during dances. Besides that, an angular movement also occurs when students change their body perpendicular position related to the ground. This can potentially reflect how balanced a student is when walking on the floor or performing dance movements. In the Básico 1 movement, students have a gentle spin in their hips when they moving forward and backwards. This information can be useful to determine whether students are moving their hips too much (see Section 8.3 for further detail).

Depending on the material or style of the students’ pants/shorts, the smartphone could have picked up more noise in the accelerometer data. The gyroscope information could help to identify this noise based on the smartphone’s change in orientation.

5.6 Video Annotation Tool

In activity recognition and ML supervised problems, it is necessary to have annotated data to use as the ground truth to train the models and evaluate the relevance of the features (Alpaydin, 2009; Atallah et al., 2011; Gupta and Dallas, 2014). In Study 2, teachers annotated the videos using a spreadsheet. To improve the videos annotation quality and the dance teachers’ experience an annotation tool was developed to be used in Study 3. A web-based annotation tool was designed based on the main rhythm skills identified from the teachers’ comments in Study 2. Figure 5.10 presents the initial version of the tool, which was improved on during Study 3 (see Section 7.3). The tool is divided into two columns. At the top-left, a widget presents the video of the student. At the top right of the interface, a list of buttons allows the teacher to annotate the video with preset labels. Each skill is represented by a group of buttons with a set colour. The button options were also based on the comments obtained from the teachers. The options for each skill were the following:
• Rhythm/tempo (options: slower/correct/faster);
• Pause (options: wrong beat/correct/no pause);
• Synchrony with beat (options: delay/correct/ahead);
• Time between movement (options: slower/correct/faster);
• Weight transfer (options: too few/correct/too much);
• Step size (options: too small/normal/too large); and
• Other mistakes (options: dance jumping/stepping strong/hip twist/moving centre).

Below the video, a timeline shows the annotation marks made by the teacher, coloured according to the skill selected (Fernandes, 2013). At the bottom left, a list details all the annotations tagged by the teacher and allows them to delete or change the position of the annotation. Teachers can complement the annotation with individual comments for each annotation. At the bottom right, a large text box is available for the teacher if they want to provide overall feedback for the student’s performance, together with buttons to save the work and go to the next video. Each teacher had a landing page where they could see the list of all the videos to be annotated, the number of annotations in each video, a flag for videos already annotated and guidelines for annotations (not shown here).

Each annotation was associated with a video time position. This time position was automatically determined by the video cursor position when the teachers clicked in one of the buttons. However, the analysis of the teachers’ annotations was done at a video level. Each video had only one associated label when using the data to train the machine learning models. (More details in Section 6.3.

The video annotation tool also proved to be a useful probe to understand the dance teachers experience with using a technological tool to support their tasks (see Section 7.3 for further detail on these experiences).

5.7 Chapter Summary

This chapter presented the rationale and description of several tools developed during the thesis. Some tools were the main artefact contributions of this thesis (RiMoDe v1
Figure 5.10: Video annotation tool featuring the video widget (top left); dance skills to be assessed (coloured buttons at the right), list of annotations (bottom), video timeline and a text box for comments (bottom right).

and v2), whereas others (mobile app, video annotation tool) helped as a support for the artefacts and for experiments with teachers and students. The RiMoDe algorithms provided a novel approach for extracting features from the motion sensors, using the context information, data transformations and the song as a reference point. As presented in Figure 5.1, the mobile app Forró Trainer collected data from the student participants, allowing an easy to use and non-obtrusive system. These data was stored in a database that will be used to develop, test and evaluate the RiMoDe algorithms. The video annotation tool allowed dance teachers to annotate the video of the participants during their dance performance. The features of the RiMoDe’s algorithm will be evaluated using the annotated data as a gold standard and ML classification algorithms, presented in Chapter 6. The created models for each dance skill were used to provide automated feedback and assessment to be presented to students and teachers, respectively. Details on this will be presented in Chapter 7.
Chapter 6

Evaluating the Features of RiMoDe

This chapter describes the evaluation of the dance features, automatically extracted from the accelerometer data, and the algorithms embedded in RiMoDe v1 and v2, which were presented in the previous chapter. A quantitative evaluation was performed with the aim of demonstrating the relevance of the features of RiMoDe when used to model the rhythmic skills of the students. A qualitative evaluation was conducted with the purpose of identifying teachers’ perspectives when assessing students and to understand the difference between the teachers’ rhythmic skills assessment and the machine learning (ML) assessment.

The first section of this chapter presents the quantitative evaluation of RiMoDe v1 using ML techniques, having the teachers’ assessments as a ground truth. Additionally, this section presents a qualitative analysis of the teachers’ assessment that seeks to understand the details of the teachers’ rhythmic assessment process. The second section presents the quantitative evaluation of the features of RiMoDe v2, which includes a deeper analysis of the motion features by evaluating 70 features, seven ML algorithms and four rhythmic skills (rhythm, pause, step size and weight transfer).

6.1 Quantitative and Qualitative Evaluation of RiMoDe v1

This section presents the evaluation of RiMoDe v1. The first subsection explains how the Experts dataset was collected and how RiMoDe v1’s parameters were calculated. The second subsection reports how RiMoDe v1 performs compared with the teachers’
6.1.1 Calibrating the RiMoDe v1 algorithm’s parameters with experts

In ML, a ground truth dataset is commonly used to test and validate a model (Chang et al., 2015). We constructed a ground truth dataset of expert Forró movements by recording expert dancers performing the Básico 1 exercise. We obtained a total of 90 × 1-minute sessions. The data was used to calibrate the RiMoDe v1 values for ratio BPM and consistency. The ground truth dataset was gathered by recording the dancing movements of five expert Forró dancers performing the Básico 1 exercise. These data was collected using only the Forró Trainer app to track experts’ movements. The experts followed the researcher’s instructions when performing their movements, which was to perform the Básico 1 movement wearing the phone inside their pocket. Different from the students’ dataset, in this data collection, no video was recorded from the experts while they were performing the movements. The average ratio BPM of the Experts dataset was 1.0 (±0.02) and consistency was 98.1% (±0.60). This ratio BPM average was used to calibrate the parameters of the RiMoDe v1 algorithm to differentiate between good and bad outcomes. During faster songs, the average consistency of the expert dancers decreased to 97.85% (SD = 0.70). Therefore, this thesis used a consistency threshold of 97% and a ratio BPM range between 0.98 and 1.02 for comparing the RiMoDe v1 algorithm with the teachers’ assessment of students’ performance.

6.1.2 Validation of features of motion sensors: Consistency and user BPM

This subsection explains the procedure followed to measure the accuracy of RiMoDe v1. During Study 2, participants were video recorded doing the Básico 1 movement while also using a smartphone to record their motions. A total of 96 × 1-minute videos were recorded. From these 96 videos, two were removed from the evaluation process.
because the system did not store the sensor data. Each video was assessed by three different teachers who annotated the video as a) On rhythm or b) Not on rhythm. In some cases, the teachers disagreed and the answer with the most votes (two) was used as the final decision. For that reason, we created two sets of cases: All Cases, which included the 94 videos; and, Unanimous Cases, a subset of All Cases (58 cases), which included only the videos for which teachers reached a unanimous decision.

To answer the same question as that of the teachers, the RiMoDe v1 algorithm used three pieces of information:

1. Song BPM: the BPM of the song, calculated by the BPM extraction algorithm (Böck et al., 2016).
2. RiMoDe v1 feature – User BPM: the overall rhythm of the student, calculated by RiMoDe v1 (Section 5.4).
3. RiMoDe v1 feature – Consistency: how much the participant varied or maintained his/her rhythm during the 1-minute exercise (Section 5.4).

During the first evaluation in this section, only the ratio BPM feature was used to evaluate whether the student was on the correct rhythm or not. Using this feature, with the $1 \pm 0.02$ threshold, and comparing it to the teachers’ assessment, the accuracy of the RiMoDe v1 algorithm was 79% for the Unanimous Cases subset, as shown in Table 6.1b.

Table 6.1: Confusion matrix comparing the teachers’ assessment (Teachers) and the RiMoDe v1 algorithmic detection (Predicted) using only the ratio BPM feature.

(a) All Cases

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<thead>
<tr>
<th></th>
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<tbody>
<tr>
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</tr>
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<td></td>
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(b) Unanimous Cases

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<table>
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<th></th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>38</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teachers</td>
<td>58</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>57%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>Recall</td>
<td></td>
</tr>
<tr>
<td>F1 score</td>
<td>72%</td>
<td>68%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>77%</td>
<td>79%</td>
</tr>
</tbody>
</table>

As some students maintained the rhythm during only part of the song, their performance throughout the 1-minute song/exercise was not enough for the RiMoDe v1
algorithm to flag them as being on rhythm (Yes). To improve the accuracy of the algorithm, we added the Consistency metric to the decision process that evaluates rhythm. With a threshold of 97% in the consistency metric (Section 6.1.1), the RiMoDe v1 algorithm reached 80% accuracy for the All Cases set and 90% accuracy for the Unanimous Cases subset. Table 6.2 illustrates in greater detail the confusion matrix and algorithm performance metric (precision, recall, F1 score and accuracy).

Table 6.2: Confusion matrix comparing the teachers’ assessment (Teachers) and the RiMoDe v1 algorithmic detection (Predicted) using ratio BPM and consistency measures.

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Teachers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>36</td>
<td>2</td>
</tr>
<tr>
<td>No</td>
<td>17</td>
<td>39</td>
</tr>
<tr>
<td>Total</td>
<td>53</td>
<td>41</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Teachers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>No</td>
<td>6</td>
<td>32</td>
</tr>
<tr>
<td>Total</td>
<td>26</td>
<td>32</td>
</tr>
</tbody>
</table>

Precision 68% Recall 95% F1 score 79% Accuracy 80%

The precision metric indicates how correct the algorithm is in identifying true positives. This is where the RiMoDe v1 algorithm underperformed the most. Compared to the Unanimous Cases subset, this is where the teachers also disagreed the most. Teachers did not have an unanimous decision in 47% (18 of 38) of the correct cases and disagreed in 38% (18 of 56) of the incorrect cases (No). The recall metric calculates how reliable the algorithm is in identifying all correct cases (Yes). This is where the RiMoDe v1 algorithm performed the best, 95% for the All Cases set and 100% for the Unanimous Cases subset. The algorithm had a good performance in avoiding false negatives (type II errors). Therefore, if used in a learning system, the algorithm may have a tendency to overestimate students’ performances in comparison to the teachers. The F1 score computes the harmonic mean between precision and recall and is commonly used as a unified metric between both. This metric compensates when models have unbalanced precision and recall. Accuracy calculates the overall performance of the algorithm considering the sample size of each class (Yes/No). For the RiMoDe v1 algorithm, the accuracy was higher than the F1 score because the algorithm was better at identifying correct (Yes) cases. However, the correct (Yes) class is underrepresented...
in this dataset because most participants were classified as using the wrong rhythm (No) by the teachers.

This subsection presented the evaluation of the first implementation of RiMoDe v1 compared with 94 cases annotated by Forró teachers. Although the RiMoDe v1 algorithm achieved high accuracy scores (90%) in the Unanimous Cases subset, some cases (6) were not classified correctly. The next subsection explores the teachers’ comments to find explanations for the misclassified cases.

6.1.3 Understanding teachers’ vocabulary on rhythm assessment

Going deeper into the analysis we sought to understand why the RiMoDe v1 algorithm misclassified some cases. The teachers’ comments for each video helped us clarify the problems. In the All Cases set, the algorithm missed only two correct cases, classifying these incorrectly. These were cases in which teachers were not unanimous. As part a of the annotation process, teachers responded to the following questions: Q1 – Is the person in the right rhythm? (Yes/No); Q2 – How much on the rhythm is the person? (Slower/Correct/Faster); and Q5 – Comment on the quality of the student’s movement. Analysing these two cases and the teachers’ answers can help us understand the differences between them and the algorithm evaluation. The two cases are described below and the name of each case follows these codes P – participant, L – lesson number (1, 2 or 3), S – session number of the video recording (up to 6 per lesson).

- Case 1 – P2-L2-S1
  - T4
    * On Rhythm: Yes
    * How much on the rhythm: Slower
    * Comment: “This is the first video that I observed the person closer to the rhythm of the music. Right after, P2 loses time and goes slower. I signed Yes, because in part of the exercise P2 was in the correct rhythm”.
  - T5
    * On rhythm: No

\(^1\)Participant 2 - Lesson 2 - Video-recorded Session 1
Chapters 6. Evaluating the Features of RIMODE

- How much on the rhythm: Slower
  - Comment: "P2 is transferring well the weight, but the movement is very mechanical, P2 needs to loosen and relax the joints, mainly the hip".
- T17
  - On rhythm: Yes
  - How much on the rhythm: Correct (on the rhythm)
  - Comment: "Almost perfect weight transfer, elbows locked, pause out of time".

- Case 2 – P7-L4-S4
  - T4
    - On Rhythm: No
    - How much on the rhythm: Faster
    - Comment: "Difficult to see the pause between the steps".
  - T5
    - On rhythm: –
    - How much on the rhythm: –
    - Comment: "I cannot assess the basic step of Xote with a baião song".
  - T17
    - On rhythm: Yes
    - How much on the rhythm: Correct (on the rhythm)
    - Comment: "Good posture, body a little stiff, good weight transfer".

In Case 1 – P2-L2-S1, all teachers identified problems in the student’s performance. T4 identified the student as Slower than the song, but tagged the video as Yes (on the rhythm) because the student was partially correct. T17 also commented that the student did not pause properly during the movement. In Case 2 – P7-L4-S4, T5 did not assess the video because she considered the movement performed by the student improper for the music. Xote is the song style that she considered to match the movement, and Baião was the song style that was playing. Baião has a faster tempo and for that
reason, according to this teacher, it is harder to dance with the Básico 1 movement. In six cases, the teachers were unanimous in saying that the student’s dancing was incorrect; however, the algorithm identified it as being correct. In one of these cases, P7-L4-S3, the participant was performing the movement 1 and 5 to the correct beat of the song; however, the movements between 1 and 5 and between 5 and 8 were faster than what they were supposed to be. All three teachers tagged the video as *Faster* than the song. The algorithm flagged the video as *Correct* because the participants had an intense movement on 1 and 5 following the tempo of the song, but what happened between these movements was not correct. In most of these six cases, the participants did not have a pause in their movement, on beats 4 and 8, as identified by some of the teachers. In addition, four of these cases corresponded to participant P4, who did not make the pauses during the Básico 1 movement. Because the algorithm works by looking for a pattern on the one intense movement in the 1-8 step movement, the result was *Yes* (On the rhythm). This means that, to improve the results, RiMoDe v1 must evaluate more details from the sensor data and identify other patterns between beats 1 and 8. This was one of the main motivators to develop RiMoDe v2 (to be presented in the next subsection, Section 6.3).

Before improving the technology by creating new features to extract more details on the movements of the students, it is possible to use the teachers’ comments to understand which other skills the teachers found important when evaluating rhythmic skills. By understanding teachers’ tacit knowledge, we can improve the technology with a more grounded understanding, becoming more connected to the users’ needs.

### 6.1.3.1 What are the teachers looking for when assessing rhythm?

An important finding of this study is the identification of the essential skills that teachers look at when they are assessing students’ rhythm. Teachers were invited to comment on each of the videos they analysed. These comments revealed important aspects of rhythm assessment. In this phase, text mining algorithms were used to extract information from teacher’s comments. First each teacher’s list of comments was treated as a document and stop words were removed. Later, the words (terms) importance was ranked using the TF-IDF strategy (Ramos et al., 2003), which favour words that distinguish documents from each other and demerit words that are common across documents. This list of ranked terms was used to select the most important term and group
them in themes found in the dance teaching literature (Côté-Laurence, 2000; Erkert, 2003; Jarmolow and Selck, 2011). Finally, the proportion of the selected terms used by each teacher (document) was calculated and summarised by themes. More details in Section 3.3.3.2.

The six main themes that emerged from the comments are illustrated in Table 6.3. The first column of the table identifies the titles of the themes, followed by the main keywords that represent the themes in the teachers’ comments. The third column explains what the theme corresponds to, in terms of skills and mistakes, and the fourth column provides examples of the teachers’ comments that include the theme and related keywords. Teachers have a rich vocabulary to refer to each theme. The variability of the vocabulary that teachers used in the study illustrates how different teachers most likely use different words with their students to explain similar concepts. This is an important aspect to consider when developing technology to support dance education, as the feedback to students and teachers may also be delivered using multiple terms to express more clearly what the technology is modelling. For instance, when talking about the skill that represents the ability of students to be synchronised with the music (theme Synchronicity), teachers may refer to this skill with concepts, such as rhythm, tempo and pace, or using a qualifier of that skill, such as slow, fast and wait. These themes are also discussed in the Discussion chapter, Chapter 8.

To understand the importance of each theme during the assessment of rhythm skills, the proportion of each theme’s keywords for all teachers’ comments was calculated and ranked (Figure 6.1). Because teachers were asked to assess rhythm, rhythm/Tempo was the most mentioned skill when assessing rhythm. This was followed by weight transfer/movement. The remaining themes are related to the quality of the movement and the skills that can help to diagnose why the student is making mistakes. For instance, in 20 cases, teachers commented that when the student looked down, they spoiled their posture and focused their attention on their feet instead of concentrating on the song.

Figure 6.1: Proportion of each theme’s keywords in the teachers’ comments
<table>
<thead>
<tr>
<th>Theme</th>
<th>Keywords</th>
<th>Details</th>
<th>Comment sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synchronicity</td>
<td>rhythm, music, tempo, counting, pause, wait, slow, fast, pace</td>
<td>-(Lack of) pause in the movement</td>
<td>Runs over the pace, [...], and without pause time in the [beat] 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Too rushed/slow</td>
<td></td>
</tr>
<tr>
<td>Weight transfer/Movement</td>
<td>movement, weight, transfer, step, pace, stride, forward, backwards</td>
<td>- Not transferring</td>
<td>[...] does not transfer the weight well with each step, being almost non-existent the second step. Work weight transfer.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Lack of agility</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Balance</td>
<td></td>
</tr>
<tr>
<td>Limbs/Joints</td>
<td>arms, feet, knees, legs, hips, joints, shoulders, elbows</td>
<td>- Joints locked (Elbows, knees, hips, shoulder)</td>
<td>Homolateral movement with a small hip twist [...] that can be harmful in the long run.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Hips moving too much</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Hips Twisting</td>
<td></td>
</tr>
<tr>
<td>Quality of the movements</td>
<td>mechanical, locked, release, relax, jump</td>
<td>- Mechanical</td>
<td>The movement is very mechanical, needs the release and relaxation of the [...].</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Relaxed</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Jumping</td>
<td></td>
</tr>
<tr>
<td>Posture</td>
<td>posture, body, chest, trunk</td>
<td>- Position of the feet on the ground</td>
<td>[The student] needs to improve the posture, leaving the chest more open [...].</td>
</tr>
<tr>
<td>Gaze</td>
<td>down, looking</td>
<td>- Looking down</td>
<td>Arms locked during dance, looking down spoiling the posture [...].</td>
</tr>
</tbody>
</table>
Furthermore, the analyses of the six themes helped to understand another aspect of the teachers’ assessments. In its current implementation, RiMoDe v1 treated all participants the same way, evaluating each of their sessions separately, without considering what happened in the previous sessions or the progress of the student in the same session. A teacher performs the assessment differently. They are able to assess more skills of a student and to adapt their assessment depending on student’s level. The rigour of the teacher evolves as the student progresses in their learning, even while looking at short videos of the same student recorded on the same day. In Figure 6.2, we can appreciate this evolution and compare the differences between the results obtained by the algorithm and teachers. P6 (Fig. 6.2a and 6.2b) could not stay on the tempo of the song at the beginning of the course, but learned this skill and had much better results by the end of the three classes. Both the RiMoDe v1 algorithm and the teachers followed the student’s evolution. Conversely, P4 (Fig. 6.2c) could follow the tempo of the song from the beginning of the course, with high consistency according to the algorithm, and did not show any improvement. By contrast, the teacher assessment was different. Even though the teachers and algorithm in many cases agreed that the student was on the tempo from the beginning of the course, the teachers perceived an improvement of the student throughout the course (Fig. 6.2d). This was because the teachers could shift their focus to more advanced aspects of rhythm, such as quality and limbs/joints. This happened in cases in which the participant had better rhythm skills than others; therefore, the teachers shifted their attention to other skills related to dance. This was highlighted by T12 who commented on student P9’s first session as follows: “The participant did not start the dance in the correct tempo of the music, and did not have the right rhythm”. The same teacher then commented about her last class as follows:

The participant is on the tempo throughout the whole video. The movement is clean and smooth, without bouncing, without twisting the trunk, stepping with the tip of the feet, using as a spring, and going with the entire foot to the front.

Another comment regarding student’s evolution was from T7 on student P1: “In this video, she stayed longer on the tempo of the song, but she needs to refine the step because she was only using the tip toe to touch the ground. At certain points, she accelerated and was out of the rhythm”.

(a) Evolution of the student’s attempts before the classes - P6 did improve - RiMoDe v1 evaluation

(b) Evolution of the student’s attempts before the classes - P6 did improve - Teachers’ evaluation

(c) Evolution of the student’s attempts before the classes - P4 did not improve - RiMoDe v1 evaluation

(d) Evolution of the student’s attempts before the classes - P4 did improve - Teachers’ evaluation

Figure 6.2: Learning evolution of P4 and P6 showing the differences between RiMoDe v1 and teachers’ assessment. Illustrating how teachers adapt their assessment depending on the students’ skill. RiMoDe v1’s charts use the Consistency metric of the student. Teachers’ charts use the number of teachers that assigned Yes / Correct regarding the performance of the students in matching the song’s tempo (Q1). X-axis represents the participants’ video sessions over the course of the three classes (three sessions per class) in chronological order.
An important point is that some teachers mentioned each theme to different extents. To highlight these differences, Table 6.4 illustrates the overall proportion of each theme in each teacher’s comments. While T7 and T17 had a balanced distribution in the use of each theme’s keywords, T15 focused her comments mainly on the first two themes, synchronicity and weight transfer/movement. With these themes in mind, we can better understand the teachers’ mindsets, regarding rhythm assessment, and design solutions that can help them assess students more effectively. Clearly, the algorithmic approach presented in this thesis, similar to other approaches mentioned in the literature review (Chapter 2) (Camurri et al., 2016a; Drobny et al., 2009; Hinton-Lewis et al., 2016; Lee et al., 2007; Thiel et al., 2014) covered only some of these skills. In this thesis, the algorithms especially covered skills regarding the overall movement of the student (weight transfer/movement) and how it is synchronised with the music (synchronicity). The results from the present study highlight that the teachers’ mindsets contained other important skills, such as quality of the movements, posture and gaze, which should be tracked when developing automated solutions to enhance dance learning. It is possible to use the same technology presented here to measure other skills including weight transfer, tempo, jumping, quality of the movement and movement of the hips.

Table 6.4: Keyword distribution of each theme in each teacher’s comments

<table>
<thead>
<tr>
<th>Theme</th>
<th>T7</th>
<th>T4</th>
<th>T5</th>
<th>T15</th>
<th>T12</th>
<th>T17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synchronicity</td>
<td>22%</td>
<td>49%</td>
<td>20%</td>
<td>39%</td>
<td>53%</td>
<td>13%</td>
</tr>
<tr>
<td>Weight Transfer / Movement</td>
<td>33%</td>
<td>30%</td>
<td>47%</td>
<td>52%</td>
<td>26%</td>
<td>26%</td>
</tr>
<tr>
<td>Limbs / Joints</td>
<td>16%</td>
<td>15%</td>
<td>15%</td>
<td>1%</td>
<td>16%</td>
<td>20%</td>
</tr>
<tr>
<td>Quality of the movements</td>
<td>13%</td>
<td>1%</td>
<td>17%</td>
<td>0%</td>
<td>0%</td>
<td>17%</td>
</tr>
<tr>
<td>Posture</td>
<td>8%</td>
<td>4%</td>
<td>0%</td>
<td>3%</td>
<td>4%</td>
<td>15%</td>
</tr>
<tr>
<td>Gaze</td>
<td>8%</td>
<td>1%</td>
<td>1%</td>
<td>6%</td>
<td>2%</td>
<td>9%</td>
</tr>
</tbody>
</table>

6.1.3.2 Understanding the differences among teachers

This subsection discusses the discrepancies found among the teachers’ judgement. The qualitative analysis of some of the responses by the teachers shed some light on understanding the complex process of assessing ‘what good rhythm looks like’.
Recalling the task of the teachers, they answered several questions during their annotation process:

Q1 In this video, is the person in the right rhythm? (Yes/No).

