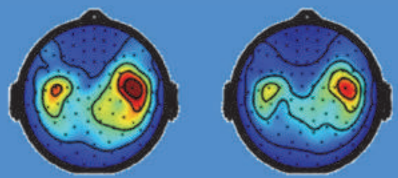
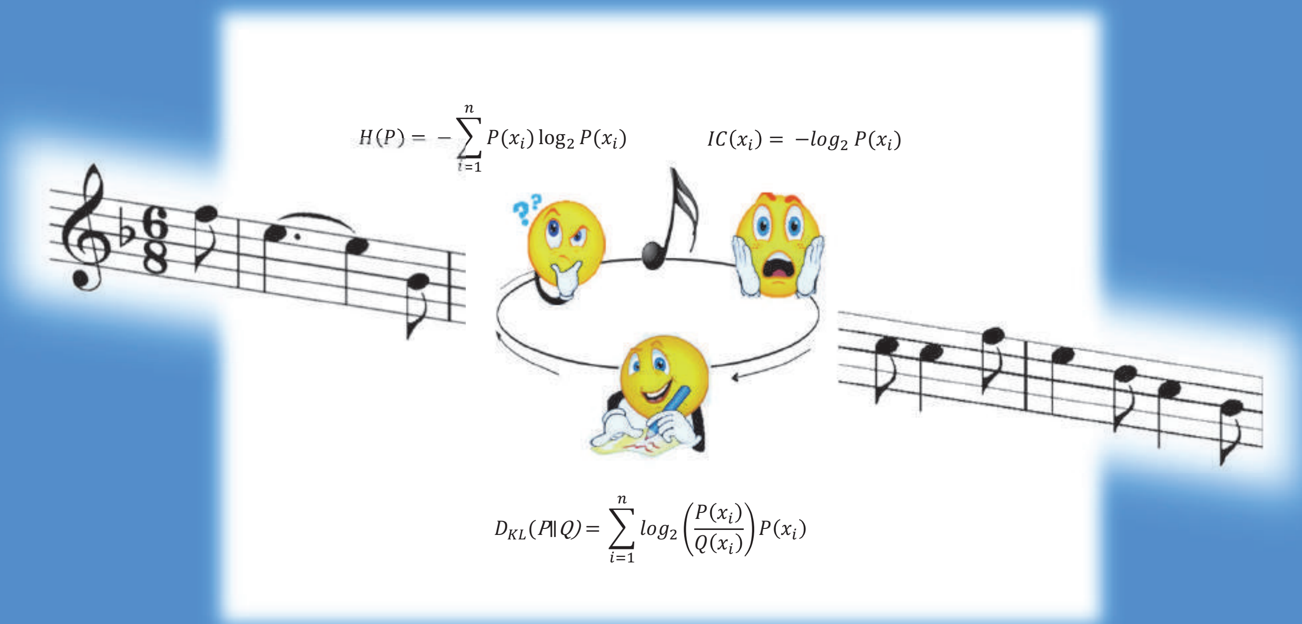
Predictive coding of musical expertise

PhD dissertation

Niels Chr. Hansen





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Predictive coding of musical expertise

PhD dissertation

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"That musical styles are internalized probability systems is demonstrated by the rules of musical grammar and syntax found in textbooks on harmony, counterpoint, and theory in general. The rules given in such books are almost invariably stated in terms of probability [...] Out of such internalized probability systems arise the expectations–the tendencies–upon which musical meaning is built."

Leonard B. Meyer (1967, p. 8)

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Preface

This dissertation is based on the following manuscripts reporting original research:

<u>Study 1</u>: **Hansen, N.C.,** & Pearce, M. (2014). Predictive uncertainty in auditory sequence processing. *Frontiers in Psychology*, *5*, 1052. doi: 10.3389/fpsyg.2014.01052

<u>Study 2</u>: **Hansen, N.C.,** Vuust, P., & Pearce, M. (under review). "If You Have to Ask, You'll Never Know": Effects of Specialised Stylistic Expertise on Predictive Processing of Music.