Q2 How much on the rhythm is the person? Too much slower/Slower/Correct (on the rhythm)/Faster/ Too much faster

Q3 What is the speed of the song? Very slow/Slow/Medium/Fast/Very Fast

Q4 How hard is it to identify the tempo of this song? Very easy/Easy/Medium/Hard/ Very hard

Q5 Please include here your comments about the quality of the student’s movement. By quality, we mean posture, arm position, legs, feet, joints movement, etc. Be as detailed as possible. Thank you.

Five annotations of T7 and T4 had a mismatch when answering Q1 and Q2. In three of these cases, they answered ‘Yes’ for Q1 and ‘Slower/Faster’, respectively, for Q2. Therefore, they contradicted themselves. In the other two cases, the teachers answered ‘No’ for Q1 and ‘Correct (on the rhythm)’ for Q2. A few possible explanations for these results are 1) a lack of attention when performing the video assessment task, 2) a more relaxed interpretation of what ‘being on rhythm’ means, especially because they had only two options to choose from, or 3) because the students were dancing for 1 minute, they varied in being ‘On rhythm’ and ‘Not on rhythm’. Similarly, some teachers expressed a direct relationship between the speed of the song (Q3) and how hard it was to identify the tempo (Q4). For example, if they flagged a song as being fast, they would flag this song as being hard to identify the tempo. Other teachers suggested a more complex relationship, where the speed of the song did not always determine how easy/hard it was to identify the tempo. The teachers could be interpreting the song using their perspective to measure the difficulty or using what they expected was the student’s perspective. For example:

- T5 used all five options when classifying the different songs’ tempo, but set all of them as ‘easy’ to identify the tempo.

- T7 featured a one-to-one relationship. When the tempo was slow or medium, the teacher stated that the music was easy. When the tempo was fast, the teacher
stated the music had medium difficulty. In other words, this teacher used tempo as a proxy for difficulty.

- T4, T15, T12 and T17 featured a more complex assessment. They believed that the tempo of the song did not correlate with how easy or hard it was to identify its tempo.

The identification of how teachers evaluated the song tempo (Q3) and how difficult it was to identify its tempo (Q4) can affect the extent to which they agreed in identifying the rhythm of a student. We calculated the inter-rater agreement between the teachers’ answers of Q1, from which we derived the following observations:

- T4 and T5 had a lower inter-rater agreement (average of 57%) compared with the other teachers. This may be explained by their different views on the relationship between song tempo and difficulty, as T5 considered all songs easy and T4 assigned different levels of difficulty for each song.

- By contrast, because T7, T15, T12 and T17 had a more structured definition of the relationship between tempo and difficulty, this was reflected in their inter-rater agreement. T7, T15, T12 and T17 had a higher rate of agreement (average of 88%) compared with each other.

These results show that rhythm in dance is a complex skill to assess. The differences between teachers’ assessments, in the present study, can be explained by three aspects:

1. How teachers classified the song’s tempo.

2. How difficult it was to perceive the song’s tempo.

3. The frequency in which teachers used the keywords of each theme.

The difference in teachers’ interpretations is an important aspect to take into account when designing systems to support their practice. Learning systems for dance should allow teachers to calibrate the machine learning models to their judgement of right and wrong. Additionally, the teachers’ differences confirm the importance of investigating the users’ context and beliefs together with the technology design. Otherwise, we can, for instance, reach to wrong the conclusions regarding what ‘rhythm’ is the technology measuring.
In sum, this subsection presented a quantitative evaluation of RiMoDe v1, using the metrics precision, recall, accuracy and the F1 score. When teachers were unanimous about the students’ rhythmic performance of the students, RiMoDe v1 had a high accuracy. Later, this subsection presented the qualitative analysis of the teachers’ assessments. Teachers have different ways of assessing rhythm, different perceptions regarding the difficulty and observe different things when assessing rhythm. The lesson learned from this is that other skills of the students’ performance should be considered when modelling rhythm and potentially using features that could allow teachers to define their own correctness criteria.

6.2 Validating the vocabulary of teachers’ rhythm assessment

The first phase of Study 3 was to evaluate with dance teachers new skills to be modelled by motion sensors and the vocabulary that best describe these skills. The interviews with 4 Forró dance teachers served as a co-design opportunity for teachers to discuss the new skills to be modelled in this thesis. More details in Section 3.4. A preset list of skills was created based on the results from Study 1, Study 2 and the limitation of the motion sensors. For instance, one of the topics found in the teachers’ comments in Study 2 was step size. The motion sensors could potentially capture this information and, for that reason, step size was included in the preset list of skills. The complete preset list of skills presented in the interviews of Study 3 included rhythm/tempo, pause, synchrony with beat, time between movement, weight transfer, step size and other mistakes, as described in Section 5.6.

During the interview, teachers assessed four videos with this preset list of skills and gave comments on the terms used to describe each skills and suggestions on how to improve the vocabulary. The four videos used in this phase presented students with different skill problems, allowing teachers to reflect on the preset list of skills presented. The main changes were regarding the term/concepts used to define the skills to be annotated. For example, for the case of rhythm and synchrony, these items were reduced to just rhythm, as teachers considered synchrony to be the same as rhythm. For the case of time between movement and weight transfer, the latter term was preferred among teachers as its meaning was clearer and it represented both concepts.
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Among the preset list of skills, four skills were selected based on the interviews outcomes with the teachers, to be annotated during the teachers’ video assessment: rhythm/tempo, pause, weight transfer and step size; plus the other mistakes group, which was optional. In particular, the concepts in the other mistakes group needed to be clarified with the teachers to agree on their meaning. The four dance skills and their options were the following:

- Rhythm/tempo (expanding RiMoDe v1 binary’s output): Slower, Correct, Faster
- Pause: Wrong Beat, Correct, No Pause
- Weight transfer: Too Few, Correct, Too Much
- Step size: Too Small, Normal, Too Large

After the interview, teachers were asked to annotated 70 1-minute videos containing student participants’ performance on the Básico 1 exercise. An average of the teachers’ annotation was used to compute the label of the first 30 videos, where all the teachers annotated the videos. The remaining 40 videos, annotated by just one teachers, received the label annotated from the correspondent teacher. This strategy was used to reduce the workload of teachers in annotating the videos, as described in Section 3.4.

According to the teachers’ interviews result, Section 4.1, the rhythm skill can be the ability of the student to have the same tempo as the song or can be the student being in sync with a specific pattern of the song. During the interview session, some teachers claimed that a few students in the videos had the same tempo as that of the song but they were not synchronised with the Zabumba (drum). For the purpose of this study, teachers were instructed to annotate Correct – Rhythm when the student had the same tempo as that of the song disregarding the sync with any specific song patterns.

Table 6.5 presents the distribution of each of the skill options in the 70 videos, as annotated by teachers. The table also includes a column called ‘mixed’, which includes cases where teachers had distinct annotations from each other or where teachers annotated multiple skill options during the same video, when the student varied their performance during the 1-minute exercise.
Table 6.5: Number of students’ sessions per dance skill

<table>
<thead>
<tr>
<th>Rhythm/Tempo</th>
<th>Slower</th>
<th>Correct</th>
<th>Faster</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>14</td>
<td>26</td>
<td>18</td>
<td>12</td>
<td>70</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pause</th>
<th>Wrong Beat</th>
<th>Correct</th>
<th>No Pause</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>19</td>
<td>32</td>
<td>14</td>
<td>5</td>
<td>70</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Weight Transfer</th>
<th>Too Few</th>
<th>Correct</th>
<th>Too Much</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>21</td>
<td>31</td>
<td>12</td>
<td>6</td>
<td>70</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step Size</th>
<th>Too Small</th>
<th>Normal</th>
<th>Too Large</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>9</td>
<td>38</td>
<td>17</td>
<td>6</td>
<td>70</td>
</tr>
</tbody>
</table>

### 6.3 Evaluation of RiMoDe v2

RiMoDe v2 aimed to unveil more details of the students’ movement by extracting more features from the accelerometer sensor and also using the song information and the gyroscope sensor. The ground truth of students’ skills were assessed by dance teachers in 70 videos. Teachers annotated the videos regarding the following dance skills: Rhythm, Pause, Weight Transfer and Step Size. Teachers’ annotations referred to the whole 1-minute students’ session and, for that reason, there was no need to automatically synchronise teachers’ annotations with the motion and song’s. Each of the 70 students’ videos were manually cut and linked to the corresponding motion and song’s data using a unique ID. More details in Section 3.4.3.

Because the number of features extracted and skills detected were increased, it was important to identify which features better mapped each skill. To evaluate the contribution of each feature to effectively model each skill, we used the following feature selection metrics (Demšar et al., 2013):

- **Gain ratio**: measures the ratio of the information gain and the intrinsic information of the attributes, which decreases the bias towards multivalued features that occurs in information gain.

- **Gini**: measures the inequality among values of a frequency distribution.

- **$X^2$ (chi-square)**: measures dependence between the feature and the class as measured by the chi-square statistic.
Relief F: quantifies the ability of an attribute to distinguish between classes on similar data instances.

To better evaluate the power of classification of the RiMoDe v2 features, other common features used in activity recognition (Ahmadi et al., 2014; Gupta and Dallas, 2014) problems were also extracted from the sensor data. In RiMoDe v2, these features were extracted from the two accelerometer waves that did not correspond to the vertical axis. Some features of the sensors were extracted specifically from the vertical axis. Additionally, the five first principal components (PCs) of the dataset were calculated, because Principal Component Analysis (PCA) is commonly used to improve ML models (Howley et al., 2005). The set of additional features were:

- Principal components: PC1, PC2, ..., PC5 from the PCA.
- \{x,y,z\}Min / \{x,y,z\}Max: the minimum and maximum raw acceleration values from each wave.
- \{x,y,z\}RawStd: standard deviation of the raw values of the waves \{x,y,z\}.
- \{x,y,z\}FilteredStd: standard deviation of the filtered values of the waves \{x,y,z\} (Section 5.4).
- \{x,y,z\}MeanDiffAccWindowed: average value of the differences of min and max of the raw acceleration values in a time window of a 8-beat size.
- \{x,y,z\}SdDiffAccWindowed: averaged standard deviation values of the differences of min and max of the raw acceleration values in a time window of a 8-beat size.
- ySumMeanGyro / ySumSdGyro: summed average and summed standard deviation of the x- and z-axis of the gyroscope sensor.
- yFinalVerticalScore: yMeanDiffAccWindowed - ySdGyro. Here, the vertical accelerometer component is compensated from the Gyroscope data. If the gyroscope data from the x-axis and the z-axis are too volatile, the smartphone was not stable on the student’s body. The gyroscope wave captures this information and compensates for the vertical axis of the accelerometer wave.
• rmseRemainder / meanTrend: root mean square error of the remainder data and mean value of the trend data of the seasonal decomposition of time series by Loess (Cleveland et al., 1990).

To evaluate how powerful the features were in modelling each skill, we used the following modelling performance metrics (Demšar et al., 2013), averaged over classes:

• Area under ROC: the area under the receiver-operating curve. It identifies the model’s capability in distinguishing classes.
• Classification accuracy: the proportion of correctly classified examples.
• F1 score: a weighted harmonic mean of precision and recall.
• Precision: the proportion of true positives among instances classified as positive.
• Recall: the proportion of true positives among all positive instances in the data.

To perform a more robust evaluation, compared to the pilot study with students (Study 2), seven different types of classification methods were used to evaluate the features: Neural Network, kNN, Tree, SVM Learner, Random Forest, Naive Bayes and Logistic Regressions. A Baseline model was used to compare with the other models, and corresponded to the most frequent class observed in the teachers’ assessments for each skill. The models were tested using the Orange software (Demšar et al., 2013) with a 5-fold stratified cross-validation. In the following subsections, the models are presented ordered of their resultant F1 score because this considered both precision and recall in the performance calculation and because the F1 score is more suitable for datasets with imbalanced classes, such as the one used in the present study. To evaluate the best model performance, McNemar’s test (Dietterich, 1998; Keller et al., 2006) was used to compare the Baseline model and the Best model. The value of McNemar’s test is zero if the models have the same errors in classifying the instances and have higher values if the models have different error rates.

Several of the features were calculated over each of the three axes of the accelerometer data, and thus the axis name was included as a prefix of the features. For example, xK-Move score, yK-Move score, zK-Move score, xMin, yMin and zMin.

The following subsections report the ML evaluation of each of the four dance skills presented before on i) the importance of the RiMoDe v2’s features when used to create
ML models and ii) the performance of the ML models when used to match the teachers annotations.

### 6.3.1 Rhythm

The rhythm skill refers to the ability of the students to be synchronised with the tempo of the song. The possible mistakes the student can make is to be *Slower* than the song or *Faster* than the song.

The best ML model for modelling rhythm using four classes (*Slower*, *Correct*, *Faster* and *Mixed*) was the one described in the confusion matrix in Table 6.6. The best model was trained using the Neural Network method (100 neurons, ReLu activation, Adam solver, Regularisation \( a=0.0008 \), 200 iterations) using the 12 first features as ordered by \( X^2 \). Table 6.7 presents the 12 features and the performance metrics for modelling the rhythm skills. The results from McNemar’s test between the Neural Network model and the Baseline model was 17.45 (\( p < 0.01 \)), which represents a great improvement when compared to the Baseline model. The average F1 score of the best ML model was 0.741, having an even balance between the average precision (0.741) and the average recall (0.743). This result was similar to that obtained by RiMoDe v1 in the *All Cases* set (F1 score = 0.79), even though in this study the ML model using RiMoDe v2 features classified four classes.

Table 6.6: Rhythm skill - Confusion matrix of the best ML model when using four classes. Comparing the teachers (Actual) assessment and the ML using RiMoDe v2 features (Predicted). Colours indicate correctly classified instances (blue) and incorrect instances (red).

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Slower</th>
<th>Correct</th>
<th>Faster</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slower</td>
<td>9</td>
<td>2</td>
<td>0</td>
<td>3</td>
<td>14</td>
</tr>
<tr>
<td>Correct</td>
<td>2</td>
<td>22</td>
<td>0</td>
<td>3</td>
<td>26</td>
</tr>
<tr>
<td>Faster</td>
<td>2</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>Mixed</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>Total</td>
<td>16</td>
<td>26</td>
<td>18</td>
<td>10</td>
<td>70</td>
</tr>
</tbody>
</table>

The new features extracted by RiMoDe v2 appeared as the top eight features, demonstrating that the new version of the rhythmic extraction algorithms were more robust than the previous version. RiMoDe v1 features were the next in the list of relevant features. Table 6.8 presents the performance of the different ML models tested.
Table 6.7: Rhythm skill – Top 12 features

<table>
<thead>
<tr>
<th>Feature Name</th>
<th>Gain ratio</th>
<th>Gini</th>
<th>$X^2$ *</th>
<th>ReliefF</th>
</tr>
</thead>
<tbody>
<tr>
<td>xK-Move closeness</td>
<td>0.275</td>
<td>0.210</td>
<td>30.352</td>
<td>0.094</td>
</tr>
<tr>
<td>zK-Move centered1</td>
<td>0.325</td>
<td>0.246</td>
<td>30.202</td>
<td>0.098</td>
</tr>
<tr>
<td>zK-Move centered7</td>
<td>0.319</td>
<td>0.225</td>
<td>29.102</td>
<td>0.106</td>
</tr>
<tr>
<td>zK-Move closeness</td>
<td>0.283</td>
<td>0.200</td>
<td>28.746</td>
<td>0.130</td>
</tr>
<tr>
<td>zK-Move score</td>
<td>0.255</td>
<td>0.191</td>
<td>27.678</td>
<td>0.095</td>
</tr>
<tr>
<td>xK-Move centered7</td>
<td>0.246</td>
<td>0.183</td>
<td>25.464</td>
<td>0.059</td>
</tr>
<tr>
<td>xK-Move centered1</td>
<td>0.256</td>
<td>0.191</td>
<td>24.550</td>
<td>0.071</td>
</tr>
<tr>
<td>6-Move score</td>
<td>0.254</td>
<td>0.179</td>
<td>24.005</td>
<td>0.099</td>
</tr>
<tr>
<td>1-Move score</td>
<td>0.189</td>
<td>0.140</td>
<td>23.557</td>
<td>0.033</td>
</tr>
<tr>
<td>bpmRatio</td>
<td>0.299</td>
<td>0.229</td>
<td>22.261</td>
<td>0.062</td>
</tr>
<tr>
<td>yBPM</td>
<td>0.184</td>
<td>0.119</td>
<td>17.669</td>
<td>0.047</td>
</tr>
<tr>
<td>zBPM</td>
<td>0.128</td>
<td>0.093</td>
<td>15.725</td>
<td>0.045</td>
</tr>
</tbody>
</table>

*Ordered by chi-square

Figure 6.3 presents the different ML models by F1 score, with changes to the number of features used to train it. The performance of a few models were between 0.6 and 0.7 when using from two to four features. This performance decreases when more features are added but increases again when the number of features reaches 10 or more. The top three models using the F1 score as a reference were the Neural Network with 12 features (0.741), kNN with two features (0.73) and SVM Learner with 12 features (0.714).

Table 6.8: Rhythm skill – Performance of models

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC</th>
<th>CA</th>
<th>F1 *</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural Network</td>
<td>0.881</td>
<td>0.743</td>
<td>0.741</td>
<td>0.741</td>
<td>0.743</td>
</tr>
<tr>
<td>SVM Learner</td>
<td>0.825</td>
<td>0.729</td>
<td>0.714</td>
<td>0.721</td>
<td>0.729</td>
</tr>
<tr>
<td>Random Forest Learner</td>
<td>0.840</td>
<td>0.629</td>
<td>0.632</td>
<td>0.642</td>
<td>0.629</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>0.864</td>
<td>0.600</td>
<td>0.622</td>
<td>0.652</td>
<td>0.600</td>
</tr>
<tr>
<td>Tree</td>
<td>0.791</td>
<td>0.629</td>
<td>0.602</td>
<td>0.587</td>
<td>0.629</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.796</td>
<td>0.629</td>
<td>0.583</td>
<td>0.609</td>
<td>0.629</td>
</tr>
<tr>
<td>kNN</td>
<td>0.711</td>
<td>0.414</td>
<td>0.405</td>
<td>0.441</td>
<td>0.414</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.500</td>
<td>0.371</td>
<td>0.201</td>
<td>0.138</td>
<td>0.371</td>
</tr>
</tbody>
</table>

*Ordered by F1 score
Figure 6.3: Rhythm skill – Comparison of different modelling algorithms by F1 score varying the number of features used (Table 6.7).

The rhythm skill was the one that the teachers annotated the most mixed cases (12 in total). Two of those cases were flagged as mixed because there was no agreement in the teachers’ annotations, and the other 10 cases were mixed because teachers annotated multiple times the same videos with distinct annotations. An example is presented in Figure 6.4, where T7, T6 and T15 annotated the video multiple times with distinct annotations. Teacher T12 only annotated once. The number of annotations for each rhythm skill option were *Correct* (6), *Faster* (3) and *Slower* (3). Because of the complexity of such cases, the ML models could not accurately model mixed cases. The kNN model, when trained with only three classes (*Slower*, *Correct* and *Faster*) assigned as *Slower* the case illustrated in Figure 6.4.

Figure 6.4: Rhythm Mixed Case – Example of a student case where teachers did multiple and distinct annotations in the same video. The Y-axis represents the teachers’ annotators 1(T7), 2(T6), 3(T15 and 4(T12). The X-axis represents the time position in which the annotation was recorded.
By removing the 12 mixed cases, leaving 58 instances and three classes (Slower, Correct and Faster), the performance of the ML models only slightly changed. The best model for the three classes was kNN (number of neighbours = 5, metric Euclidean, weight uniform) using the two first features ordered by Gini. This was a similar model to that presented in Figure 6.3, kNN, using two features. This model’s F1 score jumped to 0.857, although this is because of the removal of the mixed class prediction performance from the F1 score average. Only three more instances were correctly classified, a total of 50 correctly classified, in comparison with the four class model, which correctly classified 47 of the three classes (Slower, Correct and Faster) instances.

The new features extracted by RiMoDe v2 added good value to the model of the rhythm skill as the best ML model maintained the previous RiMoDe v1 F1 score when modelling the four classes (F1 score = 0.741) and showed great improvement when modelling the three classes (F1 score = 0.857). Using more details of the accelerometer wave and the song’s beat position as a reference to extract features proved to be very relevant when modelling the rhythm skill of Forró dance students.

6.3.2 Pause

The pause skill refers to the ability of the student to pause or slow down their movement during steps 4 and 8 of the Básico. There are two types of common mistakes: 1) the student does not pause at all during the Básico 1 or 2) the pause is at the wrong time, for instance, at step 1 or 5. The pause skill was expected to have good results when modelled using the new RiMoDe v2 algorithm, because the algorithm uses more information from the song’s profile to match the accelerometer data. Table 6.9 contains the performance of the top six features for modelling pause, ordered by $X^2$. Selecting the top six features by their $X^2$ importance produced the best results for most classification algorithms. Table 6.10 presents the performance of the models, complemented by Figure 6.5. The Neural Network had the best performance and its resulting confusion matrix is presented in Table 6.11. McNemar’s test result between the Neural Network and the Baseline was 15.75 ($p < 0.01$), which represents a good improvement when compared to the Baseline model. The model presented an average F1 score of 0.744, which was very similar to the best ML model for the rhythm skill (0.741), although the model had a higher average recall (0.771) compared to the average precision (0.721). This improvement occurred because the ML model classified correctly more instances
in the pause skill than the previous ML model for the rhythm skill. A possible explanation for this is that the most representative class, Correct – Pause, was annotated 32 times by teachers compared to 22 instances for Correct – Rhythm. This imbalance of class tends to favour the ML model for pause to classify correctly more instances. As the teachers observed fewer pause skill mistakes than that of rhythm skills, it would be beneficial to validate this ML model in additional instances where students had pause mistakes.

Table 6.9: Pause skill – Top six features

<table>
<thead>
<tr>
<th>Feature Name</th>
<th>Gain ratio</th>
<th>Gini</th>
<th>X² *</th>
<th>ReliefF</th>
</tr>
</thead>
<tbody>
<tr>
<td>zK-Move centered 1</td>
<td>0.2350</td>
<td>0.1847</td>
<td>24.0499</td>
<td>0.0789</td>
</tr>
<tr>
<td>zK-Move score</td>
<td>0.2139</td>
<td>0.1667</td>
<td>23.3267</td>
<td>0.0583</td>
</tr>
<tr>
<td>zK-Move closeness</td>
<td>0.1994</td>
<td>0.1553</td>
<td>23.3267</td>
<td>0.1049</td>
</tr>
<tr>
<td>xK-Move closeness</td>
<td>0.2228</td>
<td>0.1670</td>
<td>22.9238</td>
<td>0.0515</td>
</tr>
<tr>
<td>zK-Move centered 7</td>
<td>0.2271</td>
<td>0.1729</td>
<td>22.1209</td>
<td>0.0579</td>
</tr>
<tr>
<td>6-Move score</td>
<td>0.1730</td>
<td>0.1118</td>
<td>19.8218</td>
<td>0.0626</td>
</tr>
</tbody>
</table>

*Ordered by chi-square

Table 6.10: Pause skill - Performance of the models

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC</th>
<th>CA</th>
<th>F1 *</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural Network</td>
<td>0.892</td>
<td>0.771</td>
<td>0.744</td>
<td>0.721</td>
<td>0.771</td>
</tr>
<tr>
<td>SVM Learner</td>
<td>0.870</td>
<td>0.700</td>
<td>0.673</td>
<td>0.654</td>
<td>0.700</td>
</tr>
<tr>
<td>Random Forest Learner</td>
<td>0.856</td>
<td>0.643</td>
<td>0.632</td>
<td>0.632</td>
<td>0.643</td>
</tr>
<tr>
<td>Tree</td>
<td>0.759</td>
<td>0.586</td>
<td>0.578</td>
<td>0.600</td>
<td>0.586</td>
</tr>
<tr>
<td>kNN</td>
<td>0.766</td>
<td>0.600</td>
<td>0.564</td>
<td>0.573</td>
<td>0.600</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>0.818</td>
<td>0.529</td>
<td>0.555</td>
<td>0.651</td>
<td>0.529</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.833</td>
<td>0.571</td>
<td>0.466</td>
<td>0.445</td>
<td>0.571</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.500</td>
<td>0.457</td>
<td>0.287</td>
<td>0.209</td>
<td>0.457</td>
</tr>
</tbody>
</table>

*Ordered by F1 score

Because the number of mixed cases was small, the Neural Network model could not correctly predict any of the mixed cases. One example of a mixed case for the pause skill is presented in Figure 6.6. In this student case, T6, T7 and T12 annotated the video multiple times with distinct annotations. T15 only annotated once, as Wrong Beat. The number of annotations for each rhythm skill option were Wrong Beat (5), Correct (1) and No Pause (7).
Figure 6.5: Pause skill – Comparison of different modelling algorithms by F1 score varying the number of features used (Table 6.9).

Table 6.11: Pause skill – Confusion matrix of the best ML model when using four classes. Comparing the teachers’ (Actual) assessment and the ML using RiMoDe v2 features (Predicted). Colours indicate correctly classified instances (blue) and incorrect instances (red).

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Wrong Beat</th>
<th>Correct</th>
<th>No Pause</th>
<th>Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wrong Beat</td>
<td>15</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td>Correct</td>
<td>1</td>
<td>29</td>
<td>2</td>
<td>0</td>
<td>32</td>
</tr>
<tr>
<td>No Pause</td>
<td>3</td>
<td>1</td>
<td>10</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>Mixed</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>23</td>
<td>34</td>
<td>13</td>
<td>0</td>
<td>70</td>
</tr>
</tbody>
</table>

The new RiMoDe v2 features were again essential for modelling the pause skill. The best ML model had a great result, even when modelling four classes. The best ML model required fewer features (six features) to achieve a good F1 score compared to the best ML model for rhythm (12 features). This is a positive result because the resultant model is less complex. Combining the detection of the pause skill to the rhythm skills could provide a good advantage for students and teachers to assess rhythmic problems.
6.3.3 Step size

A common mistake for beginner students is having a step size that is as long as when they are walking. Potentially, the accelerometer would have higher values when the student has a long and large step and lower values if the student is doing too small a step.

The step size skill had the best modelling performance among the four skills. The confusion matrix presented in Table 6.12 shows that the number of Correct cases was much higher than that of the other classes, which explained the model’s higher performance. The best model was generated using SVM Learner (polynomial kernel, g=0.15, c=0.07, d=3.0) with the nine top features ranked by $X^2$. McNemar’s test result between the SVM Learner model and the Baseline model was 14.45 ($p < 0.01$). The model had a F1 score of 0.789, having a higher average precision (0.827) than that of the average recall (0.8). Similar to the best ML for the pause skill, it is important to validate the best ML model for step size skill with other instances that contain step mistakes.

The top nine features are presented in Table 6.13. The top features demonstrate that the z-axis and the y-axis are the ones that most represent the step size skill. The z-axis is the one that records the back and forward movement of the Básico exercise, and the y-axis records the vertical fluctuations (see Figure 5.2 for the mobile axes). The step size skill described how much variations existed in the z- and y-axes. PC1 corroborated this assumption because it stored 23% of the dataset’s variance. Table 6.14 presents the rank of the different ML methods ordered by the F1 score. Figure 6.7
CHAPTER 6. EVALUATING THE FEATURES OF RIMODE

Table 6.12: Step size skill – Confusion matrix of the best ML model when using four classes. Comparing the teachers (Actual) assessment and the ML evaluation (Predicted). Colours indicate correctly classified instances (blue) and incorrect instances (red).

<table>
<thead>
<tr>
<th></th>
<th>Too Small</th>
<th>Normal</th>
<th>Too Large</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Too Small</td>
<td>6</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Normal</td>
<td>0</td>
<td>37</td>
<td>1</td>
<td>0</td>
<td>38</td>
</tr>
<tr>
<td>Too Large</td>
<td>0</td>
<td>7</td>
<td>10</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Mixed</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>6</td>
<td>49</td>
<td>12</td>
<td>3</td>
<td>70</td>
</tr>
</tbody>
</table>

presents the evolution of the performance of the methods, according to the F1 score, while increasing the number of features used as input.

The step size skill is a very important skill in Forró, especially because beginner students commonly have long step sizes. Being able to correctly assess the step size skill is an important addition to the pool of skills assessed. Even though RiMoDe’s features were not relevant in modelling the step size skill, the results showed a positive indication towards creating systems that can support social partner dances.

Table 6.13: Step size skill – Top nine features

<table>
<thead>
<tr>
<th>Feature Name</th>
<th>Gain ratio</th>
<th>Gini</th>
<th>$X^2$ *</th>
<th>ReliefF</th>
</tr>
</thead>
<tbody>
<tr>
<td>zMin</td>
<td>0.182</td>
<td>0.094</td>
<td>19.779</td>
<td>0.070</td>
</tr>
<tr>
<td>PC1</td>
<td>0.234</td>
<td>0.120</td>
<td>19.640</td>
<td>0.075</td>
</tr>
<tr>
<td>zFilteredStd</td>
<td>0.192</td>
<td>0.094</td>
<td>19.485</td>
<td>0.073</td>
</tr>
<tr>
<td>zRawStd</td>
<td>0.204</td>
<td>0.103</td>
<td>18.663</td>
<td>0.079</td>
</tr>
<tr>
<td>zMax</td>
<td>0.161</td>
<td>0.074</td>
<td>18.335</td>
<td>0.095</td>
</tr>
<tr>
<td>yFinalVerticalScore</td>
<td>0.172</td>
<td>0.106</td>
<td>16.791</td>
<td>0.060</td>
</tr>
<tr>
<td>yFilteredStd</td>
<td>0.174</td>
<td>0.118</td>
<td>16.681</td>
<td>0.057</td>
</tr>
<tr>
<td>zMeanSize</td>
<td>0.245</td>
<td>0.132</td>
<td>16.662</td>
<td>0.071</td>
</tr>
<tr>
<td>ymeanDiffAccWindowed</td>
<td>0.163</td>
<td>0.097</td>
<td>15.764</td>
<td>0.067</td>
</tr>
</tbody>
</table>

*Ordered by chi-square
Table 6.14: Step size skill – Performance of the Models

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC</th>
<th>CA</th>
<th>F1</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM Learner</td>
<td>0.846</td>
<td>0.800</td>
<td>0.789</td>
<td>0.827</td>
<td>0.800</td>
</tr>
<tr>
<td>Neural Network</td>
<td>0.834</td>
<td>0.714</td>
<td>0.704</td>
<td>0.710</td>
<td>0.714</td>
</tr>
<tr>
<td>kNN</td>
<td>0.790</td>
<td>0.671</td>
<td>0.641</td>
<td>0.702</td>
<td>0.671</td>
</tr>
<tr>
<td>Random Forest Learner</td>
<td>0.783</td>
<td>0.657</td>
<td>0.629</td>
<td>0.611</td>
<td>0.657</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.750</td>
<td>0.629</td>
<td>0.580</td>
<td>0.612</td>
<td>0.629</td>
</tr>
<tr>
<td>Tree</td>
<td>0.698</td>
<td>0.557</td>
<td>0.546</td>
<td>0.541</td>
<td>0.557</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>0.719</td>
<td>0.500</td>
<td>0.490</td>
<td>0.575</td>
<td>0.500</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.500</td>
<td>0.543</td>
<td>0.382</td>
<td>0.295</td>
<td>0.543</td>
</tr>
</tbody>
</table>

*Ordered by F1 score

Figure 6.7: Step size skill – Comparison of different modelling algorithms by F1 score varying the number of features used (Table 6.13).

6.3.4 Weight transfer

Another hard skill for beginner students to learn is weight transfer. Related mistakes include 1) to step too hard on the floor, transferring too much weight; and 2) transferring too little weight or not at all. Depending on how soft or hard the student lands their feet on the ground, this is going to change the amplitude of the y-axis. Both y-axis features and RiMoDe v2 features were ranked as the relevant features to model the weight transfer skill (Table 6.15). If the student does not transfer their weight properly, then they will not generate a wave pattern similar to the one presented in Figure 5.5a.
This skill was the one with the least cases correctly classified (47 out of 70 cases). Even though the models for weight transfer had lower performance compared to the models of the other skills, the best ML model had better performance than that of the Baseline model. The performance of the models is presented in Table 6.16, complemented by Figure 6.8, which presents the performance evolution of the ML methods by increasing the number of features according to Gini’s rank.

The best ML model for the weight transfer skill was the one using Logistic Regression with the top 10 features as ranked by Gini. The resulting confusing matrix is presented in Table 6.17. McNemar’s test result between the Logistic Regression model and the Baseline model was 9.375 ($p < 0.01$), the lowest among the four skills. The
model had a F1 score of 0.629, having a higher recall (0.671) than precision (0.616). This indicates that further analysis of the motion data is required to better model the weight transfer skill. According to the ranking of the features (Table 6.15), there is an indication that the y-axis can be a good starting point for extracting new features. RiMoDe v2 focused on extracting features from the Básico movement characteristics that are more related to the z- and x-axes.

Table 6.17: Weight transfer skill – Confusion matrix of the best ML model when using four classes. Comparing the teachers (Actual) assessment and the ML evaluation (Predicted). Colours indicate correctly classified instances (blue) and incorrect instances (red).

<table>
<thead>
<tr>
<th></th>
<th>Too Few</th>
<th>Correct</th>
<th>Too Much</th>
<th>Mixed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Too Few</td>
<td>16</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>21</td>
</tr>
<tr>
<td>Correct</td>
<td>2</td>
<td>27</td>
<td>2</td>
<td>0</td>
<td>31</td>
</tr>
<tr>
<td>Too Much</td>
<td>0</td>
<td>8</td>
<td>4</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Mixed</td>
<td>2</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>43</td>
<td>7</td>
<td>0</td>
<td>70</td>
</tr>
</tbody>
</table>
6.3.5 Annotation agreement of the teachers

To compare the annotation agreement of the four teachers, the Kappa Fleiss index (Fleiss, 1971) was used. This calculates inter-rater agreement for categorical data. For the rhythm skill, the Kappa value of the four teachers was 0.666 (p = 0), and for the weight transfer skill, the Kappa value was 0.125 (p = 0.005). Overall, the teachers agreed much more when annotating rhythm than when annotating weight transfer. Although, comparing the agreement of pairs of teachers, the figures were quite different. For example, T1 and T4 had a Kappa value of 0.75 when annotating rhythm and T2 and T4 had a Kappa value of 0.47 when annotating weight transfer.

6.3.6 Comparing RiMoDe v1 and v2

This subsection compares how much RiMoDe v2 features improved the classification of the students’ Rhythm skills in comparison to RiMoDe v1 features. For this comparison, the best model was used for RiMoDe v2 (Neural Network with 12 features) and the same strategy used for RiMoDe v1 (decision tree with 2 features). These models were used to classify the students’ sessions dataset from Study 3 (70 sessions). The McNemar’s test results, comparing each model with the Baseline (Constant model), gives RiMoDe v1 10.45 (p < 0.01) and RiMoDe v2 17.45 (p < 0.01). This result demonstrates that the RiMoDe v2 features give a higher improvement to correctly classify the Rhythm skill when compare to RiMoDe v1. Figure 6.9 show a comparison of both models with the Baseline using the ROC curve. The purple line represents RiMoDe v2 model, the green line represents the RiMoDe v1 model, the blue line the Baseline model and the grey line represents a 50% chance. The performance of each model is identified by the area under each curve (AUC). A bigger area AUC correspond to a better model. In all comparisons RiMoDe v2 model is better than RiMoDe v1, in special to classify the Mixed label where RiMoDe v1 is worst than the Baseline model, Figure 6.9c. Additionally, Table 6.7 also demonstrate that the features from RiMoDe v2 scored better than RiMoDe v1 features (I-Move score and bpmRatio) in the importance rank.
(a) Model’s evaluation for the Correct class  
(b) Model’s evaluation for the Faster class  
(c) Model’s evaluation for the Mixed class  
(d) Model’s evaluation for the Slower class

Figure 6.9: ROC curve comparison between RiMode v1 (green), RiMode v2 (purple), Constant (blue) and the 50% models in classifying the 70 labelled sessions, from dataset of Study 3, in the Rhythm skill. The bigger the area under the curve (AUC), the better the model in correctly classifying the students sessions. The number attached to each line represents the point on the ROC curve achieved by the classifier if it predicts the target class when the probability is equals or exceeds 0.5 – the higher the better.
### 6.3.7 Limitations

Student participants could potentially vary their performance in a 1-minute session. In Study 2, a few teachers stated that the students varied their performance during the 1-minute exercise. In this study, Study 3, the annotation process attempted to capture this variability; however, there were not enough samples showing these changes in students’ movement, based on the teachers’ annotation. With limited data points, it was not possible to model the variation of students’ behaviour during the 1-minute exercise. In addition, the lack of mixed cases reduced the prediction power of the models to predict mixed cases. To overcome this problem, the feature of RiMoDe’s could be used in a raw format instead of as a label (i.e., Slower, Correct and Faster), and the information regarding the students’ performance could be presented to the teachers in a different format, for example, as a chart. Figure 6.10 shows the variation of student’s BPM, calculated with RiMoDe v1, over a 1-minute song. With this information, the teacher could potentially identify the needs and difficulties of this student at the beginning of the student’s practice.

![Figure 6.10: Case P16 S1 B Post1 - Variation of the student’s BPM during the 1-minute exercise. The horizontal line shows the song’s BPM.](image)

The weight transfer skill was the skill that had lower improvement in the classification model compared with the Baseline model. A possible explanation is that, for teachers, the main weight transfers in the Básico movement occur in four steps, i.e. at the extremes of the movement, on steps 1 and 5, and when the student is coming back to the middle, on steps 2 and 6. Ideally, it would be good if these moments in the steps could be distinguished in the features of the motion sensors, which would enable...
teachers to label differently when the student’s problem occurs in these different parts of the movement.

6.4 Chapter Summary

This chapter presented both quantitative and qualitative evaluations of the algorithms proposed in this thesis. RiMoDe v1 achieved up to 90% accuracy in the binary problem of deciding whether the student is on the correct or incorrect rhythm. The qualitative analysis of Study 2 led to the understanding of other skills that teachers observe when assessing rhythm. This knowledge was used to evolve RiMoDe into v2, extracting more features from the motion sensor waves. The relevance of these features was tested using ML models over the four skills related to rhythm learning. Out of the 70 cases annotated by teachers, 27 were classified correctly by the ML models in all four skills and 43 were classified incorrectly in at least one skill. A total of 10 of the 70 cases were misclassified in two skills at the same time, and nine cases were incorrectly classified in three skills at the same time.

McNemar’s test results of the best models compared with the Baseline models were the following: rhythm (17.45), pause (15.75), step size (14.45) and weight transfer (9.375), all with statistical significance ($p < 0.01$). Rhythm had the best performance compared to the Baseline model and weight transfer had the worst. All the ML models, the best model for each skill, were better than the Baseline model. However, the weight transfer model had an F1 score that was less than 0.7; therefore, the model should be used with caution to predict the weight transfer skills of the students. The models of the other skills had F1 scores greater than 0.74; therefore, these models were more reliable and could be used by teachers to support the assessment of their students.

After evaluating the features and quality of the ML models, it is important to understand how this information can be used in the context of dance classes. The next chapter evaluates the use of the output from the RiMoDe v1 and v2 algorithms with student participants and Forró dance teachers.
Chapter 7

Providing Automated Feedback and Assessment on Rhythmic Skills

This chapter presents two approaches for using the data from the sensors and the models, described in the previous chapters, with dance students and teachers. The purpose of this chapter is to provide validation in addition to the machine learning (ML) validation, by collecting the experiences of users using automatic feedback and assessment.

The first approach used the data from RiMoDe v1 and presented this to students to inform them about their performance of the dance exercises using the mobile app. Different data representations (e.g. numbers, charts and text) were used in a report to try and understand how student participants made sense of the collected motion data. The second approach used the data from RiMoDe v2 to provide enhanced rhythmic assessment information to teachers regarding the performances of the students. To collect the perceptions of teachers, they were exposed to the students’ video-recorded performances together with an automatic assessment of the students’ performance. Additionally, this chapter will present complementary findings on the use of video annotation as a tool to support teachers in assessing and providing feedback to students, regarding rhythmic skills.

7.1 Automatic Assessment Evaluation with Students

This section reports the results from Study 2, when participants were exposed to their dance performance data. After taking three dance classes and using the Forró Trainer
mobile app during the performances, they evaluated the different ways that the data collected by the app could be represented. The research question that guided this part of the study expands RQ3:

- RQ3.1 - How do students make sense of the automatic assessment data?

The focus was to assess the rhythm skills data, which was automatically generated and represented in different formats. These data could be relevant for students to track and assess their rhythm performance, allowing feedback for the students. The rhythm-related features proposed for this study are described below:

- **Practice.** Mastering motor learning skills is strongly correlated with repeated practice (Karni et al., 1998). In dancing, a learner needs to practise not only to strengthen the body in preparation for the continued physical activity but also to develop coordination and other key physio-cognitive skills required for the dance style (Green, 2002). **How do we model this feature?** By logging the number of times a student practised using the learning app.

- **Rhythm BPM.** Students must understand rhythm to learn how to dance properly (Côté-Laurence, 2000). Keeping accurate timing is crucial in dance. Good rhythmic skills imply precisely synchronised body movements with the beat of the song, and this synchrony must be maintained throughout the entire song. To assess whether a student moves their body to the rhythm of song, the beats of the song can be compared with the timing of the student’s body movements. **How do we model this feature?** Using the algorithm described in Section 5.4, we calculated the average BPM from the student’s motion data.

- **Rhythm consistency.** As mentioned above, students must maintain the correct BPM throughout the entire song, and across several practices. **How do we model this feature?** We calculate the CoV of the student’s BPM across the 1-minute dancing exercise. This information represents how well the student is able to keep the rhythm during the exercise.

- **Body motion.** This feature refers to the extent to which a student is aware of whether their body movements are in tune to the music. When students are fully aware of how their body is moving and have control over this movement,
they can properly communicate their movement and perform the dance effectively (Green, 2002). **How do we model this feature?** Decompose the student’s movement into the acceleration data extracting acceleration patterns, rhythm and consistency for each of the three axes (x, y and z).

### 7.1.1 Providing visual and narrative feedback

After collecting motion data, validating ML models and inferring the indicators that were important based on key literature, the next challenge was to define how to present the dance automatic assessment in a way that made sense to the users. Four different approaches were explored to provide feedback to the students about the features listed in the previous section:

- **Summaries/Tables.** This representation provided the student with an overview of different aspects of their performance. The summary contains averages and standard deviations of the features mentioned before, aggregated by different characteristics of each feature, for instance, exercise type, music type, axes of the body (e.g. see Tables 7.2, 7.3, 7.4 and 7.5).

- **Visualisations.** Charts were built presenting the temporal aspects of the data, for example, the student’s performance during one exercise or how the student evolved during the week (e.g. see Fig. 7.1).

- **Narratives.** Narrative stories were created similarly to the feedback that the dance instructor would provide. For example, “We suggest you to practise more often, both daily and weekly. It is important to recall the movements we do in class” (e.g. see Table 7.1). These narratives would be automatically generated by configuring rules or using more sophisticated methods (Knaflic, 2015).

- **Social comparison.** Students were provided with ways to compare their progress against other learners and against the teacher (gold standard). This is a common strategy in learning that may benefit students, called open social modelling (Guerra, 2016).
Table 7.1: Examples of Narrative Feedback

<table>
<thead>
<tr>
<th>Practice</th>
<th>Diagnosis: you have an average of two practice sessions per day and had 12 days without practice. Most of your practice sessions were performed during class. Actionable feedback: you could practise more often daily and weekly. It is important to recall the movements we do in class.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rhythm BPM</td>
<td>Diagnosis: Dear student, you have no correct attempt while doing the tap exercise. In all the nine attempts you were slower than the song. Actionable feedback: We suggest you practice more of the tap exercise until you can consistently achieve the correct rhythm. The tap exercise will help you develop your ability to listen properly to the rhythm of the song.</td>
</tr>
<tr>
<td>Rhythm consistency</td>
<td>Diagnosis: Dear student, you have an average consistency of 98.56% on the Básico 1 exercise. Your lowest consistency was 95.71% doing the Danielle song. Actionable feedback: The result of your consistency score along your practice of the Básico 1 exercise is really good. The lowest consistency score doesn’t seem to be a problem since you recovered the score in the following attempts.</td>
</tr>
<tr>
<td>Body motion</td>
<td>Diagnosis: Dear student, your best attempt has higher speed when compared with your worst attempt. Actionable feedback: A higher speed means that your movements were more defined and clear, it means you were more precise on the movement. You should aim to have more precision and confidence in your movement, your dance will be clearer and your partner will better understand your movements.</td>
</tr>
</tbody>
</table>
7.1.2 Modelling and data representations

To display information regarding the four features of the dance students, the above four types of data representation were selected, i.e., summary, visualisation, narrative and social comparison. Although the students could do other exercises using the Forró Trainer app, this study is based on the data collected when they were performing the Básico 1 to exercise. The next sections describe how each feature was represented, with examples. A full sample of what was presented to the students is included in Appendix A.2.

7.1.2.1 Representation of the practice data

**Summary.** The summary table of the practice data shows the number of times the student practised each exercise and the number of attempts for each level. The student could also see the total number of times practised and the period (in days) when the practice occurred (see Table 7.2).

<table>
<thead>
<tr>
<th>Time practised for each exercise</th>
<th>Time practised for each level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tap</td>
<td>9</td>
</tr>
<tr>
<td>Weight transfer</td>
<td>10</td>
</tr>
<tr>
<td>Walking</td>
<td>1</td>
</tr>
<tr>
<td>Básico 1</td>
<td>21</td>
</tr>
</tbody>
</table>

**Visualisation.** Two bar charts were presented, containing: 1) the frequency that the student practised each exercise per day, and 2) how many times they practised each level per day. Distinct colours for each exercise and each level made the bar charts easier to read (e.g. see Fig 7.1a).

**Narrative.** For all students, feedback was provided as a text narrative that included two parts: a diagnosis narrative and an actionable narrative (which suggests what the student can do to fix a problem). See an example narrative in Table 7.1, row 1.

**Social comparison.** The summary used in the social comparison compares the students with their peers. The first table uses the number of times practised (as in Table 7.2) and the second table is about consistency during the Básico 1 exercise (as in Table 7.4).
7.1.2.2 Representation of rhythm BPM data

This table organised the data by exercise and level, but also presented the number of times the student was moving their body in time, slower or faster than the song.

**Visualisation.** This visualisation presents two boxplot charts side by side that show the comparison between the student’s worst and best result (based on their rhythm and consistency performance) for the song ‘Nosso Xote’ while doing the Básico 1 exercise. The boxplot summarises the data regarding the rhythm of the student during their attempt. Usually, their rhythm varied a lot in the worst case but not in the best case (e.g. see Fig 7.1c).