<u>Study 3</u>: **Hansen, N.C.,** Loui, P., Vuust, P., & Pearce, M. (in prep.). Statistical Learning as Entropy Minimisation.

<u>Study 4</u>: **Hansen, N.C.,** Nielsen, A.H., Møller, C., Pearce, M., & Vuust, P. (in prep.). Enhanced feature processing in musicians: Expertise modulates the additivity of the MMNm response.

Chapters 1, 2 and 5, furthermore, include translated and reworked excerpts from:

Hansen, N.C. (2015). Nye perspektiver på studiet af musikalsk ekspertise ["New perspectives on the scientific study of musical expertise"]. *Danish Musicology Online* (Special Issue 2015: Music and Brain Research), 69-101.

In addition to the core project, the following papers were submitted, accepted, or published during the time of PhD enrolment:

Gebauer*, L., Witek*, M., **Hansen, N.C.**, Thomas, J., Konvalinka, I., & Vuust, P. (under revision). Oxytocin improves prediction in social interaction. *Scientific Reports*.

Hansen, N.C., Sadakata, M., & Pearce, M. (2016). Non-linear changes in the rhythm of European art music: Quantitative support for historical musicology. *Music Perception 33*(4), 414-431. doi: 10.1525/mp.2016.33.4.414

Ross*, S. & **Hansen*, N.C.** (2016). Dissociating prediction failure: Considerations from music perception. *The Journal of Neuroscience*, *36*(11), 3103-3105. doi: 10.1523/jneurosci.0053-16.2016

Hansen, N.C. (2013). Cognitive approaches to analysis of emotions in music listening. In: M. Zatkalik, D. Collins, & M. Medic, *Histories and Narratives of Music Analysis* (pp. 597-627), Cambridge, UK: Cambridge Scholars Publishing.

** shared first authorship*

English summary

The fascinating powers of musical expertise make it a natural object of scientific enquiry. Previous research on this topic, however, has been to a large extent underpinned by romanticised concepts of genius and excellence leading to a view of experts as individuals blessed with skills that are primarily elusive, innate, all-or-nothing, beneficial, and creative. This dissertation, in contrast, casts musical expertise in scientific terms, recognising it to be empirically investigable, acquired, continuous and multidimensional, adaptive as well as potentially maladaptive, and relevant to both the production and perception of music.

By casting musical expertise as gradual optimisation of predictive coding mechanisms, this phenomenon becomes compatible with key theories in cognitive psychology and neuroscience. In this way, aspects of expert processing can be modelled computationally using information theory and investigated empirically with available behavioural and neurophysiological methods. The introductory chapter concludes by devising a novel framework facilitating scientific studies of musical expertise along these lines through the lens of six analytical perspectives. These relate to the origin of expertise, its cognitive representations, predictive uncertainty, predictive flexibility, and its conscious availability and neural correlates.

The first three studies used behavioural probe-tone methods to address questions regarding the predictive coding of musical expertise, focusing on its manifestation, specialisation, and acquisition. Study 1 found that predictive uncertainty of melodic pitch expectations can be characterised in terms of the Shannon entropy of conditional probability distributions acquired through statistical learning of music over long time spans. Correlational fit between expectations and probabilistic structure in music was a linearly increasing function of experience, leading musicians to predict with lower degrees of uncertainty in general and

experience greater prediction error than non-musicians specifically in contexts containing high degrees of decodable probabilistic structure.

Study 2 found that stylistic specialisation in jazz resulted in improved access to conscious introspection of one's own uncertainty about the continuation of improvised solos by Charlie Parker. In other words, whereas professional musicians trained in jazz or classical music did not differ on explicit expectedness processing, they differed on uncertainty processing. Moreover, the fact that classical and non-musicians refrained from misapplying their well-developed knowledge of general tonal music in stylistically irrelevant contexts supports theories of cognitive firewalls restricting the scope of predictive processing.

Study 3 found that statistical learning of musical sequences can be modelled as minimisation of the relative entropy between listener expectations and the probabilistic structure of music. Consistent with predictive coding theory, this process took place across timescales and exposure corpora and was not affected by musical expertise when controlling for prior long-term exposure.