### Table 7.3: Example of rhythm BPM 7.1.2.2 – Summary

<table>
<thead>
<tr>
<th>Rhythm Evaluation by Level in Básico 1 Exercise</th>
<th>Total</th>
<th>Too Slow</th>
<th>Correct</th>
<th>Too Fast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow Paced</td>
<td>11</td>
<td>0</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>Medium Paced</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Fast Paced</td>
<td>8</td>
<td>1</td>
<td>7</td>
<td>0</td>
</tr>
</tbody>
</table>

**Narrative.** These narratives focused on the student’s mistakes of performing slower/faster than the songs and suggesting exercises that could improve their listening skills regarding rhythm (Table 7.1, row 2).

7.1.2.3 Representation of rhythm consistency data

**Summary.** Consistency represents the overall variability of the student’s rhythm during a 1-minute exercise. If the student maintains the same rhythm throughout the entire song, their score would be close to 100%. The score decreases if the student does not maintain a regular consistency thus, losing the rhythm during the exercise. A consistency score below 97% means the student struggled to follow the rhythm. The summary table contains the minimum, maximum, average and standard deviation for consistency organised by exercise and level (see Table 7.4).

**Visualisation.** Focusing on one specific song/exercise, the student progress is presented using a line chart that contains all the attempts by the student to perform to the song ‘Nosso Xote’ (slow level), exercise Básico 1. Ordered by the time of the attempt, the line chart contains coloured dots representing whether the student’s attempt was correct (green), slower (blue) or faster (red) than the song (e.g. see Fig. 7.1b).
Figure 7.1: Sample of the visualisations used in the student’s report. a) show the numbers of times the students practice each day of the week, distinguishing the level of the exercise (7.1.2.1), b) the progress of the student between attempts in one song, with icons indicating correct (green), slower (blue) or faster (red) attempts (7.1.2.3), c) comparison between worst and best student’s attempts with a boxplot chart (7.1.2.2) and d) student’s movement BPM during one attempt; student made a mistake at 40s (7.1.2.4).
CHAPTER 7. PROVIDING AUTOMATED FEEDBACK AND ASSESSMENT

Narrative. Students were given details about their consistency and recommendations for exercises to do, based on their main weaknesses or strengths detected in past exercises (Table 7.1, row 3).

Table 7.4: Example of rhythm consistency 7.1.2.3 – Summary

<table>
<thead>
<tr>
<th>Exercise Level</th>
<th>Total</th>
<th>Min (%)</th>
<th>Mean (%)</th>
<th>Max (%)</th>
<th>Standard Deviation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow Paced</td>
<td>11</td>
<td>97.8</td>
<td>98.6</td>
<td>99.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Medium Paced</td>
<td>2</td>
<td>98.6</td>
<td>98.6</td>
<td>98.6</td>
<td>0.0</td>
</tr>
<tr>
<td>Fast Paced</td>
<td>8</td>
<td>95.7</td>
<td>97.7</td>
<td>98.8</td>
<td>0.9</td>
</tr>
</tbody>
</table>

7.1.2.4 Representation of body motion data

Summary. The summary shows the student’s movement on the three axes (x, y and z). The first table presents the student’s rhythm (BPM) and consistency for each axis in both practices (Table 7.5). In good performances, all axes presented the same BPM value and had good consistency values. The second table shows the raw accelerometer data mean and standard deviation, for the three axes and both cases. In the raw acceleration data, the standard deviation of experts was usually higher than the values of the not good data samples.

Table 7.5: Example of body motion 7.1.2.4 – Summary

<table>
<thead>
<tr>
<th>Movement Rhythm – Worst × Best – Nosso Xote (BPM = ~142.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Worst</td>
</tr>
<tr>
<td>Best</td>
</tr>
</tbody>
</table>

Visualisation. Two visualisations presented the comparison between the worst and best attempts. The first consisted of two line charts that presented the different rhythms the student performed in their sessions. In a perfect scenario, with 100% consistency, the chart would have a flat line, indicating that the student had the same rhythm throughout the entire song. In a bad scenario, fluctuations would be seen along the chart (e.g. see Fig. 7.1d). The second visualisation presented two waves (line charts) of the accelerometer data of one of the student’s axes. In a good attempt, the
chart would have a sinusoidal-like shape, with a regular period between peaks. In a bad case, the wave would present an irregular distance between peaks (e.g. see Fig. 7.2).

![Time series of motion data from a participant while performing a dance exercise. Relative to the z-axis, which represents the back-and-forth movement of Básico 1 in the sagittal/longitudinal plane. Red dots show peaks detected using RiMoDe v1.](image)

**Figure 7.2:** Time series of motion data from a participant while performing a dance exercise. Relative to the z-axis, which represents the back-and-forth movement of Básico 1 in the sagittal/longitudinal plane. Red dots show peaks detected using RiMoDe v1.

**Narrative.** The student should have the same rhythm in all axes, a constant rhythm during the entire song and a higher standard deviation in the accelerometer data. After explaining the student’s own data to them, suggestions are given on how to achieve a better performance (Table 7.1, row 4).

**Social comparison.** The comparison used for body motion is a visualisation comparing the student’s data with the teacher’s data. The chart presents the accelerometer information of the student’s best attempt and the teacher’s best attempt, Figure 7.3.

### 7.1.3 Data representation evaluation by the participants

A summary of the students’ usage of the Forró Trainer app and the data used to create the data representations is presented in Table 7.6. Interesting information can be obtained from this table, for example, Student 1 was second in the number of times of they practised, a total of 64 times, but they had a low average score (93.76); Student 7 was the most engaged using the app, a total of 98 sessions, with the highest maximum score; and all students achieved a high consistency score at least once (see Max column). In columns 5–7, students’ patterns can be identified regarding them being faster or slower than the song. Columns 8–11 show statistical information regarding the consistency score of students while practising the song ‘Nosso Xote’(slow pace).
Figure 7.3: The chart presents the accelerometer information comparing the student’s best attempt and the teacher’s best attempt relative to the z-axis. The teacher pattern has evenly distributed peaks detected, while the student had one problem around 40s. The student’s ‘crispy’ wave is due to smartphone hardware differences.

This information is important because it demonstrates that students had different score results to each other.

Participants evaluated each of the data representations using a 5-Likert scale questionnaire regarding the clarity and usefulness of representation. A questionnaire that evaluated multimodal feedback for traditional education assessments (Phillips et al., 2016) was used as a reference to create the questions. More details of the protocol are described in Section 3.3 and Appendix, Section A.2. Table 7.7 depicts the results of the quantitative part of the students’ responses. Average columns are colour-coded from red (minimum average value) to dark green (maximum value). The standard deviation cells are coloured the opposite, from dark green (minimum standard deviation value) to red (maximum value). Dark green average (avg) cells depict higher participants’ agreement. If the standard deviation (std) cell is also a dark green colour for
Table 7.6: Summary of students’ sessions

<table>
<thead>
<tr>
<th>Student ID</th>
<th># of Sessions at Básico 1 exercise</th>
<th>Rhythm at Básico 1</th>
<th>Consistency at Básico 1, song ‘Nosso Xote’</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slow Paced</td>
<td>Medium Paced</td>
<td>Fast Paced</td>
</tr>
<tr>
<td>Student 1</td>
<td>43</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>Student 2*</td>
<td>5</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Student 3</td>
<td>8</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>Student 4</td>
<td>12</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Student 5</td>
<td>14</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>Student 6</td>
<td>11</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>Student 7</td>
<td>39</td>
<td>14</td>
<td>45</td>
</tr>
<tr>
<td>Student 8</td>
<td>15</td>
<td>13</td>
<td>7</td>
</tr>
<tr>
<td>Student 9</td>
<td>16</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Student 10**</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

Columns 2-4: Number of times practise in each level, 5-7: Detail of wrong attempts compared to the song, 8-11: Statistics on the consistency score

* Did the exercises without attending to the classes ** Withdrew from the study

Table 7.7: Results from the 5-Likert scale for the participants’ interviews, showing the average and standard deviation for each group of questions.

<table>
<thead>
<tr>
<th>Summary</th>
<th>Visualisation</th>
<th>Narrative</th>
<th>Social Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clarity</td>
<td>Usefulness</td>
<td>Clarity</td>
<td>Usefulness</td>
</tr>
<tr>
<td>Practice</td>
<td></td>
<td>Avg</td>
<td>Std</td>
</tr>
<tr>
<td>Rhythm BPM</td>
<td></td>
<td>4.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Rhythm Consistency</td>
<td>3.7</td>
<td>1.3</td>
<td>3.4</td>
</tr>
<tr>
<td>Body Motion</td>
<td></td>
<td>4.3</td>
<td>0.9</td>
</tr>
<tr>
<td>Consistency</td>
<td></td>
<td>3.9</td>
<td>1.1</td>
</tr>
<tr>
<td>Clarity</td>
<td>Usefulness</td>
<td>Clarity</td>
<td>Usefulness</td>
</tr>
<tr>
<td>Practice</td>
<td></td>
<td>4.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Rhythm BPM</td>
<td></td>
<td>4.2</td>
<td>1.0</td>
</tr>
<tr>
<td>Rhythm Consistency</td>
<td>3.3</td>
<td>1.1</td>
<td>3.7</td>
</tr>
<tr>
<td>Body Motion</td>
<td></td>
<td>3.1</td>
<td>1.4</td>
</tr>
</tbody>
</table>

the same line/column, then that average point has a low variance, demonstrating more relevance for the combination (avg and std). Based on the results shown in Table 7.7, we can observe that personalised narrative feedback was the most preferred data representation, with the highest point of clarity and usefulness, especially when representing information about rhythm consistency and rhythm BPM (column 5, rows 3, 4, 5 and 6). Body motion was the type information with more opportunity for improving data representation and further exploration because students could not understand the data (rows 7 and 8). The visualisation of consistency and rhythm BPM also opened an interesting opportunity because students could not understand the visualisations provided (column 4, rows 3, 4, 5 and 6). Therefore, different visualisations could be better understood by the students.
CHAPTER 7. PROVIDING AUTOMATED FEEDBACK AND ASSESSMENT

The visualisation results are strongly influenced by the type of visualisations chosen to represent the information. Charts with bar, line and boxplot elements were used. This suggests that visualisations must be tailored for particular information to increase the potential usefulness of these data for dance students.

During the interview, some students commented that they would like to see the visualisations together with the personalised narrative feedback, so they could learn how to interpret the visualisation and later rely just on the visualisations. Student 2 said,

I would like to put a chart or graph related to this feedback, and then I can learn about this feedback, and then I can diagnose the chart after seeing this. After learning about the chart [together with the narrative feedback], I can see the chart and know what it means.

For the summary, students suggested colour coding the cells of the table to highlights the good/bad data. Student 4 said, “If it has some kind of colours and visual clues on the tables, it would be good for me”. The summary comparing the performances of the students was appreciated by high-performance students and disliked by low-performance students, even though low-performance students reported being motivated to improve. Student 5 mentioned, “I really want to do more [exercises], so I can beat everyone else. I really want to work hard now”, while Student 1 mentioned, “It does not improve my confidence, because everyone is better than me” and Student 5 commented “This makes me feel really good, I didn’t practice as much as other students but my average is quite high”.

For body motion information, some students suggested using a drawing of a human body to present information about the x/y/z axes, suggesting that this would make the data representation clearer. For instance, Student 1 was confused, “Which is the most important information here?”. Student 9 suggested, “It would be good to explain in terms of your body, like forwards, backwards, left and right instead of xyz” and Student 7 commented, “If you want people to understand it, it would be better to have a diagram, xyz”. For visualisations and summaries, all students reported the need to have a baseline metric, where they could compare their data with the expected or expert data. Student 4 asked, “The consistency is low compared to what?”. 
They also would like to have a place to define their goals. Student 1 mentioned, “If you have a kind of threshold for goal settings” and Student 4 commented, “I can set different targets and different goals in the number of exercises”.

The results presented in this section show that RiMoDe v1 is able to extract simple yet useful features using motion sensors, such as practice, rhythm and consistency. Features such as body motion must be better communicated. The results are limited to the environment in which the study was carried out. In a live scenario, with students from a dance school, the feedback must be adapted to their vocabulary and must consider the students’ motivation to learn as these are different from a controlled experiment. The results also demonstrated that students could interpret only some of the data and relate them to actions that would improve their learning. With this in mind, it was important to take some steps back and understand how the data collected could be better represented. The focus of the next study was to investigate how teachers could make sense and make use of the information extracted from motion sensors, to help students better understand the data and suggest potential strategies to improve their skills.

7.2 Investigating Automatic Assessment with Dance Teachers

This section reports on the results from Study 4, described in Section 3.5. The study used videos as a way for teachers to experience the automatic assessment of dance students’ performance. The automatic assessment contained the skill set proposed from Study 3, i.e. rhythm, pause, weight transfer and step size. From the data obtained from interviews with teachers, the next sections address the following RQs:

- RQ3.3 How do teachers benefit from automatic assessment when assessing students’ video performance?

- RQ3.4 How would teachers use the automatic assessment in their context as dance teachers?

Semi-structured interviews were conducted with eight teachers with the objective to collect their perceptions when using the rhythmic automatic assessment. The interviews were composed of four steps: assessment of five videos, assessment of five
videos with the automatic assessment, discussion about the automatic assessment with the videos and discussion about the automatic assessment in the context of the teachers’ dance teaching. Each interview took an average of 1 hour and 53 minutes (±27 minutes). Some teachers explicitly demonstrated their excitement in participating in the interview as they saw it as an opportunity to reflect on their dance teaching practices (T6, T8 and T15). T8 said, “Really? Is it over? It was so much fun, I want to do it again!”, and T6 mentioned, “Every time I talk [to you] I feel like I’m expanding [my knowledge] and I’m convinced that what I’m saying makes sense”.

7.2.1 How do teachers benefit from automatic assessment when assessing students’ video performance?

Teachers followed different strategies to assess the students’ performance using videos. Some of them would first watch the entire video before giving their answers. Others would assess the student while the video was being played, sometimes pausing the video to add a comment. Depending on the student’s problems, their stage of development or the teachers’ strategy, teachers would differentiate the information they would use to diagnose and the information they would give to the student as feedback. In most cases, the diagnoses contained more detailed information about the student’s performance than the feedback. The feedback would only contain information relevant to the student’s current stage of development. This occurred especially for students who were in the early stage of development. In cases where the student was more advanced, the teachers would be transparent and the feedback to the student would be the same as the teacher’s diagnosis.

Teachers mentioned that some aspects of the students’ performance could not be assessed because they were dancing alone (T7) and because they were performing only the Básico step (T6). Another teacher mentioned that it was their first time assessing students with videos, in comparison to assessing their own students in the classroom (T18). T19 mentioned the feeling that their assessment skills were being tested and that assessing a video is different from assessing a student in the classroom as the angle of the video allows the teacher to see the entire body of the student and better perceive their body coordination, and it also allows them to pause, rewind and replay the video.

In most cases, teachers reported that the student’s performance was easy to assess. Teachers said the performance was harder to assess in some videos because of the
following reasons: 1) the student was in the very early stage of learning and there was nothing to say besides “go to the class” (T6, video 10), or 2) it was hard to find something wrong with the student’s performance (T15, video 3), or 3) the teacher could not precisely distinguish whether the student had rhythm or coordination problems (T19, video 5).

Regarding the automatic assessment results, teachers mentioned that these helped as a confirmation/comparison of what they had already perceived (T6, T7 and T15) or as a pre-assessment that helped them imagine what the student’s performance would be like (T8 and T15). Teachers found the automatic assessment very accurate, reporting that the automatic assessment was 70%–80% accurate (T18) or had only 1–3 errors out of 20 items assessed (T7, T8, T15 and T19). Teachers reported that they would increase their trust in the automatic assessment if they were more experienced and had more exposure to it (T6, T8 and T19) or if the system was trained solely with their own data (T7). T7 participated in all the studies of this thesis and demonstrated a deep understanding of how the technology worked - models are trained with annotated data.

In summary, the use of technology was new for the teachers. The first benefit that the teachers perceived was that the automated assessment created a structured way to assess their students. Similar to what was reported in Study 1 (Section 4.1.2), most teachers did not use any tools to support their teaching practice. Also, it was shown that teachers required more time to understand the automatic assessment and how to obtain benefits from it. T7 wanted to tailor the automated assessment to his needs and his own judgement of right and wrong. Even though the teachers had limited experience with the use of technology, they did have some ideas on how automatic assessment could be used in their context as dance teacher. Additional statistical information regarding the teachers’ assessment can be found in the Appendix, Section B.1.

### 7.2.2 Hypothetical scenarios for using automatic assessment

Teachers were asked to imagine scenarios in which they could see the benefit of using the automatic assessment, in their context, to assess their own students. The scenarios that teachers imagined can be divided into the following groups: **time**: use it before, after or during classes; **scale**: for private, small or large classes; **proximity**: regular, workshop or distance students; and **access**: to teachers, students or the school. Most teachers referred to more than one of these four aspects when imagining the scenarios.
All teachers reacted positively to thinking about how an automated assessment could improve their teaching practices.

**Time – when to use the assessment.** Before the class, students could practice with the automatic assessment to improve their skills (T6) and, based on the assessment results, be more aware on which skills they needed to focus when taking the class (T15). Some teachers said they would use an assessment tool during the classes to let students practise by themselves while they gave individual feedback to other students (T15 and T19). The main benefit that teachers imagined was to allow students to practise as homework and receive automated results (T6, T7, T8 and T15). T15 and T8 mentioned the need to allow students to view the teacher’s feedback when practising by themselves so they could recall the teacher’s recommendation as the automated assessment would not suffice to provide a clear message. For the teachers, the assessment information could also be used to assess the effectiveness of the class plan (T15 and T19) and the students’ overall performance and difficulties encountered (T15). T15 commented, “This [automated assessment] turns out to be a feedback to the teacher on what he is teaching effectively or not. It is a guide to what students are absorbing”.

**Scale of the class.** Teachers were unanimous in saying that large cohorts were the scenario in which the automatic assessment would be the most useful. The automatic assessment could guide and speed up the students’ assessment by the teachers, and students would have access to a pre-assessment before talking with the teacher (T6, T8, T15 and T19). Accessing aggregated information of students was mentioned by teachers (T19), which could be used also to assess students from private classes (T15).

**Proximity to the students.** Teachers reported that they were more interested in using the automatic assessment for regular students as they would be continuously working with them and would be able to work on the feedback for these students (T6, T15 and T19). Some teachers mentioned that, for workshop students who they usually do not know, the automatic assessment could help allocate the students to the most appropriate workshop level, matching the students’ assessment and the workshop’s level of difficulty (T8 and T15).

**Access to information.** Students, teachers and the schools could benefit from accessing the automatic assessment information. For the students, teachers reported that this information would allow students to recall their progress, recognise this evolution and be more aware of their dance learning (T6, T7, T8 and T15). Additionally, students would be more independent and more motivated to undertake their learning.
as they would spend more time engaged with the learning content (T6 and T15). In the same way that the teachers filtered their feedback to students, giving limited and precise information when compared to their complete and holistic diagnosis, teachers mentioned that the automatic assessment could also be filtered based on the needs of the students or their stage of development (T15). T6 wondered how this new tool would change the relationship between teachers and students. From T6’s perspective, the automatic assessment could bring teachers and students closer to each other, as this resource shows the interest of the teacher in the student’s development. Additional studies are required to assess how the automatic assessment would change the relationship between teachers and students and other aspects of the dance learning. T7 also mentioned the automatic assessment information could be used for student competition or comparison with other students from the same class or other places, increase the interaction among students, and thus creating a social network where the students would not feel alone when practising.

For teachers, the automatic assessment information could help them to improve the assessment of the students’ evolution (T6 and T15), be more efficient (T6 and T8) and plan and evaluate the teachers’ work (T7, T8 and T15). Teachers also mentioned that this tool could allow teachers pre-assess beginner students and help decide on their class levels (T7 and T19).

For the school, the automatic assessment could be a resource to assess the students’ progress, the overall development of the class, the teachers’ performances and the efficiency of teaching methodologies. Some teachers mentioned that it could help to train and support teachers at the beginning of their teaching career or help teachers that have difficulty assessing students’ development (T6 and T15).

Study 4 explored the perceived accuracy and potential uses of the automatic assessment by teachers. The automatic assessment provided an additional layer of information for teachers to guide and compare their assessments. Teachers also reported several ways in which the automatic assessment could be used both inside and outside dance classes. The features proposed in this thesis, via RiMoDe algorithms, proved to be valid, when evaluated against ML algorithms, and useful when used to provide automated assessment for dance teachers.
7.3 Video Annotation Tool to Support Dance Teaching

This section presents additional material that helps to understand how social partner dance teachers perceive the use of technology to support their teaching activities. As part of Study 3, teachers were introduced to the video annotation tool through a semi-structured interview session while they were using the tool (see Section 3.4 for methodology details). During this phase, teachers were able to negotiate with the researcher the terms to be used in the video annotation as well as improvements to the interface. At the end of the study, after having annotated 40 videos each teacher, they were invited to discuss their experience with using the video annotation tool in a follow-up interview. This study contributes to address RQ3 by answering the following research question:

- RQ3.2 - How do teachers perceive the use of technology to support their dance teaching?

7.3.1 Interview Using the Video Annotation Tool

The interview served as a co-design opportunity for the teachers. In terms of the interface, teachers did not add any suggestions. What was suggested to include a button that could save all annotations simultaneously and to include a page that contained a list of all videos, highlighting those that had already been annotated. As presented in Section 6.2, the main changes were regarding the terms/concepts used to define the features to be annotated. For example, for rhythm and synchrony, these items were reduced to just rhythm, as teachers considered synchrony to be the same as rhythm. For the case of time between movement and weight transfer, the last term was preferred among teachers as its meaning was clearer and it represented both concepts.

There was no consensus among teachers on the order that they would perform the annotations. Some preferred to annotate while the video was playing for the first time, others opted to watch the video once and then annotate on the second viewing. For complicated cases, they would watch the video several times before making a decision. They also mentioned that annotations would not match exactly the moment where the movement happened in the video, and that there was a delay.
7.3.2 Follow-up Semi-structured interview

For all teachers, it was the first time that they had used an online tool to assess students. As T2 reported, “I have never imagined myself doing an assessment online”. The four teachers were positive about using this type of tool as an additional form of communication with their students, especially owing to the lack of time in the classroom and for those students who were shy or had problems in receiving feedback face-to-face. For example, T1 said, “With this tool I would be able to reach out students that sometimes don’t come to ask feedback during the classes because they are too shy or not yet familiar with the teachers”.

An important observation was that teachers expressed that they would like to adapt the tool to the vocabulary they used in their classes or school. Because it was a video, they enjoyed the flexibility of playing, pausing, rewinding and going forward as they wished, in contrast with a face-to-face assessment where they needed to rely on their memory. T1 said, “When doing the assessment using the tool you have much more peace of mind to stop the video and reflect on what is really wrong with the student”. The online aspect of the tool made teachers think of possibilities for assessing students from other cities or countries or even implementing an online learning system, as well as using this method as an extra service for their classroom students. T1 said, “It would be good to include this online assessment as an additional role for the teacher or add it as an extra service for the students”. T3 commented,

With this tool I would be able to assess other people, people who may even know my work but do not live near or cannot take my classes at that time, or outsiders. A different mode, like an online class, but it will not be the lesson but the assessment itself.

The main findings of this last phase of the study were the insights that teachers reported because of their experience with the video annotation tool. Teachers reported that the use of the tool reinforced their belief that students’ mistakes are related. For instance, a student may not be on the rhythm because they are not transferring their weight properly, which might be influenced by their step size (T2). Additionally, some mistakes might be related to the current stage of learning (T1). For instance, if the video was recorded before the class, students’ mistakes might be linked to the fact that they forgot the concepts of the previous class (knowledge still in process), whereas if the video
was taken after the class, the mistake might be linked to consolidated knowledge. T1 said,

There are videos in which the student has a fixed behaviour, for example, it is slower [than the music] during the whole video. This is a student who, independently from having learned the right skill or not, it shows knowledge that s/he has, it is solid.

Additionally, all teachers mentioned that it was relaxing to give feedback online, as opposed to face-to-face because they did not have the pressure of having to provide spontaneous feedback. For example, T1 said: "If you are the teacher in front of the student, you have the pressure of giving the feedback on the fly. If you have more time, the feedback would be more precise”.

An important insight from T2 was the possibility of using the tool as a teacher training system. This could be used for new teachers and tutors so they can learn how to assess students, recognise which themes are more important to pay attention to and learn the vocabulary used by the school. Among experienced teachers, the tool could be used to agree on terms and concepts, refresh their knowledge and compare their results with other teachers to gain new perspectives or enhance their perceptions (T2). T1 also said,

This can be an important tool for examiner training, people who are learning to do this can see the possible mistakes and learn how to identify them. It would allow novices to reflect calmly, and slowly learn to identify the mistakes more quickly. The tool is powerful for this.

Although it was not the main focus of this study, we evaluated teachers’ perceptions regarding the usability of the tool. Teachers required a few interactions with the researcher and the guides to be confident in undertaking the work by themselves. After the learning period, they felt confident and reported that it was easy to use and the elements such as the big buttons, different colours for each theme, timeline, list of annotations and comment box made the work much faster. Functioning as a double feedback for the teachers, the timeline and the list of annotations made it easy for teachers to know that their actions were captured by the system, identify mistakes and keep track of their work progress. T3 said, “Everything I was tagging was there. In the video itself, below, and in the list”. They disliked when they had to annotate one video
multiple times in the same theme (slower/faster/correct/slower), the list of annotations that were out of the screen limit and the colour of the remove button that was the same as the ‘other mistakes’, and they would like to have other categories of skills including posture and flow.

When asked to compare providing feedback with and without the tool, teachers were in favour of the online tool as it integrated the skill categories and comments with the video. However, T4 mentioned that using another tool, such as a simple spreadsheet, would give them the freedom to express themselves and have different ideas on what to say about the video. The teacher expressed this as follows, “We do not think so out of the box since we have the options [buttons]”. This is an interesting contrast that must be carefully evaluated when designing a video annotation tool, i.e. should the annotations be open or have fixed labels?

In summary, teachers enjoyed having more time to assess and reflect on their feedback, in comparison to face-to-face feedback. Teachers envisage novel pedagogical approaches that could be facilitated by video annotation. Some imagined using this tool for online learning, for sharing knowledge with other teachers and for teacher and examiner training.

There is a trade-off between allowing teachers to use free text to assess dance videos and scaffolding this process by using predefined labels. Although both options were provided, teachers still felt the provision of the buttons guided them towards using the vocabulary provided. Even though this vocabulary was extracted from expert teachers, teachers still considered that they each use a very specific vocabulary within their close community or school. This suggests that it may be desirable to allow teachers to customise the annotation labels using their own vocabulary. Although focusing on a very specific dance style only can be seen as a limitation of our study, it would have been challenging to reach consensus on the tool’s design and usage with teachers from different styles (El Raheb et al., 2018a).

7.4 Chapter Summary

This chapter presented different ways of using technology to support social partner dance students and teachers. The automatic assessment helped students track their
learning progress and obtain insights on which areas of their learning must be improved. Although it was a first attempt on the use of automatic assessment with the students, it provided valuable knowledge to develop or evolve systems that aim to support dance students. In the evaluation of RiMoDe v2, used to enhance the assessment of videos, teachers had very positive experiences with using the information. The automatic assessment of four rhythmic skills (rhythm, pause, step size and weight transfer) helped teachers confirm their beliefs and guide their assessment. To illustrate the potential usefulness of the automated assessment, teachers presented several scenarios where the automatic assessment of rhythmic skills could be used. The use of a video annotation tool by teachers also helped this thesis and future researchers to understand the different aspects of the teachers’ work that could be supported using technology.
Chapter 8

Discussion

The purpose of this thesis was to support the teaching of dance skills related to rhythm, using motion sensors from smartphones. The findings demonstrated that it is indeed possible to extract rhythmic information from smartphone sensors and that the information collected can support students and teachers. However, much care must be taken when using technology to model dance, as an algorithmic approach to assessing dance skills and qualities can be misleading. This chapter discusses the findings of this thesis, the overarching emerging lessons, and how these findings relate to current literature. As there is very little literature on social partner dance teaching, this chapter will expand the discussion by comparing the results to other dance styles and formats and to motor learning literature.

The first section presents a discussion of social partner dance education regarding the dance skills required for students to learn and teachers’ strategies for assessing performance and giving feedback. Section two discusses the technical contributions of this thesis, RiMoDe v1 and v2. In the third section, the theoretical and technical parts of the thesis are contrasted. Section four discusses the use of automatic assessment to support students and teachers. The studies reported in this chapter will be referred to by number, as follows:

- Study 1: Teacher Interviews
- Study 2: Pilot Study with Students
- Study 3: Improving Algorithm and Skill Descriptors
- Study 4: Investigating Automatic Assessment with Dance Teachers
8.1 Social Partner Dance Education: Dance Skills, Assessment and Feedback

In order to automatically assess students using technology, there should be a skill to be assessed. From my experience as a dance facilitator, together with the literature on dance education (Côté-Laurence, 2000; Erkert, 2003; Jarmolow and Selck, 2011; Wright, 2013), rhythm seemed to be an interesting skill to start with. Study 1 confirmed that dance teachers find rhythm an important and difficult skill for Forró students to learn. Teachers also reported several other dance skills that are important for dance learning and their relationship with rhythm. The other dance skills include coordination, balance, weight transfer, spatial awareness, posture, connection and psychological skills. This list of skills was confirmed and enhanced when, in Study 2, the teachers’ comments on student participants’ rhythm assessment were analysed. Some details of the teachers’ assessments were exposed, such as the quality of students’ skills, reported as slow, fast, relaxed, mechanical and jumping.

The list of dance skills reported by the Forró dance teachers is in line with the literature on other social partner dances (Jarmolow and Selck, 2011; Wright, 2013), modern dance (Erkert, 2003), ballet (Côté-Laurence, 2000) and forms of dance education (McCutchen, 2006). This same literature also reports the qualities of these skills. In some cases, the literature gives a different name for the same skill. Rhythm can be framed as tempo (McCutchen, 2006), count (Jarmolow and Selck, 2011) or musicality (Erkert, 2003); Posture can be related to frame (Wright, 2013) and holds (Jarmolow and Selck, 2011). Rhythm was carefully investigated by Côté-Laurence (2000) regarding its role in ballet training. Several parallels can be made with what Forró teachers reported such as rhythm being essential and basic for dance, its relation to musicality, that it is a prerequisite to all other abilities, and that it is difficult for many students.

By investigating rhythm with several Forró dance teachers, this thesis contributes to obtaining a better understanding, especially in the field of social partner dances, on the role of rhythm in dance education and especially how rhythm relates to other dance skills. Different from instruction books (Jarmolow and Selck, 2011; Wright, 2013), the thesis situates the question of rhythm in the authentic context of dance teachers’ practices. The different methods used in this thesis collected not only what teachers
think, but also how effectively they use their knowledge to assess students’ rhythmic skill.

Study 1 also reported the different assessment strategies that teachers use to assess students’ rhythmic skills and how they approach feedback. Teachers mainly assess students by observing and dancing with them and give feedback orally. Study 4 presented more detail on how teachers assess and provide feedback to students. The main finding, compatible with results of Study 1, is the fact that some teachers differentiate diagnosis (what they see) and feedback (what they say). Study 3 also contributes to the understanding of how teachers assess and give feedback. Teachers reported that, in face-to-face assessments, they rely too much on memory and that sometimes they feel pressure when giving face-to-face feedback to students.

The literature on dance and motor learning confirm the assessment strategies of Forró dance teachers when they use observation (Jarmolow and Selck, 2011), kinaesthetic information (Krasnow and Wilmerding, 2018), and exams/tests and the use of technology (Schmidt and Wrisberg, 2008). A difference in the way Forró dance teachers approach assessment is the lack of rubrics, guidelines or grading systems when assessing students common in the literature (McCutchen, 2006; Wright, 1996). Not found in the literature, Forró teachers also reported to assess students outside the classroom in events like parties, festivals and workshops. Regarding feedback, no difference was found between Forró teachers and literature. Compared to the work by Côté-Laurence (2000), Forró teachers use similar strategies to give verbal feedback and demonstrate dance movements.

As Forró is a social partner dance, originating from popular manifestations (Packman, 2012; Loveless, 2010), the significant difference from what was found in the literature is the role that the ‘social’ factor plays in the assessment, feedback and topics that teachers focus on Forró dance classes. Forró teachers pay special attention to students’ enjoyment, even as part of their syllabus topics related to social development and even ensuring that students are first relaxed and confident before teaching dancing skills. This special care is important because social partner dance students have different motivations (Maraz et al., 2015; Jarmolow and Selck, 2011) when compared to students from other dance styles (Nieminen, 1998). Social dancers’ goals are to socialise and enhance their mood while ballet or competitive dancers’ goals include fitness, performance and preparing for a career. Although different dance styles have distinct characteristics, students still need to learn the basics (such as rhythm) to be
able to enjoy dancing. This discussion helps to position the rhythm question within the literature and to show the relevance of the topic. The technology developed in this thesis can also be useful for other social partner dance styles, other dance styles as well as motor learning fields related to rhythm.

8.2 Feature Evaluation and Machine Learning Model Accuracy

The technical contributions of this thesis, the algorithms of RiMoDe v1 and v2, have been tested with machine learning methods in Study 2 and 3, respectively. In Study 2, the accuracy of RiMoDe v1 was high for first-round implementation. The motion features extracted modelled the teachers’ rhythmic assessments with an F1 score of 0.79 for the All Cases set and 0.87 for the Unanimous Cases set. It was a great result, particularly considering that teachers disagreed on several cases. As a comparison, using the strategy proposed in previous research (Lee et al., 2007; Kuhn et al., 2011; Jap, 2019), which considering of the use of Fast Fourier Transform to model rhythmic movements from accelerometer data, gives an F1 Score of 0.45 when modelling the All Cases set and an F1 Score of 0.62 when modelling the Unanimous Cases, using a k-nearest neighbours algorithm.

Study 3 expanded the evaluation by using additional RiMoDe v2 features, statistical motion features used in previous studies and by testing several machine learning models. The results showed that RiMoDe features were relevant when modelling Rhythm, Pause and Weight Transfer skills, but not for Step Size skill. The best machine learning models for each skill had the following F1 score: Rhythm (0.741), Pause (0.744), Step Size (0.789) and Weight Transfer (0.629). However, McNemar’s test shows that the Rhythm model was most effective in reducing the model’s error when compared with the Baseline model.

We need to take caution when comparing these values with the literature. First, few of the studies from the literature produced results related to the modelling of rhythm. Second, the sensors they used to capture the motion are different; the methods for data annotation are different, and the activities modelled also differ. This thesis used smartphone motion sensors to collect motion data, as well as multiple teachers to annotate
the data, and different activities or movements were not modelled but rather the different skills required to perform one movement. It is important to keep these differences in mind when interpreting the discussion.

The first research to propose an algorithmic solution to model rhythm using motion sensors, although important in advancing the field, did not validate their results (Lee et al., 2007), which makes it difficult to compare with the results of this thesis. Also using Fast Fourier Transform to model the motion rhythm, Kuhn et al. (2011) obtained 0.89 accuracy when discriminating dance from other activities (walking, toe-tapping and standing) in a four-class classification problem. They used smartphone motion sensors and annotated the data based on the experimental protocol they asked participants to follow. Participants were asked first to dance, then toe-tap and finally walk, with 12 minutes allocated for each activity. A novelty of this thesis, compared to the previously cited work, was to use not only the song’s tempo to compare with motion features but to use song features as a reference to extract motion features. The strong beats of the song were used to segment the motion data and to compare with the peaks detected.

Recent studies have already used the ideas of this thesis to develop their work in an attempt to model dance in different ways. Faridee et al. (2018) used multiple motion sensors to model different dance steps of a classical Indian dance style obtaining, in the best model, accuracy of 94.20%. The researchers themselves annotated the data using videos recorded from participants and deep learning algorithms. In an attempt to model Salsa dance, Senecal et al. (2018) used Motion Capture (MoCap) to classify the level of expertise of dancers in six dance qualities. Collecting a large dataset, with 260 sessions (26 different couples × 10 songs), the researchers proposed a number of statistical features to model the dance qualities, using the song as a reference to extract the features. They called these sets of features Music-related Motion Features (MMF). Although the researchers did not use statistical or machine learning methods to validate their features, they claimed to have success using four out of eight of the proposed features. In both previous works, the authors reported encountering problems when using multiple sensors and data sources. In this thesis, the use of motion sensors and sound from smartphones made it easy to synchronise the data by using the smartphones’ internal clocks as a reference.

This thesis also presented important methodological improvements when compared to previous research on human motion analysis (Lee et al., 2007; Kuhn et al.,
CHAPTER 8. DISCUSSION

2011; Faridee et al., 2018; Senecal et al., 2018): 1) The studies defined one specific movement to be modelled. This is compatible with the dance teachers’ teaching strategies and allowed for the establishment of a more accurate model of rhythmic skills. Distilling the dance movement across several skills allowed teachers and students to better understand the information and potentially improve the students’ learning. 2) The use of external dance teachers to annotate the data helped to prevent biases that may have resulted from having the researchers annotate the data. Additionally, in Study 2, Study 3 and Study 4, teachers did not know the students in the videos, which reduced possible bias in their assessments. Transparency and bias in machine learning models are important topics to be addressed when automating human tasks.

8.2.1 Biases, Transparency and HCI in Machine Learning

This section presents a discussion on some of the challenges of using machine learning when attempting to automatise human processes.

Bias. Teachers had several disagreements regarding the videos’ assessments for Study 2 and Study 3. The results of such studies show that dance teachers had different interpretations of whether the students were in the correct rhythm or not, the importance of each skill and on how to classify the song’s tempo. For instance, teachers’ inter-rater agreement on students’ performance varied from 0.47 (Kappa) to 0.75; when assessing students, the use of terms related to synchrony with the song varied among teachers from 13% to 53%; T5 found it easy to identify the song’s tempo, while other teachers related the song’s difficulty to its tempo. These different interpretations may be biased by teachers’ expectations, culture and experiences. Teachers’ biases may influence systems that use the teacher’s opinions to train models of dance movements, skills and qualities. There is a growing body of research seeking to understand and prevent biases in machine learning (ML) and artificial intelligence (AI) (Kleinberg et al., 2016; Angwin et al., 2016; Gajane and Pechenizkiy, 2017). Systems can potentially discriminate people based on age, gender, race and socioeconomic status. This thesis minimises such problems by evenly recruiting teacher annotators across gender and geography. Also, student participants had equal opportunities to participate in the data collection, disregarding age, gender and race.
Transparency. In this thesis, the creation of features from the motion sensor data and from the songs was a manual process. It was a design-based decision to generate features that are connected with the context (the song – eight-beat cycle and the Básico movement – six movements) instead of using statistical features as in most of the other research that uses motion sensors. This strategy follows recent research that advocates the creation of ML and AI algorithms that can be explained and interpreted (Doshi-Velez and Kim, 2017; Miller, 2018). For instance, deep learning algorithms are becoming increasingly popular for their superior performance when compared to traditional algorithms, but they can create a black box that prevents users from understanding how the system made decisions (Marcus, 2018). As in this thesis, the features were created manually and, by using contextual information, the system allows users to understand which characteristics of the motion data are connected to the students’ rhythmic skills.

HCI. The involvement of teachers throughout the entire project represented an invaluable contribution to the project. Besides compensating for the bias of my role as dance facilitator in this research, the variety of opinions and experience drawn upon allowed this research to step inside different classrooms. The technology becomes more connected with real-world experiences and more authentic those who are the final object of this research. The analysis of the interviews with teachers in Study 3 and Study 4 demonstrated that teachers drew several benefits from using technology to support their practice and students’ learning. The approach of using HCI methodologies to enrich ML development has been supported by several authors (Gillies et al., 2016; Smith et al., 2018; Yang et al., 2018b,a) At the same time, teachers become more connected with the research community and with the myriad of new possibilities to conduct their work. As reported by other researchers (Cober et al., 2015; Könings et al., 2014; Matuk et al., 2016), through research, teachers are able to reflect on the way they currently work, reinforcing their ideas or improving them. In this thesis, the tools and methodologies used as part of the research data collection could also be useful for practitioners to improve their teaching strategies.
8.3 Understanding the Gap between Dance Teachers and Algorithmic Assessment

Study 2 revealed that an algorithmic approach to measuring and assessing rhythm in dance, despite having quantitative results with high accuracy, can be misleading in making visible important aspects of rhythmic assessment when qualitatively compared with how dance teachers approach the same problem. It is important to highlight the differences between technology and dance teachers and, most importantly, acknowledge these differences when attempting to incorporate these technologies in-the-wild. The target users of the RiMoDe algorithmic solution are the teachers and students; hence, they need to understand what the numbers or decisions made by the system mean according to their context.

The six themes identified from teachers’ comments when assessing rhythmic performance, Table 6.3, can serve as a basis for future work focused on developing automated assessment and feedback systems for dance education. Below is a discussion, for each theme, of the teachers’ perspectives, how they can be understood in the literature, the current solution offered by RiMoDe, and other possible technological approaches to modeling the skills of each theme.

8.3.1 Synchronicity

This is the main skill of interest in this thesis and it has been widely explored throughout the thesis’ chapters. Regarding the Forró dance teachers that participated in Study 2, they were concerned with whether the students’ rhythm was correct (e.g. it matches the tempo of the song), for how long they stayed in the correct rhythm during the exercise, if a student is faster or slower than expected, or if pauses are performed properly. Some of these elements are specific to certain styles of partner dance (Wright, 2013) (like the pause in the fourth beat of the bar for Forró), but being able to dance to the proper tempo of the song is required for all dance styles (Côté-Laurence, 2000; Erkert, 2003; McCutchen, 2006).

On the technological side, as presented in Chapter 6, the accelerometer-based algorithms did quite well in detecting several rhythmic skills of the dancers, using the wave’s peaks and valleys and matching this data with the song. The major difference
between the dance teachers and technology in this theme was precision, and the corresponding degree of flexibility in interpreting movement as 'being in rhythm'. As it was seen from the variation in the teachers’ assessments of rhythm, Section 6.1.3.1, they were able to assess individual students with varying degrees of tolerance, depending on their personal levels of strictness and what factors they were taking into account, including the skill level of the student and the difficulty of the song. RiMoDe v2 showed that it is possible for accelerometer-driven algorithmic solutions to measure and predict more complex features of the rhythmic pattern of movement as the teachers do. However, there is still a need to provide user interfaces with user-controlled parameters to vary tolerances for assessing the 'correct' rhythm. For experienced dancers, the character or personality of their dancing may be expressed through playing with the rhythm, which involves deviating from the strict rhythm or tempo of the music. This poses additional challenges to algorithmic approaches. The use of Music Information Retrieval algorithms (Lartillot and Toiviainen, 2007; Böck et al., 2016) could expand the song’s features available for training models to identify such subtleties in the dancers’ performances.

8.3.2 Weight Transfer/Step

This was the second most common theme among the dance teachers’ comments. It refers to the motor action of the Básico 1 step, which is to properly transfer the weight from one leg to the other and to move the body together with the weight transfer. The dance teachers observed how much weight the student transfers from one leg to the other while going forward or backwards. In parts of the movement, there must be a total transfer of the weight and, in other parts, it must be partial. The teachers noticed that most of the students’ problems resided in not transferring the weight when they should. They also commented that the length of the students’ steps influences how correct the movement is. In dance as a whole, transferring weight occurs using many other parts of the body. It requires higher-order body control, coordination and balance (McCutchen, 2006). In some dance styles, the control of weight goes beyond using the ground, as dancers fight gravity with jumps in the air (Erkert, 2003). The accelerometer can also measure the transfer of weight but to a certain limit, as shown in Section 6.3. The approach using just one three-axis accelerometer positioned on the hip area can only detect the movements of the hips and infer some weight transfer information. On the
other hand, dance teachers can judge many parts of the body at the same time, having a more robust assessment answer to the students’ performance. There is an opportunity to increase the precision and the range of movement being detected by having multiple accelerometer sensors (Hinton-Lewis et al., 2016) and/or using other sensors like gyroscopes and pressure sensors (Aylward and Paradiso, 2006). Although, adding more sensors increases the complexity of development, modelling and deployment (Senecal et al., 2018; Piana et al., 2016), as well as decrease comfort and accessibility.

8.3.3 Limbs/Joints

As the students’ progress and improve their rhythmic ability, the teachers start refining their assessment of the students’ movements using more detailed information, to diagnose and solve a student’s problems. As the main part of the Básico 1 movement occurs in the lower part of the body, teachers are more concerned about the toes, feet, ankles, legs, knees and hips. However, the upper body limbs and joints also play a role in the way dancers contact the ground or lift from the ground. The relation between limbs is also important for teachers. When the left leg goes forward, in which direction is the student moving their right arm, if any? In dance, other parts of the body, like muscles, tendons and lungs, are put together in subjects of anatomy, kinesiology, body conditioning, strength and cardiorespiratory (McCutch en, 2006; Erkert, 2003). RiMoDe is not able to detect limb or joint movement in this current version, as it is designed to be worn inside the student’s trouser pockets. Smartwatches are an easy and scalable option that can be incorporated into the RiMoDe algorithm. The arms’ motion data could identify if students have their movements synchronised with the music, their own body and their partner (Senecal et al., 2018). Increasing the number and type of sensors that may be used to model dancing features can contribute to detecting the elements of this theme. For example, it could be possible to include sensors to measure muscular activity, heartbeat, skin conductance and breathing (Françoise et al., 2014). As mentioned before, there is a trade-off between the number of different sensors providing multidimensional data and the wearability and ease of use for the student.
8.3.4 Quality of the Movements

The depth of analysis by the teachers can go further and become quite subjective. In Table 6.4, half of the teachers used terms referring to quality (17% when compared to all themes) while the others mentioned very little (1%) or nothing regarding quality. Teachers want students’ movements to be natural, relaxed and fluid, not mechanical or rigid. Some of the keywords in this theme refer to aspects linked to emotion and energy states, like relaxation and release. Particularly for Forró dance, the teachers do not want students to dance with too much vertical change, or jumping. In the dance literature, this theme involves terms like aesthetics, tone, timbre and energy (McCutchen, 2006), which are widely used in contemporary dance (Erkert, 2003). In social partner dance, terms like swing and sway (Jarmolow and Selck, 2011) refer to dancers’ styling. The RiMoDe algorithmic approach allows for the use of gyroscopes to detect, for example, excess hip movement in Forró dancers. In this theme, the addition of more sensors will not add much information. What is more relevant here is to model the expert’s movement and generate the expected data to be matched with the student’s data. A common approach to computationally measuring the quality of movement is the use of Laban Movement Analysis (LMA) (Larboulette and Gibet, 2015). LMA is a method to describe human movement using categories that express body, effort, shape and space. For instance, using accelerometers, researchers were able to classify aspects of effort such as space, time, weight and flow (Guest, 2014). In another study, Kikhia et al. (2014) described which parts of the body are most suitable to place accelerometer sensors in order to identify different body movements as understood by the Laban Effort Framework. They achieved an average accuracy of 81% in detecting the movement, but also acknowledged that experts may have a different opinion on the movements detected.

8.3.5 Posture

This theme has some similarities with the Limbs/Joints theme, but here the teachers were concerned with the overall picture of how the student is using the body. Most of the time, when teachers refer to posture, they mean that the student must keep an upright posture with head, trunk and thighs aligned, chest forward and open, normal back curve and abdomen flat. This is particularly important in partner dance where usually the couple is dancing in an erect position (Wright, 2013), but other forms of
dance may require the body to acquire other shapes than upright. This thesis’ approach of using the accelerometer on the hips could largely detect unbalanced posture using gyroscope data. Even though in one study (Hinton-Lewis et al., 2016) the authors used accelerometer data to detect the correct postures of ballet students, current fabric technology and bending sensors (Iituka et al., 2015) may provide for a more accurate way to measure the dancer’s required posture. The use of pose detection algorithms in videos also offers great potential in the detection of posture problems in dance students (Cao et al., 2017, 2018). One of the challenges with partner dance is the mutual posture of the dancing couple. Any technical solutions will also need to take into account the interrelationship between individual postures.