Study 4, lastly, used MEG to show greater under-additivity of the MMNm response in musicians compared to non-musicians, specifically for the pitch component when sounds were presented in a musical context. This may be interpreted as training-induced plasticity of the neural mechanisms for auditory feature processing.

Following up on the initially presented analytical framework, it is concluded that musical expertise to a large extent originates from statistical learning under (possibly) innate constraints. This phenomenon manifests itself as sophistication of cognitive representations, minimisation of the uncertainty of musical predictions, development of specialised contextual knowledge, and greater explicit access to this knowledge. These changes do not only captivate the audiences, but also shape the brains of the experts themselves.

Danish summary

Den musikalske ekspertises fascinationskraft gør den til en naturlig genstand for videnskabelige undersøgelser. Tidligere forskning på dette felt har imidlertid været præget af et romantiseret genibegreb, hvilket har resulteret i et forfejlet syn på musikalsk ekspertise som udelukkende uhåndgribelig, naturgiven, alt-eller-intet, gavnlig og skabende. I modsætning hertil anskues musikalsk ekspertise i nærværende afhandling i et videnskabeligt perspektiv, hvorved den anerkendes som empirisk begribelig, tilegnet, kontinuerlig og flerdimensionel, adaptiv såvel som potentielt maladaptiv og relevant både i forhold til at skabe og opfatte musik.

Når musikalsk ekspertise forstås som gradvis optimering af de kognitive mekanismer for *predictive coding*, bliver den forenelig med førende teorier inden for kognitiv psykologi og neurovidenskab. Dermed kan ekspertens mentale processer studeres med informationsteoretisk computermodellering, adfærdsforsøg og neurofysiologiske metoder. Seks analytiske perspektiver foreslås her i relation til ekspertisens ophav samt dens mentale repræsentationer, forventningssikkerhed, forventningsfleksibilitet, bevidsthedstilgængelighed og neurale korrelater.

De tre første studier bestod i adfærdsforsøg, hvor lytteren vurderede, hvor godt en given tone fortsatte en melodisk kontekst. Hermed undersøgtes spørgsmål vedrørende *predictive coding* af musikalsk ekspertise med fokus på, hvordan ekspertisen kommer til udtryk, hvordan den specialiseres, og hvordan den tilegnes. Studie 1 viste, at forventningsusikkerhed i forhold til melodiske forventninger om tonehøjde kan karakteriseres ved Shannon-entropien af konditionelle sandsynlighedsfordelinger, som lytteren har tilegnet sig gennem statistisk læring af musik over længere tidsforløb. Korrelationen mellem lytterens forventninger og sandsynligheder i musikken viste sig at være en lineært stigende funktion af musikalsk erfaring. Således forudsiger musikere generelt med mindre usikkerhed

samt oplever større *prediction error* end ikke-musikere, sidstnævnte specifikt i sammenhænge med store mængder statistisk struktur, som kan afkodes.

Studie 2 fandt, at stilistisk specialisering inden for jazz førte til bedre adgang til bevidste mentale processer vedrørende ens egen usikkerhed om forløbet af improviserede soloer af Charlie Parker. Selvom professionelle musikere inden for jazz eller klassisk musik ikke adskilte sig med hensyn til bevidst adgang til bagudrettede forventningsprocesser, så var der med andre ord forskelle, når det gjaldt fremadrettet usikkerhed. At klassiske musikere og ikke-musikere afstod fra at gøre fejlagtig brug af deres veludviklede kendskab til generel, tonal musik i stilistisk irrelevante sammenhænge som denne, støtter ydermere teorien om kognitive firewalls.

Studie 3 fandt, at statistisk læring af musikalske forløb kan modelleres som minimering af den relative entropi mellem lytterens forventninger og sandsynligheder i den musikalske struktur. I overensstemmelse med *predictive coding* fandt denne proces sted over korte og lange tidsforløb med flere forskellige musikalske materialer, og den var ikke afhængig af foregående musikalsk træning.

Studie 4 anvendte til sidst magnetoencefalografi (MEG) til at påvise større under-additivitet i det magnetiske *mismatch negativity*-respons (MMNm) hos musikere sammenlignet med ikke-musikere. Dette var specifikt for afvigelser indeholdende ændret tonehøjde, når de blev præsenteret i en musikalsk sammenhæng. Dette antyder, at neural processering af auditoriske *features* påvirkes af musikalsk træning.

I lyset af den førnævnte analytiske forståelsesramme konkluderes det til sidst, at musikalsk ekspertise i vid udstrækning er tilegnet under (muligvis) medfødte fysiologiske begrænsninger. Ekspertisen kommer til udtryk som sofistikering af mentale repræsentationer, minimering af forventningsusikkerhed, kontekstafhængig specialisering samt større bevidst adgang til den tilegnede viden. Disse forandringer fascinerer ikke kun publikum, men former også ekspertens egen hjerne.

Acknowledgements

Doing a PhD is no walk in the park. In fact, it is more like getting frantically lost in a thick wilderness with little hope of ever escaping again. For this reason, over the years, numerous people with a doctorate degree have warned their compatriots and loved ones against ever embarking on such a treacherous journey. What many recipients of such advice, including myself, have failed to realise, however, is that this type of guidance is in fact based on empirical evidence sampled, cross-checked, and validated by people with the highest available training in the scientific method. Luckily, with invaluable help from a long list of people that I will try to acknowledge here, I am now finally encountering a clearing where a little light penetrates the forest canopy; who knows, maybe this is even the end of the bushes?

I am, first of all, deeply grateful to my supervisors, Peter Vuust and Marcus Pearce, for giving me the opportunity to conduct this research project and for accompanying me on my first expedition into the murky waters of academia. I also owe thanks to Psyche Loui for taking up a supervisory role in relation to Study 3 and to Andreas Højlund Nielsen for doing so for Study 4. I admire Psyche's exemplary sense of order, allowing her to locate old data files and meticulously account for past methodological decisions. Similarly, Andreas showed his undeniable dedication by providing verbose answers to technical questions, often at ungodly hours of the day.

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(although she did assure me that I was merely freeing her from tiresome research-related tasks including “listening to recordings of people who mostly can't sing”). Also many thanks to Christopher Bailey for introducing me to the blessings of MEG machinery and for readily remedying the unpredictable breakdowns (technical and mental) that this oftentimes entails. I further owe thanks to Dora Zeidler for MRI assistance, and not least for shielding me against Torben Lund’s mid-experiment experimentation aiming to increase the (already quite mind-boggling) number of display screens constituting the highly esteemed MINDLab Experimental Core Facilities.

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my part. I truly enjoyed being part of the unique atmosphere that is MARCS, which I hope to come back to and re-experience shortly. At Queen Mary in London, Marcus never ceases to offer great hospitality, always worthy of the royal appellation of his institution. I also thank Helle Skaarup and the rest of the community at Løgumkloster Refugium for providing greatly cherished opportunities for full immersion, garnished with South Jutlandic delicacies and warm, encouraging conversations, during the final writing phase of this project. Similarly, many heartfelt thanks go to my parents for providing no less favourable conditions when this phase unavoidably protracted itself, and to my brother Jens for breaking ground into academia, thus mitigating potential collisions.

I wish to thank music itself. Without it, life would be deprived of not only this dissertation, but indeed many beautiful things. This gratitude extends to the Sundanese *gamelan degung* which became the soundtrack of my dissertation writing. Who knows, maybe one day we will succeed in designing experiments that fully salute the magic that music has to offer. One extraordinary person who unmistakably possessed the wizardry to release this spell was my piano teacher and dear friend and mentor, Anne Øland. Although we sadly lost her during the work on this dissertation, her dedication and ingenuity endure in her students' multifaceted musical undertakings, including my own.

Lastly, I am deeply grateful to Rebeka. That I am because no matter whether you are going for a walk in the park or on a dangerous wilderness expedition, having a kind, loving, and supportive travel partner always makes for a more successful and enjoyable journey.