### 8.3.6 Gaze

Last but not least, gaze in the teachers’ comments of this study was specific to the case when a student looks down to follow what their feet and legs are doing, ruining their posture. In partner dance, gaze may also refer to the subtle connection that must exist between partners while they are performing (Wright, 2013). In other dance styles, this may refer to the connection with the audience and a way to emphasise expression and emotions (McCutchen, 2006; Erkert, 2003). The use of accelerometers, as used in RiMoDe, offers little ability to track gaze. In this case, head tracking with tilt sensors could provide some information on inferred gaze direction. One study used eye-tracking to observe ballet dancers’ gait abilities (Panchuk and Vickers, 2011). Eye gaze tracking or facial recognition could provide additional detailed information on the use of gaze by social partner dancers.

This section used the six themes, defined as parts of Study 2, to explore the literature on how other dance styles use and refer to these topics, and different technological approaches could be used to support the teaching and learning of these topics. It is important to observe that every technology will have advantages and disadvantages when compared to each other. It is also important to understand the dance context and involve dance experts in the process of developing supporting technologies, so these differences can be evaluated and expressed by such systems.
8.4 Making Sense of Motion Data

This thesis explored the used of motion data, modelled using RiMoDe, to support students in tracking their learning and teachers in assessing students’ rhythmic skills. In Study 2, reported in Section 7.1, students were informed about how they performed while practising individually, using several data representations. In Study 4, reported in Section 7.2, teachers had the support of an automatic assessment to assess students’ video-recorded performance.

The results of Study 2 showed that students could make good use of the data representations using RiMoDe v1’s output. The best results are linked to the use of the RiMoDe’s output using textual information and recommendations on how to improve students’ performances. Students also liked to compare their results with their peers. However, students had difficulty interpreting charts, especially those containing raw accelerometer data. The challenge of using motion data as feedback was also reported in several works (Drobny et al., 2009; Kawakami and Fujinami, 2008; Hadjakos et al., 2008; Matsumura et al., 2011). The use of visualisations was also poorly understood by students’ learning percussion (Matsumura et al., 2011) and piano (Hadjakos et al., 2008). As relating motion sensor data to performance is a complex task, this thesis contributes to the field by reporting that the use of textual information to explain motion data and provide recommendations to students may constitute a better approach to providing feedback. Textual information can be illustrated with the use of charts until students learn how to interpret the visualisations.

For Study 4, four rhythmic skills, modelled using RiMoDe v2, were presented to teachers to support their assessments of student video-recorded performances, according rhythm, pause, weight transfer and step size. The automatic assessment helped teachers to guide their assessment, confirm their assumptions and anticipate students’ performances. The study also reported that teachers could imagine several situations within their current teaching strategies that would benefit from the use of automatic rhythm assessment. The results are novel in the field of dance education, as no researcher has previously attempted to use motion sensing technology to improve dance teachers’ activities. However, technology has been successfully used to improve teaching in other educational scenarios such as tertiary education. For instance, technology is already used for students to practise and receive feedback outside the classroom (Ihantola et al., 2010; McBroom et al., 2016), help teachers to improve their teaching
practices (Sergis and Sampson, 2017), and help teachers to cope with large cohorts (Saunders and Hutt, 2015). It is expected that dance teachers could get similar benefits if the same strategies used to support teachers from tertiary education were combined with motion data from dance students. Study 4 highlighted the fact that teachers would like to use the tools developed in this thesis to train and support beginner teachers, as well to compare and evaluate their teaching methodologies.

More research is needed to explore the use of sensors and motion data to support dance education. This includes research on several parts of the process, including devices, human movement modelling, data representations and use in authentic contexts. This thesis helped to extend knowledge of the field by developing new methods for modelling rhythm from motion data and using the output to support students and teachers. The extensive use of knowledge about Forró dance and the involvement of dance teachers in all phases of this thesis were critical to technology development. However, it is important to acknowledge the limitations of the methodologies and techniques used in this thesis.

8.5 Limitations

In Study 1, the topics covered in the interviews were very broad, which hinders obtaining a better understanding in specific areas, for instance, what rhythm means and what are its different interpretations and related skills. It would have been interesting to include a few additional questions for teachers, such as: What do you mean by rhythm? What other skills are related to rhythm skill acquisition? How do you give feedback to students regarding rhythm skills? What teaching strategies do you use to teach rhythmic skills?

Another limitation of Study 1, like the other studies, is that many of the interviews and other types of inputs from teachers were done in Portuguese. Translating some of the terms may have influenced some of the study’s results. Some terms like rhythm, weight transfer, confidence and feedback have a counterpart with the same literal and semantic meaning. Although, some terms can have subtle differences like posture (mental, physical), assessment, evaluation, diagnosis, rubrics and social development. Additionally, quotes from teachers were amended as most teachers used slang or expressions that carry cultural meaning. I did my best to ensure that all teachers
understood the questions and tasks in the same way. During the coding of interviews, a dialogue with other researchers was carried out to make sure that quotes and terms carried the same meaning as what the teachers expressed.

Unfortunately, for geographical reasons, teachers could not be present to participate in the research. This limited their involvement and the direction of the research. It was only possible for this project to conduct a technical validation of the algorithms and a conceptual evaluation of the dance terminology.

In Study 2, it could be the case that the high accuracy obtained was not because of the rationale of the study, but because the movement was very simple. Study 2 did not compare RiMoDe v1 features with the statistical motion features common in activity recognition literature. Study 3 addressed these problems by also including statistical features in the list of features to be used by classification algorithms (machine learning).

It is important to state, and it was observed by teachers during the studies, that students were being assessed while dancing alone. This was the case for Studies 2, 3 and 4. It is a common strategy found in the social partner dance literature (Wright, 1996; Jarmolow and Selck, 2011; Flippin, 2013; Allen, 2002) and for Forró teachers to ask students to practise individually before partnering up. Although they were performing an exercise used in dance classes, Básico 1, the results given by the technology and the assessment of the teachers could differ if participants were dancing in pairs. Also, the studies were carried out in a laboratory, which might also give different results than in a dance classroom environment.

The RiMoDe features are likely to be extendable for assessing students when dancing together. A few researchers proposed features extracted from motion sensors to compare the movement of two dancers (Camurri et al., 2016a). Also, the rationale used to create RiMoDe features (using information from the context as a reference) can be used to extract features of skills related to the students when dancing with a partner (Senecal et al. (2018)).

8.6 Application to other fields

As discussed in the Chapter 2, other fields of research also use sensors to model human movement and use this information to generate information not available before.
Fields such as martial arts (Corbí and Santos, 2018), musical instruments (Hadjakos et al., 2008), sports (Hassan et al., 2017), handwriting (Amma et al., 2014), cooking (Stein and McKenna, 2013) and virtual reality (Hu et al., 2016). The strategies used in this thesis, to derive motion features using the context information, could also be useful in those field to improve the modelling of human movement. More precisely, the rhythmic features developed in this thesis can be directly used in fields such as sports and musical instruments learning. Rhythm is fundamental for sports motor skills performance (MacPherson et al., 2009).

Aside from the strategies for deriving motion features, this thesis methodology on involving teachers and students from a community of practice could shed light for other researchers on which methodologies and methods to use to derive knowledge from their participants. In particular, the method of using an online video annotation tool, making it easier for teachers to annotate video outside the lab and to expand the data collection. Additionally, the visualisations and feedback of motion data have also not been extensively explored in the current literature, and the proposition made in this thesis can be useful for other fields related to human movement such as the one mentioned before.

8.7 Chapter Summary

This chapter discusses the results of this thesis when compared to the literature. The methodology in this thesis proved to be successful as many of the results were compatible with what is found in the literature. Additionally, the results presented expand the knowledge in several fields according to the following points:

- **Social Partner Dance Theory**: As a social partner dance, Forró teachers focus more on enjoyment than technical skills, and the assessment of their students goes beyond the classroom;

- **Human Movement Analysis**: Model rhythm in human movement using the song’s strong beat as a reference to detect peaks and valleys; validate ML models using dance teachers as annotators;
• Technology Applied to Dance Education: The use of automated rhythmic assessment could allow students to practise alone and receive feedback, as well as allow teachers to evaluate their teaching methodologies.
Chapter 9

Conclusions and Future Directions

This chapter provides a summary of the results from this thesis using the RQs as a starting point. The RQs are presented in the following sections, and outline and discuss the key contributions linked to them. Table 9.1 presents the chapters related to each research question, and the contributions and answers for each research question. The final sections of this chapter conclude the thesis and provide indications for future development in this field.

9.1 Research Questions Revisited

9.1.1 Research Question 1: How do Forró dance teachers approach teaching of rhythmic skills?

Secondary Research Questions

- RQ1.1 – What are the skills required for Forró students to learn to dance?
- RQ1.2 – How do Forró dance teachers assess students’ rhythm skill development?
- RQ1.3 – What are the types of feedback that Forró dance teachers commonly use?
- RQ1.4 – What is the vocabulary used by teachers when assessing students’ rhythm skills?
Table 9.1: Summary of the conclusion chapter showing RQs, chapters related to them, contributions and answers.

<table>
<thead>
<tr>
<th>Research Questions (RQ)</th>
<th>Chapters</th>
<th>Contributions</th>
<th>Answers</th>
</tr>
</thead>
<tbody>
<tr>
<td>RQ1 – How do Forró dance teachers approach teaching of rhythmic skills?</td>
<td>2, 4, 6, 8</td>
<td>Important aspects of Forró teaching Gap between teachers and algorithms</td>
<td>Teachers mostly use observation to assess students and use other rhythm-related skills to complement the assessment.</td>
</tr>
<tr>
<td>RQ2 – How can we use motion sensors to extract rhythm-related information that enables the support of dance rhythm assessment and learning?</td>
<td>5</td>
<td>Algorithms able to extract relevant features from the motion sensors (RiMoDe, RiMoDe v2) Tools to support dance rhythmic skills teaching (Forró Trainer, Video Annotation Tool)</td>
<td>The apparatus must have capabilities to model at least parts of the student’s movement. The platform needs to include in its design relevant information from the context. The designer needs to be aware of the context so that the resultant platform is meaningful for the users.</td>
</tr>
<tr>
<td>RQ3 - Is the extracted information valid, useful and relevant for teachers and students?</td>
<td>6, 7</td>
<td>Accurate ML models, rhythmic related data representations, automatic rhythm assessment evaluation</td>
<td>Technically valid, using ML methods Students could make sense of some of the information. Teachers made better use of the information and could connect with their current approaches.</td>
</tr>
</tbody>
</table>
• RQ1.5 – Which vocabulary do teachers use to represent the new rhythm skills detected by the algorithm?

Throughout the chapters of this thesis, there are several areas where the teachers’ approach to rhythmic skills assessment have been discussed. Chapter 2 introduced how the literature deals with rhythm and dance learning, which includes other skills related to dance and other motor learning scenarios in which rhythm is also important. The literature shows that teachers have different strategies for developing rhythmic skills in dance students, and that rhythmic skills involve cognitive and motor abilities. Other fields have also approached rhythm learning, including playing instruments and sports.

The thesis narrowed down the development of rhythmic skills and in Chapter 4 investigated how Forró teachers approach this question. Using semi-structured interviews, teachers navigated through several aspects of their teaching activities. Study 1 revealed that rhythm plays an important role in Forró learning and teachers must cover many topics to educate their students to become a social dancer. The topics included motor skills, such as balance and posture, and cognitive skills such as social openness and musicality. Teachers listed a number of strategies to assess and provide feedback to students.

In Chapter 6, Section 6.1.3, the thesis gained a deeper understanding of how teachers assess rhythm, other skills related to rhythm and the vocabulary that teachers use. Study 2 showed several terms that teachers use when assessing rhythm. In addition, it was shown that teachers disagree when assessing rhythm and give importance to different aspects of the students’ performance. The skills assessed by teachers helped the thesis frame the algorithm outputs in those terms. In Study 3, Section 7.3, the thesis negotiated with teachers the best terms to be used to represent what the motion sensors and algorithms were modelling from the students’ movement. Starting with rhythm, the thesis ended with four skills: rhythm, weight transfer, pause and step size.

9.1.2 Research Question 2: How can we use motion sensors to extract rhythm-related information that enables the support of dance rhythm assessment and learning?

Secondary Research Questions
• RQ2.1 – How do we translate motion data to rhythm information?
• RQ2.2 – What is the accuracy of the RiMoDe v1 algorithm?
• RQ2.3 – How do we improve the extraction of features from the translated motion data to rhythm information?
• RQ2.4 - What is the accuracy of the new features of the RiMoDe v2 algorithms?

deciding on the hardware, we need to develop algorithms that can translate the rhythmic data captured into information that can be useful for dance students and teachers.

The main contribution of this thesis, regarding the technological aspect, was the rationale of using the context information to design the features to be extracted from the motion sensors. Chapter 5 described in detail the rationale as well as the tools and algorithms that were created to achieve the TOs. First, the chapter described the hardware used, the movement Básico 1 and the mobile app Forró Trainer. These components were used in the studies to collect and guide the participants’ movement. Later, the chapter introduced RiMoDe, an algorithm that used information from the Forró dance to guide the design of two motion sensor features. Consistency and user BPM were the first features presented in the thesis.

The following section, Section 5.5, presented RiMoDe v2. After the lessons learned from Study 2, new ideas led to the design of features that could capture more detail from the students’ movement. The design continued to use as its foundation context information of the number of movements the students performed, the number of beats in the song and the expected time window of the movement. With the new features, the system could detect other rhythmic skills including weight transfer, pause and step size. The chapter concluded by introducing a video annotation tool, used in Study 3, to collect data from teachers assessing participants’ performances.

In Chapter 6, RiMoDe v1 and v2 were validated using ML methods. Using the data collected during Study 2 and Study 3 (96 and 480 videos, respectively), this chapter presented performance metrics of the ML models that used the features extracted from the motion sensors. The first section, Section 6.1.2, presented the validation of RiMoDe, reaching 90% accuracy in the cases where teachers were unanimous. The qualitative evaluation showed that teachers had a more complex assessment of the students’ performance, summarised as the six themes. The section also presented the
teachers’ disagreements and how each teacher focused on different aspects of the students’ movement.

Section 6.3 presented a more thorough validation of the features extracted by the RiMoDe v2 algorithm. This section compared the new features with the statistical features, used several classification algorithms and evaluated which combination better modelled the four rhythmic skills. RiMoDe v2 features outperformed the statistical features in three of the four skills, rhythm, pause and weight transfer. The statistical features had better performance when modelling the step size skill. Using McNemars test, it was found that the classification models were statistically better than the baseline and that rhythm was the skill with the most improvement.

9.1.3 Research Question 3: Is the extracted information valid, useful and relevant for teachers and students?

Secondary Research Questions

• RQ3.1 – How do students make sense of the automatic assessment data?
• RQ3.2 – How teachers perceive the use of technology to support their dance teaching?
• RQ3.3 – How do teachers use the automatic assessment to assess students’ video performance?
• RQ3.4 – How would teachers use the automatic assessment in their context as dance teachers?

The last RQ of the thesis went back to the community to evaluate how the technology developed was perceived and how it could benefit students and teachers. Chapter 7 concentrated on the contributions regarding the evaluation of the rhythm automatic assessment by the teachers. The investigation with dance students in Study 2, presented in Section 7.1, showed that the data collected from motion sensors could have a positive influence on the students’ awareness of their own learning progress. The data allowed students to see their progress and receive automated feedback. Study 2 also showed the need for deeper investigation regarding how to better represent motion sensor data. Students had difficulty interpreting the charts and information related to the raw sensor data.
Section 7.2 reported on the results from Study 4, where the teachers experienced the automatic assessment compared to the video recordings of students’ performance. The teachers used the automatic assessment to compare with their mental model after seeing the videos or imagining the students’ performance before watching the video. Teachers found the automatic assessment to be accurate but would have liked to experience the technology more to trust it more. Teachers would also like to customise the name of the skills and have the model trained based on their opinion. A simple benefit that the teachers reported was to have the assessment structured in topics and with pre-determined options.

Section 7.2 also presented several ideas from teachers on how they would use the automatic assessment with their current teaching strategies. The hypothetical scenarios that teachers imagined were divided into four groups: time, scale, proximity, and access. The main benefits teachers found were to allow students to assess their own learning progress and the possibility of using the information to evaluate teachers and their teaching methodologies.

Complementary to Study 4, Study 3 also collected from teachers their experience using technology. In that study, teachers used a video annotation tool to assess and give feedback to students. Reported in Section 7.3, teachers said they would use the tool to train new teachers and saw benefit in having a structure to guide their assessments. Additionally, a surprise finding from the study was that teachers felt less pressure when providing feedback using a tool compared to giving feedback in a face-to-face scenario.

9.2 Future Work

The novelty of this research and the rapid development of technology enables a number of possible directions for future work. These include validating the current technology in a Forró dance classroom, using the smartphone sensors to model other Forró movements, extracting more information from the song to improve the models and using more sophisticated technology to improve the smartphone models.
9.2.1 Validating the current technology in a Forró dance classroom

An important step when researching the use of technology to support social partner dance is to deploy the technology proposed in this thesis in an authentic context of a Forró class. Future research could investigate whether the automatic assessment helped students during their learning process and helped teachers improve their methodologies. Also, it would be interesting to understand how the automated assessment changed the dynamic of the social partner dance class, as well as the relationship between students and teachers.

9.2.2 Using smartphone sensors to model other Forró movements and skills

Another interesting investigation would be to evaluate which other dance movements, from Forró dance to other social partner dances, could be modelled using the features of the RiMoDe algorithms. This research could help understand how extensible these features are, and whether they can be used to model other skills related to dance or the rhythmic skills of other dance movements. It is expected that the features presented in this thesis could be used in other social partner dance styles, as they have similar dance movements to that of Forró, although further studies are required to validate these claims. One example is a study that used similar strategies as described in this thesis, using the song to extract what was called Music-related Motion Features (MMF), to model Salsa dance movements (Senecal et al., 2018).

9.2.3 Extract more information from the song to improve the models

The song may have a great influence in the students’ learning progress. In this thesis, rhythmic features of the song were used to match with the students’ movement, such as those determined the pace of the song and when the beats of the song occurred. The song contains other information that can affect the student when they are practising dance exercises, such as melody, pitch, tone and the number of instruments. Using music information retrieval algorithms (Böck et al., 2016; Lartillot and Toiviainen, 2007) could enable the investigation of RQs related to this topic.
9.2.4 Use more sophisticated technology to improve the smartphone models

As described in Section 8.3, other technologies could be used to enhance the social partner dance class. These technologies could also be applied to enhance the motion data used by RiMoDe algorithms to assess students’ dance skills. For instance, a motion capture (MoCap) system could help to associate which other parts of the body are detected by the motion sensors of a smartphone. The smartphone would be placed in a specific position of the student’s body, at the same time as the student is being monitored by a MoCap system. Later, ML algorithms could be used to identify which parts of the body of the student, tracked by the MoCap system, affected the motion sensor data, collected by the smartphone.

9.2.5 User centred studies on visualisation

In Section 7.1, several visualisation were tested with students, but did not produce good results. A user centred methodology must be applied in future studies to carefully evaluate with dance teachers and students which types and formats of visualisation are most suitable for communicating technical data within the context of students progress in learning how to dance.

9.3 Final Reflections

This thesis explored the use of motion sensors to extract rhythmic information from students’ dance movements and to use this information to inform teachers and students. The studies utilised the dance community to develop a technology more connected with real-life scenarios. The methodologies used in this thesis can provide insights to researchers interested in other types of dance or other motor learning activities. As a starting point, researchers can use an exercise relevant to learning that skill and develop features and information related to their own context. Additionally, researchers can use this thesis to gain insights on how to involve the community to help develop technological tools to support learning.
Appendix A

Study Questionnaires

A.1 Study 1

The interview questions and related research questions for this study are listed below:

- RQ1.1 - What are the skills required for Forró students to learn to dance?
  - Which aspects are more important for beginner students?
  - Which aspects do beginner students face more difficulty?

- RQ1.2 - How do Forró dance teachers assess students rhythm skill development?
  - What do you use to monitor your students?
  - How do you do it?
  - Do you use any tool/resources?
  - What are the elements that you find important to be monitored?
  - Do you track students learning outside the class?
  - Do you use email, messenger, social media? (online)
  - Are these tools enough to track students?
  - What are the problems/deficiencies?
  - What do you need (to improve)?

- RQ1.3 - What are the types of feedback that Forró dance teachers commonly use?
– How aware are students regarding their own difficulties and limitations?
– What are your strategies for providing feedback to your students?
– Do your strategies change depending on the student’s profile? Elaborate

A.2 Study 2

The following pages contain a sample of a student report, used during the final interview with participants.
Sample’s Dossie

The aim of this interview is to get insights and feedback from you on how the data collected by a wearable sensor can be used to increase the awareness of Forró dance students regarding rhythm skill acquisition. Your role in this interview is as a dance student.

It is important to remind you that there is no right or wrong answer. We are interested in exploiting your particular perception of the data collected and some examples of how to present it. The examples are intended to be food for thoughts and not final and correct solutions of how the data should be presented. Some examples are intentionally bad.

In this interview, the term data representation is used to describe any form of information provided to the participant. In learning feedback is describe as information provided to the student that is actionable and help to change/improve the student’s learning/performance.

1) Describe the data collected
Think aloud - reflecting about your suggestions on which data are interesting,

Data collected
   Number of times you did each exercise/song
   When you did the exercises: date, time
   Performance of each exercise: consistency, BPM
   Detailed movement of your body x,y,z
   Acceleration of your movement
   Speed in which you move forward and backward
   Distance you travel in each movement
   Clickstream: date and time of when you click in each button of the app

a) Which of this data do you think could help you in learning dance?

b) How would you interpret this data so it could help you in learning dance?

c) How would you visualize this data so it could help you in learning dance?

d) How would you combine this data to help you in learning dance?
2.1) List of Data Representation
Those are draft-representations to discuss with you better ways to show information and improve how the best way to give student feedback.

A.1) Practice - Summary

<table>
<thead>
<tr>
<th>Times practice for each exercise</th>
<th>Times practice for each Level</th>
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<tr>
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<tr>
<td>Weight Transfer</td>
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<td>Walking</td>
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Total of 41 practices in 20 Days.

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**Satisfaction (Open comments)**
How satisfied were you with the summary?

How would you present this information differently?

Other comments?
The visualization used language (or symbols, numbers, images, charts) that was easy to understand

The visualization had a clear message

The visualization was not confusing

The visualization helped me gain constructive insights that I would be able to use to improve my dance learning

The visualization was useful

The visualization improved my confidence for completing future assessment tasks

**Satisfaction** (Open comments)

How satisfied were you with the visualization?

How would you present this information differently?

Other comments?
A.3 ) Practice - Diagnosis + Actionable Feedback

1) Diagnosis: Dear student, you have an average of 2 practices per day and 12 days without practice. Most of these practices were performed during the classes.

**Actionable Feedback**: We suggest you practice more often regarding the number of days in the week and also more times of practice per day. It is important to keep the movements, we exercise in class, alive in your mind so you can improve.

2) Diagnosis: Dear student, you have practice 1 time the Walking exercise.

**Actionable Feedback**: We suggest you practice more the Walking exercise since you are at the start of the learning process of Forró dance. It’s important to strengthen the fundamentals of Forró dance practicing all types of exercises.

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**Satisfaction** (Open comments)
How satisfied were you with the feedback?

How would you present this information differently?

Other comments?
B.1) Learning Consistency - Summary

### Consistency by Exercise:

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<th>Mean (%)</th>
<th>Max (%)</th>
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### Consistency by Level in Basic 1:

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<td>Fast Paced</td>
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### Clarity

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### Satisfaction (Open comments)

How satisfied were you with the summary?
How would you present this information differently?
Other comments?
### Clarity

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### Satisfaction (Open comments)

How satisfied were you with the visualization?

How would you present this information differently?

Other comments?
Learning Consistency - Diagnosis + Actionable Feedback

1) Diagnosis: Dear student, you have an average consistency of 98.56% on the Basic 1 exercise. The lowest consistency was 95.71% doing the Danielle song.

Actionable Feedback: The result of your consistency score along your practice at the Basic 1 exercises are really good. You can increase the challenge of the exercise trying faster songs. The lowest consistency score doesn't seem to be a problem since you recovered the score in following attempts. An average higher than 98% is considered very good. A score higher than 99% would be excellent.

2) Diagnosis: Dear student, your average consistency score while doing the Weight Transfer is 92.75%.

Actionable Feedback: We suggest you practice more the Weight Transfer exercise so you can reach scores higher than 98%. The Weight Transfer exercise will help you developing mobility in your joints and hips.

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Satisfaction (Open comments)
How satisfied were you with the feedback?

How would you present this information differently?

Other comments?
C.1) Going with the Music (BPM) - Summary

### Rhythm Evaluation by Exercise (tolerance = 5%):

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<th>Too Fast</th>
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<td>Tap</td>
<td>9</td>
<td>9</td>
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<td>0</td>
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<td>Weight Transfer</td>
<td>10</td>
<td>2</td>
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<td>2</td>
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### Rhythm Evaluation by Level in Basic 1 (tolerance = 5%):

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**Satisfaction** (Open comments)

How satisfied were you with the summary?

How would you present this information differently?

Other comments?
C.2) Going with the Music (BPM) - Visualization

### Clarity

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**Satisfaction** (Open comments)

How satisfied were you with the visualization?
How would you present this information differently?
Other comments?
C.3) Going with the Music (BPM) - Diagnosis + Actionable Feedback

1) Diagnosis: Dear student, you have no correct attempt while doing the Tap exercise. In all the 9 attempts you were slower than the song.

   **Actionable Feedback:** We suggest you practice more the Tap exercise until you can consistently achieve correct rhythm. The Tap exercise will help you developing your ability to listen properly to the rhythm of the song.

2) Diagnosis: Dear student, when you are not on the rhythm you are most of the time slower than the rhythm.

   **Actionable Feedback:** We suggest you listen to more Forró songs as this is going to develop your ability to follow the rhythm of the songs. You can also practice the Tap exercise to evaluate you listening ability.

<table>
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**Satisfaction (Open comments)**

How satisfied were you with the feedback?

How would you present this information differently?

Other comments?
D.1) Body Awareness - Summary

**Movement Rhythm - Worst x Best – Nosso Xote (BPM = ~142.5)**

<table>
<thead>
<tr>
<th>Case</th>
<th>X axis (Lateral)</th>
<th>Y axis (Vertical)</th>
<th>Z axis (Depth)</th>
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<tr>
<td></td>
<td>BPM</td>
<td>Consistency (%)</td>
<td>BPM</td>
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<tr>
<td>Worst</td>
<td>135.26</td>
<td>72.69</td>
<td>142.83</td>
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<tr>
<td>Best</td>
<td>142.83</td>
<td>98.58</td>
<td>143.74</td>
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**Raw Acceleration (m/s^2) - Worst x Best – Nosso Xote**

<table>
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<tr>
<th>Case</th>
<th>X axis (Lateral)</th>
<th>Y axis (Vertical)</th>
<th>Z axis (Depth)</th>
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<td>Worst</td>
<td>0.22</td>
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<td>Best</td>
<td>-0.29</td>
<td>1.78</td>
<td>-9.67</td>
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**Clarity**

- The summary used language (or symbols, numbers, images, charts) that was easy to understand
  - [ ] Strongly disagree
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  - [ ] Agree
  - [ ] Strongly agree

- The summary had a clear message
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- The summary was not confusing
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**Usefulness**

- The summary helped me gain constructive insights that I would be able to use to improve my dance learning
  - [ ] Strongly disagree
  - [ ] Disagree
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  - [ ] Agree
  - [ ] Strongly agree

- The summary was useful
  - [ ] Strongly disagree
  - [ ] Disagree
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  - [ ] Agree
  - [ ] Strongly agree

- The summary improved my confidence for completing future assessment tasks
  - [ ] Strongly disagree
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**Satisfaction (Open comments)**

- How satisfied were you with the summary?
- How would you present this information differently?
- Other comments?
D.2a) Body Awareness – Visualization 1

The visualization used language (or symbols, numbers, images, charts) that was easy to understand

The visualization had a clear message

The visualization was not confusing

The visualization helped me gain constructive insights that I would be able to use to improve my dance learning

The visualization was useful

The visualization improved my confidence for completing future assessment tasks

Satisfaction (Open comments)

How satisfied were you with the visualization?

How would you present this information differently?

Other comments?
## D.2b) Body Awareness – Visualization 2

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### Satisfaction (Open comments)

- How satisfied were you with the visualization?
- How would you present this information differently?
- Other comments?
D.3) Body Awareness - Diagnosis + Actionable Feedback

1) Diagnosis: Dear student, your best attempt has a higher standard deviation in all 3 axes when compared with your worst attempt.

Actionable Feedback: A higher standard deviation means that your movements were more defined and clear, it means you were more precise on the movement. You should aim to have more precision and confidence in your movement, your dance will be clear and your partner will better understand your movements.

2) Diagnosis: Dear student, in your worst attempt some patterns were detected on the second movement of the 1,2,3,4 cycle.

Actionable Feedback: Usually, the first movement of each cycle is the one with more intensity since it is the beginning of the movement, when you are going to express to your partner what is your intention for the following movement. You don’t need to worry about it that much since most of your attempts have a good consistency.

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Satisfaction (Open comments)
How satisfied were you with the feedback?

How would you present this information differently?

Other comments?
**E.1) Teacher / Social Comparison - Summary**

### Times practice for each exercise

<table>
<thead>
<tr>
<th>Exercise</th>
<th>Your</th>
<th>Average per Student</th>
<th>Name</th>
<th>You</th>
<th>Average per Student</th>
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<tbody>
<tr>
<td>Tap</td>
<td>9</td>
<td>20</td>
<td>Percussion</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Weight Transfer</td>
<td>10</td>
<td>2</td>
<td>Slow</td>
<td>21</td>
<td>27</td>
</tr>
<tr>
<td>Walking</td>
<td>1</td>
<td>0</td>
<td>Medium</td>
<td>4</td>
<td>9</td>
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<tr>
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<td>21</td>
<td>27</td>
<td>Fast</td>
<td>12</td>
<td>12</td>
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### Consistency by Level in Basic 1:

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<tr>
<th>Exercise Level</th>
<th>Your mean (%)</th>
<th>Social Mean (%)</th>
<th>Your Std Dev (%)</th>
<th>Social Standard Deviation (%)</th>
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</thead>
<tbody>
<tr>
<td>Slow Paced</td>
<td>98.56</td>
<td>94.36</td>
<td>0.53</td>
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<tr>
<td>Medium Paced</td>
<td>98.59</td>
<td>94.45</td>
<td>0.00</td>
<td>6.84</td>
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<tr>
<td>Fast Paced</td>
<td>97.69</td>
<td>93.82</td>
<td>0.94</td>
<td>6.77</td>
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### Satisfaction (Open comments)

How satisfied were you with the summary?

How would you present this information differently? Other comments?
### Clarity

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### Satisfaction (Open comments)

How satisfied were you with the visualization?
How would you present this information differently?
Other comments?
3) General Questions

Go back to 1), then come back here.

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<tr>
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<th>Strongly agree</th>
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<tbody>
<tr>
<td>I found learning to dance more interesting after using the app</td>
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<tr>
<td>I enjoyed more learning to dance after using the app</td>
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<tr>
<td>I think more about learning to dance after using the app</td>
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<th>Strongly agree</th>
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</thead>
<tbody>
<tr>
<td>To me, the app exercises were challenging.</td>
<td></td>
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<tr>
<td>I am enthusiastic about doing the app exercises.</td>
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<tr>
<td>When I am doing the app exercises, I forget everything else around me.</td>
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<tr>
<td>Time flies when I am doing the app exercises.</td>
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<table>
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<th>Neither agree nor disagree</th>
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<tr>
<td>The app motivated me to toward learning how to dance</td>
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<td>The app motivated me to practice dance more often</td>
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<tr>
<td>I feel the app helped me practice at home</td>
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</table>

**Data Representations**

1. Which is the Best one? Why?

2. Which is the Worst one? Why?

3. What were aspects of all the data representations provided that you liked the most?

4. What were aspects of all the data representations provided that you liked the least?
A.3 Study 3

Post Interview with Dance Teachers About the Dance Video Evaluation Tool

We would like to know about your experiences using the Web Video Evaluation Tool for dance.

Please rate how important it is for you to evaluate your students? (7-likert scale)

Can you please elaborate on the reason for your score?

Q1. How and why do you currently evaluate (keep track) your dance students?

Q1.1. How do you plan your students evaluation? Comment on any tools and/or other resources you use to evaluate them.

Q1.2. What are the challenges and barriers.

Q1.3. How would you use the Video Evaluation Tool to evaluate your students?

Q2. Please describe how you currently provide feedback to your students.

Q2.1. Do you use any tool to assist in providing feedback?

Q2.2. What are the challenges and barriers?

Q2.3. How would you use the Video Evaluation Tool to as a way to provide feedback to your students?

Q3. Comment on what you think about the Video Evaluation Tool

Q3.1. How would you integrate this into your current practice?

Q3.2. Did you use any rubrics/reference to guide your answers when using the tool?

Q3.3. Was the tool easy to use?

Q3.4. Did you learn something using the tool?

Q3.5. Would you use the tool in the future?

Q3.6. Did you need support to use the tool?

Q3.7. What you liked most about the tool?

Q3.8. What you disliked most about the tool?

Q3.9. Comment on how often would you use the Video Evaluation Tool?

Q3.10. What information would you like to see (or are in excess) inside the tool?

Q3.10.1 Comment on why or why not

Q4. Comment on what you think about the tool’s interface

Q4.1. How your actions were reproduced on the interface?

Q4.2. Did the system use language/words that match your context?

Q4.3. Were you able to recognise when you made a mistake using the tool?
Q4.4. How did you undo/cancel actions that you made by mistake?
Q4.5. Were there any ambiguous or confusing functions in the tool?
Q4.6. How did you track in the system the previous action that you made?
Q4.7. Which system’s functions allowed you to speed up your work?
Q4.8. Were the buttons and colours of the system easy to understand and use?
Q4.9. Did you have any need for documentation to understand how to use the tool?
Q4.10. Was the system easier to use than you expected?
Q4.11. Which system functions matches with context of your work?
Q4.12. How would this system enhance your capabilities as a teacher?
Q5. Could you compare your experience using a spreadsheet and the Video Tool to evaluate student’s videos?

A.4 Study 4

The protocol of the semi-structured interview followed the steps below:

- Teacher evaluates five students using just videos, and is asked the following questions
  - Which is the diagnosis for this student?
  - Which feedback would you give to this student?
  - How easy/hard is it to evaluate this student? Comment on that.

- Teacher evaluates five students using videos containing an automatic assessment of the student (Figure A.1), answering the same questions as before;

- Ask the teacher about their experience using automatic assessment during the videos evaluation. The questions below was used to guide the conversation:
  - How did the automatic assessment helped you to diagnosis the student performance? Why?
  - How did the automatic assessment helped you to elaborate the feedback to the student performance? Why?
  - How did the automatic assessment changed the efficiency of how you evaluated the videos?
– How accurate were the automatic assessment assigned to the student’s performance?
– Would you trust the automatic assessment assigned to the students’ performance?
– What were the differences between evaluating the videos with or without the automatic assessment?

• Formulate hypothetical scenarios for using automatic assessment. Question to guide the conversation:

– What is your current strategy to collect and analyse your students’ performance?
– How the information (metrics) would be helpful for you to have in these different scenarios?
  * Different moments - Inside the class: beginning, middle, end; Outside the class: to plan the next class, to evaluate previous classes
  * Different scales - 1-on-1, 10 students, 70 students
  * Different proximity - Regular weekly class, workshop, distance
  * Different stakeholders - Teacher, student, school
– Which context do you think this information would be useful? (tailored the questions for each context)
– How this information (metrics) can/could help you?
– How would/could you integrate this additional information (metrics) in your current practice?
– Would this information improve your confidence in diagnosing and providing instructive feedback to students?
Figure A.1: Screen-shot of video and the automatic assessment presented to the teachers.
Appendix B

Complementary Results

B.1 Study 4: Teachers’ Insights

Teachers spent an average of 4.2 minutes (±1.4 minutes) to evaluate each video. There was no significant differences between the average time taken to evaluate each video (ANOVA: $F = 1.534$, p-value $= 0.1530$), Table B.1, but there was significant difference between some of the teachers (ANOVA: $F = 3.572$, p-value $= 0.002$), Table B.2. Table B.3 shows the statistical comparison of the teachers that had significant time difference. T18 was the teachers who took longer to evaluate videos and T8 the teacher who spend less time evaluating. This time difference is mostly related to the speed in which they talk rather than the quality or quantity of the evaluation.

There was significant difference between the time teachers took to evaluate videos without or with the automatic assessment (t-Stat $= 2.093$, p-value $= 0.043$), Table B.4. Without the automatic assessment teachers would spend more time talking about several other aspects of the student’s performance, while with the automatic assessment they more concentrated in the four skills presented. Some teachers would read the automatic assessment before evaluating the video and some only after. The main benefit that most teachers found in the automatic assessment is helping as a reference / guide / template for the diagnose and feedback as well as giving focus and recalling important aspects to assess (T6, T7, T15, T19). This is more related in having the skills display in the screen rather than having them automatically assessed. Teachers also mentioned the need to include more aspects on the list such as posture and relaxation, not only basic things (T6, T8, T15)
APPENDIX B. COMPLEMENTARY RESULTS

Table B.1: Comparison between the videos’ average evaluation time.

<table>
<thead>
<tr>
<th>Video Order</th>
<th>Video Case</th>
<th>Automatic Assessment</th>
<th>Average Time (minutes)</th>
<th>StDev Time (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>P3 S3 Pre3</td>
<td>No Problem</td>
<td>5.0</td>
<td>1.2</td>
</tr>
<tr>
<td>2</td>
<td>P15 S3 Post2</td>
<td>Step - Too Large</td>
<td>4.1</td>
<td>1.3</td>
</tr>
<tr>
<td>3</td>
<td>P7 S3 Post4</td>
<td>Weight Transfer - Too Few</td>
<td>4.0</td>
<td>1.5</td>
</tr>
<tr>
<td>4</td>
<td>P9 S1 Pre4</td>
<td>Pause - No Pause</td>
<td>4.3</td>
<td>0.9</td>
</tr>
<tr>
<td>5</td>
<td>P5 S2 Pre4</td>
<td>Rhythm - Slower</td>
<td>5.0</td>
<td>1.3</td>
</tr>
<tr>
<td>6</td>
<td>P14 S3 Post1</td>
<td>Pause - Wrong Beat</td>
<td>4.5</td>
<td>0.9</td>
</tr>
<tr>
<td>7</td>
<td>P13 S1 Pre3</td>
<td>Weight Transfer - Too much</td>
<td>4.4</td>
<td>2.1</td>
</tr>
<tr>
<td>8</td>
<td>P11 S1 Pre2</td>
<td>Step - Too Small</td>
<td>3.4</td>
<td>0.9</td>
</tr>
<tr>
<td>9</td>
<td>P6 S2 Pre5</td>
<td>No Problem</td>
<td>3.7</td>
<td>1.4</td>
</tr>
<tr>
<td>10</td>
<td>P16 S1 Pre1</td>
<td>Rhythm - Slower</td>
<td>3.4</td>
<td>1.1</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td>4.2</td>
<td>1.4</td>
</tr>
</tbody>
</table>

Table B.2: Comparison between the average of teachers’ evaluation time. The teacher who spend more time on average is highlighted.

<table>
<thead>
<tr>
<th>Teacher</th>
<th>Average Time (minutes)</th>
<th>StDev Time (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T6</td>
<td>4.0</td>
<td>0.9</td>
</tr>
<tr>
<td>T7</td>
<td>3.6</td>
<td>1.0</td>
</tr>
<tr>
<td>T8</td>
<td>3.1</td>
<td>1.1</td>
</tr>
<tr>
<td>T12</td>
<td>3.9</td>
<td>1.2</td>
</tr>
<tr>
<td>T14</td>
<td>4.5</td>
<td>1.5</td>
</tr>
<tr>
<td>T15</td>
<td>4.5</td>
<td>0.8</td>
</tr>
<tr>
<td><strong>T18</strong></td>
<td><strong>5.6</strong></td>
<td><strong>1.3</strong></td>
</tr>
<tr>
<td>T19</td>
<td>4.2</td>
<td>1.8</td>
</tr>
<tr>
<td>Average</td>
<td>4.2</td>
<td>1.4</td>
</tr>
</tbody>
</table>

Table B.3: Tukey HSD Test for average evaluation time comparisons of teachers with significant statistical difference

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Tukey HSD Q statistic</th>
<th>Tukey HSD p-value</th>
<th>Tukey HSD inference</th>
</tr>
</thead>
<tbody>
<tr>
<td>T18 x T7</td>
<td>5.1108</td>
<td>0.012</td>
<td>* p&lt;0.05</td>
</tr>
<tr>
<td>T18 x T8</td>
<td>6.3043</td>
<td>0.001</td>
<td>** p&lt;0.01</td>
</tr>
</tbody>
</table>
Table B.4: Comparison between the average evaluation time without and with automatic assessment

<table>
<thead>
<tr>
<th>Without-With</th>
<th>Average Time (minutes)</th>
<th>StDev Time (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without</td>
<td>4.5</td>
<td>1.3</td>
</tr>
<tr>
<td>With</td>
<td>3.9</td>
<td>1.4</td>
</tr>
<tr>
<td>Average</td>
<td>4.2</td>
<td>1.4</td>
</tr>
</tbody>
</table>
Appendix C