Niels Chr. Hansen

Aarhus, January 2016

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Abbreviations

ANOVA	Analysis of Variance
BOTH	Combined short- and long-term sub-models
BP	Bohlen-Pierce (Scale)
cHPI	Continuous Head-Position Indicators
EAN	Early Anterior Negativity
ECG	Electrocardiography
EEG	Electroencephalography
EOG	Electrooculography
ERF	Event-Related Field
ERP	Event-Related Potential
P	Pitch deviant (Study 4)
PI	Pitch and Intensity double deviant (Study 4)
PIL	Pitch, Intensity, and Location triple deviant (Study 4)
fMRI	Functional Magnetic Resonance Imaging
Gold-MSI	Goldsmiths Musical Sophistication Index
Hz	Hertz
I	Intensity deviant (Study 4)
IL	Intensity and Location double deviant (Study 4)
IC	Information Content
ICA	Independent Component Analysis
IDyOM	Information Dynamics of Music (Model)
L	Location deviant (Study 4)
LP	Location and Pitch double deviant (Study 4)
LTM	Long-Term sub-Model
M	Mean
MEG	Magnetoencephalography
MIDI	Musical Instrument Digital Interface
MMN(m)	Mismatch Negativity (magnetic counterpart)
ms	Milliseconds (i.e. 0.001 second)
µs	Microseconds (i.e. 0.000001 second)
SD	Standard Deviation
SLH	Statistical Learning Hypothesis
SOA	Stimulus Onset Asynchrony
STM	Short-Term sub-Model
tSSS	Temporal Signal Source Separation

1. Introduction

Although it remains to be fully understood why human cultures evolved music, as far back in time as our eyes and ears reach, one thing we know for sure is that music fascinates us. One particularly prominent source of this fascination is the excellence with which musical experts who are especially skilled in their profession transmit their messages in sound. Every day this fascination lures thousands of individuals from the safety of their armchairs into the unchartered territory of concert halls and music venues, sometimes traversing long distances, sacrificing considerable amounts of time and finances on such activities, seemingly with little or no evolutionary purpose. For audiences, live music provides a rare opportunity to experience the expertise of leading musical stars first-hand; this may in turn nurture the hope that they can achieve similar levels of musical proficiency and excel themselves someday.

The role of expertise as a catalyst for musical aspiration and idolisation makes it a natural object of scientific enquiry. This interest emerges most clearly from musicological reference works, including biographies and music history textbooks, where significant composers (DeNora, 1997; Elias, 1993; Fanning, 2003; Higgins, 2004), instrumental virtuosos (Garcia, 2004; Southall, 1979), influential music teachers (Sand, 2005), and even instrument makers (Faber, 2006) are regularly labelled as musical geniuses. This discourse has a close affinity with the Romantic concept of genius, which, as a minimum, can be traced back to Jean-Jacques Rousseau in the second half of the 18th century (Rousseau, 1768).[1] Despite its appeal, however, this conception of musical excellence tends to evade critical scrutiny, leading musicologists themselves to conclude that "[m]usic historians have not yet dealt with the concept of genius in any systematic manner" (Lowinsky, 1964, pp. 322-3). Consequently, systematic studies of musical excellence have never become a core

[1] There are even indications that related concepts of musical genius may have played a role earlier in music history, albeit with a slightly different meaning (Higgins, 2004; Lowinsky, 1964).

part of the musicological curriculum (e.g., Beard & Gloag, 2004; Christ & Marvin, 2008; Clarke & Cook, 2004; Cook, 2000; Williams, 2001).[2]