Study 1: Coding examples

The following pages contain a sample of the coding process regarding the Dance Skills category. The last table shows a summarisation of the teachers comments across the different categories.
<table>
<thead>
<tr>
<th>T#</th>
<th>Research Question</th>
<th>Interview quotation</th>
<th>Key point</th>
<th>Code</th>
<th>Categories</th>
<th>Axial Coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>RQ1.1 - What are the skills required for students to learn to dance?</td>
<td>If someone is with the intention of becoming a good dancer [...] then I evaluate many things I evaluate posture, musicality, the capacity of maintaining, conserving, dealing with the distances, axis, balance, control, use of the energy in the body, [...] And to external factors as if they respect the dancefloor and people around.</td>
<td>Skills required to be a good dancer includes: posture, musicality, distance (space), axis, balance, control, energy, use of space, respect</td>
<td>Posture is an important dance skill, Spatial awareness / use of space / distance is an important dance skill, Axis / Balance is an important dance skill, Control is an important dance skill, Energy is an important dance skill, Respect is an important dance skill</td>
<td>DANCE SKILLS, posture, DANCE SKILLS, spatial awareness / use of space / distance, DANCE SKILLS, axis / balance, DANCE SKILLS, control, DANCE SKILLS, energy, DANCE SKILLS, respect</td>
<td>posture → dance skills, spatial awareness → dance skills, use of space → spatial awareness, distance → spatial awareness, axis → balance, control → motor coordination, energy → dance skill, respect → mental posture</td>
</tr>
<tr>
<td>T1</td>
<td>RQ1.1</td>
<td>I think those who are starting to learn how to dance should concentrate a lot on finding a good position to embrace the other person something that is comfortable for them. I pay attention if they are hurting each other.</td>
<td>The embrace and comfort are important for students learning how to dance so they don't hurt each other</td>
<td>Being comfortable is important for partner dance, Students should not hurt each other</td>
<td>DANCE SKILLS, embrace, DANCE SKILLS, comfort, DANCE SKILLS, not hurt</td>
<td>embrace → connection with the partner, comfort → connection with the partner, not hurt → connection with the partner</td>
</tr>
<tr>
<td>T1</td>
<td>RQ1.1</td>
<td>I pay attention if they're sticking to the music, if they are able to understand what they are listening to and if they're enjoying their time</td>
<td>Rhythm is important for students, Student should enjoy their time learning</td>
<td>Rhythm → dance skills, enjoyment → relaxation → psychological</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>RQ1.1</td>
<td>Students have difficulties in relating themselves with someone else because when you ask people to walk they can walk but walking with someone in front of you is not something you are used to doing</td>
<td>Students have difficulties to move together with someone else.</td>
<td>It is not natural to walk with someone in front of you</td>
<td>DANCE SKILLS, move together</td>
<td>move together → connection with the partner, rhythm → dance skills, spatial awareness / use of space → spatial awareness, connection with the partner, relaxation → psychological</td>
</tr>
<tr>
<td>T1</td>
<td>RQ1.1</td>
<td>They have the difficulty with coping with the music with finding the beat finding what is in between the beats and flowing with the music, not only with the strong beat [...] and coordinating what they're doing because dancing is mostly a combination of coordinations and they have difficulties in organizing that in a harmonic way, what's the leader wants to do with the follower wants to do and vice versa.</td>
<td>Students have difficulty to find the rhythm of the music, flowing with the music, having multiple coordination with themselves and with the partner.</td>
<td>Rhythm and musicality are difficult for student, specially to coordinate several motions with them and the partner</td>
<td>DANCE SKILLS, rhythm, DANCE SKILLS, musicality, DANCE SKILLS, partner coordination</td>
<td>rhythm → dance skills, musicality → dance skills, motor coordination → dance skills, partner coordination → connection with the partner, connection with the partner, rhythm → dance skills, spatial awareness / use of space → spatial awareness, connection with the partner, relaxation → psychological, connection with the partner, posture → dance skills, posture → spatial awareness, vision → dance skills, personality → creativity → dance skills</td>
</tr>
<tr>
<td>T2</td>
<td>RQ1.1</td>
<td>(PT) A maior dificuldade que eu vejo é a transferência de peso a pessoa dominar o peso [...] a segunda dificuldade que eu vejo é o dançar colado [...] a terceira é a questão da musicalidade, do aluno está dançando fora do ritmo (EN) The biggest difficulty I see is the weight transfer the person mastering the weight [...] the second difficulty I see is the dancing very close to each other [...] the third is the question of musicality, the student that dances outside the rhythm</td>
<td>The biggest difficulties that student has in transferring weights, dancing very close to each other and following the rhythm of the music</td>
<td>Weight Transfer is difficult for student to learn, Student are uncomfortable dancing too close to another person, Rhythm is difficult for students to learn</td>
<td>DANCE SKILLS, rhythm, DANCE SKILLS, musicality, DANCE SKILLS, dance very close, DANCE SKILLS, weight transfer, DANCE SKILLS, dance close to another person, DANCE SKILLS, movement</td>
<td>rhythm → dance skills, musicality → dance skills, weight transfer → dance skills, student → dance skills, posture → dance skills, axis → balance, control → motor coordination, respect → mental posture</td>
</tr>
<tr>
<td>T3</td>
<td>RQ1.1</td>
<td>So for me, connection, musicality, improvisation and also [...] followers should learn how to be more active</td>
<td>Important elements of dance includes posture, connection, musicality, improvisation and active followers</td>
<td>Connection is an important dance skill, Musicality is an important dance skill, Improvisation is an important dance skill, Followers is an important role</td>
<td>DANCE SKILLS, connection, DANCE SKILLS, musicality, DANCE SKILLS, improvisation, DANCE SKILLS, follower</td>
<td>connection with the partner, posture → dance skills, musicality → dance skills, improvisation → dance skills, dance close to another person, posture → dance skills, axis → balance, control → motor coordination, respect → mental posture</td>
</tr>
<tr>
<td>T4</td>
<td>RQ1.1</td>
<td>(PT) Coisas que me chamam atenção são postura, agilidade, equilíbrio. Isso na parte física. Um pouco de personalidade, isso chama atenção também, a pessoa que tem algo que é dela. (EN) Things that catch my attention are posture, agility, axis, balance. This in the physical part. A lot of personality, this also catches the eye, the person who has something that is hers.</td>
<td>Important elements of dance includes posture, agility, axis, balance and personality.</td>
<td>Posture is an important dance skill, Agility is an important dance skill, Balance is an important dance skill, Personality is relevant for students to have</td>
<td>DANCE SKILLS, posture, DANCE SKILLS, agility, DANCE SKILLS, axis, DANCE SKILLS, personality</td>
<td>posture → dance skills, agility → motor coordination, axis → balance, control → motor coordination, personality → dance skills, posture → dance skills, dance very close → connection with the partner, posture → dance skills, axis → balance, control → motor coordination, respect → mental posture</td>
</tr>
<tr>
<td>T4</td>
<td>RQ1.1</td>
<td>(PT) Também a capacidade do casal se intreigir, um dançar para o outro, olhando no olho do outro, se a pessoa consegue ter esse relação com o outro e se juntar com outro na dança. (EN) Also the ability of the couple to interact, dance to each other, looking into each other's eyes, if the person can have this relationship with each other and join with each other in the dance.</td>
<td>Students should be able to interact with each other in the dance, looking to each other.</td>
<td>Eye contact is important for dance Interaction is important for dance</td>
<td>DANCE SKILLS, eye contact, DANCE SKILLS, interaction</td>
<td>eye contact → connection with the partner, interaction → connection with the partner, rhythm → dance skills</td>
</tr>
<tr>
<td>T4</td>
<td>RQ1.1</td>
<td>(PT) O mais importante é dançar de acordo com um músic (EN) The most important thing is to dance according to the song</td>
<td>Rhythm is the most important for students to learn</td>
<td>Rhythm is an important dance skill</td>
<td>DANCE SKILLS, rhythm</td>
<td>rhythm → dance skills</td>
</tr>
<tr>
<td>T#</td>
<td>Research Question</td>
<td>Interview quotation</td>
<td>Key point</td>
<td>Code</td>
<td>Categories</td>
<td>Axial Coding</td>
</tr>
<tr>
<td>----</td>
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</tr>
<tr>
<td>T4</td>
<td>RQ1.1</td>
<td>(PT) Então acho que é coisa básica: eixo, condução, transferência de peso e aprender brincando, aprendendo se divertindo isso é o mais importante para quem está começando. (EN) So I think the basic thing: axis, leading, weight transfer and learning by playing, learning having fun is the most important thing for those just starting out.</td>
<td>Important dance skills for beginner to learn are axis, leading, weight transfer and learn by having fun</td>
<td>DANCE SKILLS, rhythm, coordination, balance, spatial awareness, fluency, leading, posture</td>
<td>DANCE SKILLS, rhythm, balance, spatial awareness, fluency, leading, posture</td>
<td>Posture → dance skills weight transfer → dance skills having fun → relaxation → psychological → dance skills</td>
</tr>
<tr>
<td>T5</td>
<td>RQ1.1</td>
<td>(PT) Isso depende muito de pessoa para pessoa pode ser coordenação, ritmo, musical, vergonha, psicológico. (EN) It depends a lot from person to person can be coordination, rhythm, musicality and psychological factors like shame.</td>
<td>Difficult skills for students to learn can include: coordination, rhythm, musicality and psychological factors like shame</td>
<td>DANCE SKILLS, coordination, rhythm, musicality, psychological (shame)</td>
<td>DANCE SKILLS, coordination, rhythm, musicality, psychological (shame)</td>
<td>Coordination → dance skills rhythm → dance skills musicality → dance skills shame → self-confidence → psychological → dance skills</td>
</tr>
<tr>
<td>T6</td>
<td>RQ1.1</td>
<td>(PT) As duas primeiras que eu trabalho é a análise da coordenação e o equilíbrio [...] A segunda coisa é ele coordenar e equilibrar os movimentos que ele faz dentro do tempo e do espaço que seria o ritmo e o espaço que é permissível para ele. Essas são as coisas que geralmente eles têm mais dificuldade. Eu vou trabalhando fluência, condução, postura e ritmo são as outras quatro coisas que eu vou trabalhar. (EN) The first two I work on is the analysis of coordination and balance [...] The second thing is that he coordinates and balances the movements he makes within time and space that would be the rhythm and space that is permissible for him. These are the things that they usually have the most difficulty with. I work fluency, leading, posture and rhythm are the other four little things that I will work on.</td>
<td>Important skill for students to learn includes: coordination, balance, rhythm, spatial awareness, fluency, leading, posture</td>
<td>DANCE SKILLS, rhythm, coordination, balance, spatial awareness, fluency, leading, posture</td>
<td>DANCE SKILLS, rhythm, coordination, balance, spatial awareness, fluency, leading, posture</td>
<td>Postural → dance skills rhythm → dance skills spatial awareness → dance skills fluency → energy → dance skills leading → dance skills posture → dance skills</td>
</tr>
<tr>
<td>T7</td>
<td>RQ1.1</td>
<td>(PT) Tem muitos elementos que tu pode avaliar numa dança, a questão de ritmo, técnica também dos movimentos, se a leitura musical dela condiz com os movimentos que ela tá fazendo [...] a expressão do corpo, qualidade movimento, a expressão facial, coordenação entre mexer braço, perna e quadril. (EN) There are many elements that you can evaluate in a dance, the question of rhythm, technique of movements, if her musical reading matches the movements she’s doing [...] body expression, movement quality, facial expression, coordination between moving arm, leg and hip.</td>
<td>Important skill for dance are: rhythm, technique, musical reading, expression, movement quality, facial expression, coordination (arm, leg, hips)</td>
<td>DANCE SKILLS, rhythm, technique, musical reading, expression, movement quality, facial expression, coordination</td>
<td>DANCE SKILLS, rhythm, technique, musical reading, expression, movement quality, facial expression, coordination</td>
<td>Rhythm → dance skills technique → dance skills musical reading → musicality → dance skills expression → energy → dance skills movement quality → technique → dance skills facial expression → mental posture → dance skills coordination → dance skills</td>
</tr>
<tr>
<td>T7</td>
<td>RQ1.1</td>
<td>(PT) O quadril envolvido e permanecer com o resto da coluna ereta, pello alberto. [...] Tem as outras pessoas que vai ter um movimento lá mais duro por causa da consciência corporal mesmo. [...] Tem a questão da coordenação quando tu vai tentar coordenar duas coisas ao mesmo tempo. (EN) The hip fitted and remain with the rest of the spine erect, chest open. [...] There are other people who will have a harder movement because of body awareness [...] There is the question of coordination when you try to coordinate two things at the same time.</td>
<td>Is important for dance that the dancer have posture, open chest, body awareness and coordination</td>
<td>DANCE SKILLS, posture, open chest, body awareness and coordination</td>
<td>DANCE SKILLS, posture, open chest, body awareness and coordination</td>
<td>Posture → dance skills open chest → posture → dance skills body awareness → spatial awareness → dance skills coordination → dance skills</td>
</tr>
<tr>
<td>T8</td>
<td>RQ1.1</td>
<td>(PT) Eu acho que eles primeiro tem que ir lá para descontrair. O ritmo sem dúvida vai fazer com que as pessoas se sintam mais confortáveis com os aspectos técnicos que nós ensinamos. Antes dos passos eles tem que conseguir ouvir a música e transformar aquilo em movimento, e essa é a parte mais difícil. (EN) I think they first have to go there to relax. The pace will undoubtedly make people feel more comfortable with the technicalities we teach. Before the steps, they have to be able to hear the music and turn it into motion, and that’s the hardest part.</td>
<td>First things for students to learn is to have fun, rhythm and rhythmic coordination</td>
<td>DANCE SKILLS, have fun, rhythm and rhythmic coordination</td>
<td>DANCE SKILLS, have fun, rhythm and rhythmic coordination</td>
<td>Have fun → relaxation → psychological → dance skills rhythm → dance skills rhythmic coordination → direction → dance skills</td>
</tr>
<tr>
<td>T#</td>
<td>Research Question</td>
<td>Interview quotation</td>
<td>Key point</td>
<td>Code</td>
<td>Categories</td>
<td>Axial Coding</td>
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</tr>
<tr>
<td>T8 RQ1.1</td>
<td>(PT) Muita gente tem dificuldade de se aproximar do outro [...] Outras pessoas têm problemas de ritmo também [...] Tudo depende da forma como o professor abordará as questões. (EN) A lot of people have difficulty getting closer to each other [...] Other people have rhythm problems too [...] It all depends on how the teacher approaches the issues.</td>
<td>Students have difficulty with dancing very close to each other and with rhythm.</td>
<td>Dance together is difficult to students.</td>
<td>DANCE SKILLS, dance close together</td>
<td>connection with the partner → dance skills</td>
<td>dance close together → connection with the partner → dance skills</td>
</tr>
<tr>
<td>T9 RQ1.1</td>
<td>(PT) O que eu vejo num casal se ele está dançando é a conexão com música e um com outro [...] A conexão entre essas três elementos para mim é a dança [...] Para ter conexão com a música é você poder viajar dentro dela você fazer no ritmo entrar na melodia e em cada instrumento e fazer o que você quiser. A liberdade de fazer o que você quiser dentro desses elementos. (EN) What I see in a couple if they are dancing is the connection with music and with each other [...] The connection between these three elements for me the person is dancing [...] To have connection with the music is when you can travel within it, you get in rhythm, get into the melody and each instrument and do whatever you want. The freedom to do what you want within those elements.</td>
<td>Important elements in dance include: connection with music, with partner, rhythm, music, creativity.</td>
<td>Connection with music is important for dance.</td>
<td>DANCE SKILLS, connection with music</td>
<td>connection with music → musicality → dance skills</td>
<td>connection with the partner → dance skills</td>
</tr>
<tr>
<td>T9 RQ1.1</td>
<td>(PT) Tem dificuldade de compreender-se, de entender onde e quando ele está parado, para ele poda abrir os caminhos para poder entender a música junto com o movimento. A maior dificuldade é de se entender e se soltar. Essas barreiras tem que ser passadas para a pessoa se sentir confortável. (EN) He has difficulty understanding himself, understanding where he is standing, that he can open the channels so that he can understand music along with the movement. The biggest difficulty is understanding and letting go. These barriers have to be passed for the person to feel confident.</td>
<td>Students have difficulty to have self-awareness, read the music, relax and have confidence.</td>
<td>Students have difficulty to have self-awareness.</td>
<td>DANCE SKILLS, self-awareness</td>
<td>self-awareness → spatial awareness → dance skills</td>
<td>students have difficulty to open themselves → openness → psychological → dance skills</td>
</tr>
<tr>
<td>T10 RQ1.1</td>
<td>If someone has is able to vary their subtleties of movement [...] when someone moves in a more intelligent way of dancing [...] different variation in their expression.</td>
<td>Dancers should be able to vary their movement and expressions, with intelligence.</td>
<td>Personality is important in dance.</td>
<td>DANCE SKILLS, personality</td>
<td>personality → creativity → dance skills</td>
<td>variation → creativity → dance skills</td>
</tr>
<tr>
<td>T11 RQ1.1</td>
<td>The ones who think they know how to dance, it’s kind of hard to break old habits [...] Also girls who used to do ballet because they usually are stiffer and they have trouble listening to the music and following the lead [...] For the guys if they have a background in martial arts especially Judo and Ju-Jitsu, they are very stiff. It is hard for students to loose old habits like ballet girls listening to the music and follow the lead, or martial arts guys to be less stiff.</td>
<td>It hard for students to loose old habits like ballet girls listening to the music and follow the lead, or martial arts guys to be less stiff.</td>
<td>It is important for students to have body awareness.</td>
<td>DANCE SKILLS, body awareness</td>
<td>body awareness → spatial awareness → dance skills</td>
<td>students have difficulty to open themselves → openness → psychological → dance skills</td>
</tr>
<tr>
<td>T11 RQ1.1</td>
<td>It’s really hard to teach people the rhythm, how to dance in the proper timing</td>
<td>It is hard to teach student to dance in the proper timing of the songs.</td>
<td>Rhythm is important for dance.</td>
<td>DANCE SKILLS, rhythm</td>
<td>rhythm → dance skills</td>
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<td>T12 RQ1.1</td>
<td>(PT) A maior dificuldade eu acho que é lidar com o novo porque a dança desafia muito tecnicamente [...] No início pode ser mais difícil aprender a técnica [...] Ritmo realmente é uma dificuldade que é presente para muitos alunos. (EN) The biggest difficulty I think, is dealing with the new because dance challenges a lot technically [...] At first it may be harder to learn the technique [...] Rhythm really is a difficulty that is present for many students.</td>
<td>Students have difficulty in learning somethings new, the technique and rhythm.</td>
<td>Novelty is hard for some students to deal with</td>
<td>DANCE SKILLS, deal with the new</td>
<td>deal with new → openness → psychological → dance skills</td>
<td>technique → dance skills</td>
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<td>T13 RQ1.1</td>
<td>(PT) Para dançar bem, ter fluência nesse diálogo corporal, [...] precisa de 3 técnicas: a técnica individual, que é ter consciência corporal; a segunda é a técnica do movimento, do desenho, da figura, do passo. Saber qual passo que eu vou fazer. Espaçal, para saber a direção que vai. Aliado a técnica individual eu consigo executar; e, Tem uma terceira técnica, que é a técnica de internelação, que precisa adaptar essas duas primeiras para poder dançar com a outra pessoa. A terceira técnica é de adaptação. Tem que ter essa flexibilidade para poder conversar com o outro. (EN) To dance well, to have fluency in this body dialogue, [...] needs 3 techniques: the individual technique, which is to have body awareness; The second is the technique of movement, drawing, figure, step. Know which step I am going to do. Space, to know the direction it is going. This allied to the individual technique I can execute; and, There is a third technique, which is the interrelation technique, which needs to adapt these first two to be able to dance with the other person. The third technique is adaptation. You have to have that flexibility to talk to each other.</td>
<td>For dance is important to: have body awareness technique, know the steps, spatial awareness individual technique, internelation and adaptation</td>
<td>Body awareness is important for dance</td>
<td>DANCE SKILLS, body awareness</td>
<td>body awareness → dance skills</td>
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<td>Technique is important for dance</td>
<td>DANCE SKILLS, technique</td>
<td>know the steps → technique → dance skills</td>
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<td>Know the steps is important for dance</td>
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<td>spatial awareness → dance skills</td>
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<td>Spatial awareness is important for dance</td>
<td>DANCE SKILLS, spatial awareness</td>
<td>individual technique → technique → dance skills</td>
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<td>Individual technique is important for dance</td>
<td>DANCE SKILLS, individual technique</td>
<td>interrelation → connection with the partner → dance skills</td>
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<td>Internelation is important for dance</td>
<td>DANCE SKILLS, internelation</td>
<td>adaptation → connection with the partner → dance skills</td>
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<td>Adaptation is important for dance</td>
<td>DANCE SKILLS, adaptation</td>
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<td>T14 RQ1.1</td>
<td>(PT) É o extremamente básico que é coordenação motora, equilíbrio, ritmo, musicalidade e um pouco de torção. (EN) It is the extremely basic that is motor coordination, balance, rhythm, musicality and a little twist.</td>
<td>Basic elements important for dance are motor coordination, balance, rhythm, musicality and a little twist.</td>
<td>Motor coordination is important for dance</td>
<td>DANCE SKILLS, motor coordination</td>
<td>motor coordination → dance skills</td>
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<td>Balance is important for dance</td>
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<td>Rhythm is important for dance</td>
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<td>rhythm → dance skills</td>
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<td>Musicality is important for dance</td>
<td>DANCE SKILLS, musicality</td>
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<td>T14 RQ1.1</td>
<td>(PT) Hoje eu considero claramente que a primeira é a coordenação motora, depois o equilíbrio e depois o ritmo dessa ordem. (EN) Today I clearly consider that the first is motor coordination, then balance, and then rhythm in that order.</td>
<td>The order of importance for students to learn is: motor coordination, balance and then rhythm.</td>
<td>Coordination is important for dance</td>
<td>DANCE SKILLS, coordination</td>
<td>coordination → motor coordination → dance skills</td>
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<td>Balance is important for dance</td>
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<td>Rhythm is important for dance</td>
<td>DANCE SKILLS, rhythm</td>
<td>rhythm → dance skills</td>
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<td>T14 RQ1.1</td>
<td>(PT) Além dessas questões técnicas tem um outro lado que é o lado psicológico. Se a pessoa é muito tímida e ou muito introspectiva, elas às vezes não consegue desenhar esse lado dançar, mas por um bloqueio psicológico. (EN) Besides these technical issues, there is another side which is the psychological side. If the person is very shy and or very introspective, she sometimes cannot awake that dancing side, more because she has a psychological block.</td>
<td>Psychological traits that can make difficult for students to learn are: being shy or introspective</td>
<td>Shyness makes difficult for students to learn dance</td>
<td>DANCE SKILLS, shyness</td>
<td>introspection → openness → psychological → dance skills</td>
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<td>In introspection makes difficult for students to learn dance</td>
<td>DANCE SKILLS, introspection</td>
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<td>T15 RQ1.1</td>
<td>(PT) Coisa que eu acho muito relevantes são a limpeza dos movimentos [...]. É possível voce sentir também a energia, se a pessoa ela tá dançando um pouco mais energico ou se ela tá buscando reprimir um pouco essa energia para tentar manter uma fluidiz. [...] Uma coisa também que é muito importante a nivel do Forró é sobre o deslocamento entre o casal. (EN) Something that I find very relevant is the cleanliness of the movements [...]. You can also feel the energy, if the person she is dancing a little more energetic or if she is trying to suppress this energy a little to try to maintain fluidity. [...] One thing that is very important at Forró level is the displacement between the couple.</td>
<td>Important elements for dance includes clean movements, energy and displacement</td>
<td>Clean movements is important for dance</td>
<td>DANCE SKILLS, clean movements</td>
<td>clean movements → technique → dance skills</td>
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<td>Energy is important for dance</td>
<td>DANCE SKILLS, energy</td>
<td>energy → dance skills</td>
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<td>Displacement is important for dance</td>
<td>DANCE SKILLS, displacement</td>
<td>displacement → spatial awareness → dance skills</td>
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<td>T15 RQ1.1</td>
<td>(PT) É muito importante a gente pensar também sobre a questão da condução e do contato. (EN) It is very important that we also think about the issue of leading/following and contact.</td>
<td>Leading and contact are important in dance</td>
<td>Leading is important for dance</td>
<td>DANCE SKILLS, leading</td>
<td>leading → dance skills</td>
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<td>Physical contact is important in dance</td>
<td>DANCE SKILLS, physical contact</td>
<td>physical contact → connection with the partner → dance skills</td>
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<tr>
<td>T15 RQ1.1</td>
<td>Very essential in the beginning is to deal with the rhythm, because it will help in tune the pair, to be together when they are dancing. This will give much more security to the student.</td>
<td>Rhythm is essential for beginner students</td>
<td>Rhythm is essential for beginner students</td>
<td>DANCE SKILLS, rhythm</td>
<td>rhythm → dance skills</td>
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<td>T15</td>
<td>RQ1.1</td>
<td>(PT) A primeira barreira do aluno é o conhecimento do próprio corpo [...] É muito imprescindível assim no começo ele vai ajudar na sintonia do par [...] Pensando sobre transferência de peso, marcação que no começo são mais um pouco mais rígidas [...] A segunda barreira que é quando o aluno ele começa a se preocupar um pouco mais com o par [...] A nossa atenção já começa a sair um pouco mais da gente para mudar a atenção um pouco maior no par. (EN) The first barrier of the student is the knowledge of his own body [...] It is very essential so in the beginning is to deal with the rhythm because it will help to tune the couple [...]</td>
<td>Thinking about weight transfer, marking that in the beginning they are a little more rigid [...] The second barrier that is when the student begins to worry a little more about the partner [...] Our attention is already starting to get a little more out of us to change the attention a little more in the partner.</td>
<td>Body awareness is important for beginners, rhythm is important for beginners, dance transfer is important for beginners, stepping is important for beginners, care about the partner is important for beginners</td>
<td>DANCE SKILLS, body awareness, DANCE SKILLS, rhythm, DANCE SKILLS, weight transfer, DANCE SKILLS, stepping, DANCE SKILLS, care about the partner</td>
<td>body awareness → spatial awareness → dance skills, rhythm → dance skills, weight transfer → dance skills, stepping → technique → dance skills, care about the partner → connection with the partner → dance skills</td>
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<td>T15</td>
<td>RQ1.1</td>
<td>I would say leading skills, following skills, things like balance, musicality, fluidity, the replication of the steps, being able to accurately replicate the fundamentals of the movement, posture, improvisation all skills the ability to not dance things in a set sequence but to improvise with the movement. Connection, like the ability to be physically close but also emotionally connected to your partner and be able to really read that other body. The ability to respond to nuances in a particular piece of music.</td>
<td>Important skills for dance includes leading/following balance, musically, fluidly, replicate steps, posture, improvisation, connection</td>
<td>Leading/following is important for dance Balance is important for dance Musically is important for dance Fluidity is important for dance Replicate steps is important for dance Posture is important for dance Improvisation is important for dance Connection is important for dance</td>
<td>DANCE SKILLS, leading/following, DANCE SKILLS, balance, DANCE SKILLS, musicality, DANCE SKILLS, fluidity, DANCE SKILLS, replicate steps, DANCE SKILLS, posture, DANCE SKILLS, improvisation, DANCE SKILLS, connection</td>
<td>leading/following → dance skills, balance → dance skills, musicality → dance skills, fluidity → energy → dance skills, replicate steps, posture → dance skills, improvisation → dance skills, connection → connection with the partner → dance skills</td>
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<td>T16</td>
<td>RQ1.1</td>
<td>The trick with the beginners is not to overwhelm them too much technical information [...] They need to have fun, they need to really enjoy the dance</td>
<td>Beginner students should have fun and not be overwhelmed with technique</td>
<td>Have fun is important for students</td>
<td>DANCE SKILLS, have fun</td>
<td>have fun → relaxation → psychological → dance skills</td>
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<td>T16</td>
<td>RQ1.1</td>
<td>I think how to use the hip, a bit of reluctance and difficulty particularly on the part of the men in using the hips, takes a while to teach the students and get them to understand in their bodies the bet hip movement comes from relaxation</td>
<td>Relax and move the hips is important for dance</td>
<td>Relaxed hip movement is important for dance</td>
<td>DANCE SKILLS, hip movement</td>
<td>hip movement → motor coordination → dance skills</td>
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<tr>
<td>T16</td>
<td>RQ1.1</td>
<td>It can sound really rhythmically complex [...] so understanding the music can be difficult and like I said something the closeness involved with the dance styles that physical closeness they can find difficult, emotionally difficult. It takes a while to develop trust and things like that [...]</td>
<td>Difficult skills for students to learn are understanding different music styles, rhythm physical closeness, emotion, trust and coordination</td>
<td>Understand different music styles is difficult for students Rhythm is difficult for students Physical closeness is difficult for students Emotional connection is difficult for students Trust is difficult for students to create Coordination is difficult for students</td>
<td>DANCE SKILLS, understand different music styles, DANCE SKILLS, rhythm, DANCE SKILLS, physical closeness, DANCE SKILLS, emotion, DANCE SKILLS, trust, DANCE SKILLS, coordination</td>
<td>understand different music styles → motor coordination → dance skills, rhythm → dance skills, physical closeness → connection with the partner → dance skills, emotion → connection with the partner → dance skills, trust → psychological → dance skills, coordination → motor coordination → dance skills</td>
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Jaques-Dalcroze, E. (1921). Rhythm, music and education. GP Putnam’s Sons.