Cognitive psychologists, on the other hand, have investigated excellence systematically for nearly half a century framing it in terms of expertise and expert performance (Ericsson, Charness, Hoffman, & Feltovich, 2006). With seminal studies by Chase and Simon (1973), de Groot (1978), and Charness (1979), this work took chess and bridge as starting points, focusing on memory, visual perception, and conscious decision making, which are all of key importance in these domains. This research endeavour gradually expanded into sports (Hodges, Starkes, & MacMahon, 2006), medicine (Schmidt & Boshuizen, 1993), military (Schvaneveldt et al., 1985), and music (Lehmann & Gruber, 2006; Sloboda, 1991), opening up new research areas such as situational awareness (Endsley, 2000) and deliberate practice (Ericsson, 2008). Predominantly, a comparative perspective was maintained, emphasising similarities across domains instead of unique qualities and peculiarities of specialised fields. This has resulted in reviews and comprehensive volumes, offering a unified account of cognitive expertise (Ericsson, 2003; Ericsson et al., 2006; Ericsson & Smith, 1991; Farrington-Darby & Wilson, 2006).

Music researchers have largely adopted this view, modelling their experiments after classical studies in cognitive psychology. For this reason, deliberate practice (Platz, Kopiez, Lehmann, & Wolf, 2014), declarative memory (Crawford, Chaffin, & Imreh, 2002), situational awareness (Geeves, McIlwain, Sutton, & Christensen, 2014; Schiavio & Høffding, 2015), and visual perception (Waters, Townsend, & Underwood, 1998) are also prominent topics in musical expertise research. Due to the aforementioned unifying aim, however, aspects with specialised relevance in musical

[2] Note that Haydon's (1941) early introduction describes the possibility of an experimental psychology approach to 'musical intelligence' (pp. 100-109). This lead was, however, never truly pursued in subsequent musicological work.

contexts, such as time criticality, prediction, and audio-motor coupling, have not always received equivalent levels of attention.

The overall goal of the current dissertation is to address this lacuna by developing, presenting, and testing a novel framework for scientific studies of musical expertise. This endeavour focuses on predictive processing, with the explicit aim of investigating specific aspects like receptive skills (in contrast to productive skills), predictive uncertainty, stylistic specialisation, and auditory feature processing which have thus far been somewhat understudied from the perspective of expertise.

In the following background chapter, I argue that the present undertaking needs to first transcend the romanticised concepts of genius and excellence that dominate much previous music-related expertise research (Section 2.1). In doing so, I adopt a musical expertise concept that accommodates the specialised characteristics of music as a cognitive domain (Section 2.2). This perspective emphasises musical learning, framing it as optimisation of predictive processing (Section 2.3). For this reason, it is compatible with key theories in cognitive (neuro)science concerning predictive coding (Section 2.4) and statistical learning (Section 2.5). Expert processing can be modelled with a range of information-theoretic concepts (Section 2.6), which, when operationalised and implemented in a computational model (Section 2.7), can be meaningfully related to empirical data obtained with behavioural (Section 2.8) and neurophysiological methods (Section 2.9). This approach is subsequently exemplified with a selection of specific research questions (Section 2.11), derived from the scientific framework (Section 2.10).

2. Background

2.1. Romanticised concepts of musical genius and excellence

An idealised concept of genius based on Romanticism pervades musicological discourse, but can also be traced in expertise research outside this sphere, for instance in the medical sciences (Robertson, 2008). In summary, this view tends to regard musical excellence as a conglomerate of (1) *elusive*, (2) *innate*, (3) *all-or-nothing*, (4) *beneficial*, and (5) *creative* properties. This is clearly evident from the article on *Genio* from *Dizionario a bibliografia dela musica* (Lichtenthal, 1826):

> "Musical genius is that [2] inborn, [1] inexplicable [4] gift of Nature, or original faculty to [5] create with facility esthetic ideas and to give them [3] the most fitting expression in the melodic and harmonic organization of tones."

The numbers inserted here refer to the five properties mentioned above; thus, it is established that genius constitutes a highly treasured ability which is present from birth, and cannot be accounted for, enabling its owner to produce not only superior, but superlative pieces of artistry. I will now outline how this genius concept directly affects contemporary research.

First, it is widely believed that musical excellence is *elusive*; in other words, it cannot–and perhaps even *should not*–be studied in systematic, let alone scientific, terms. This is evident from numerous musicological accounts associating expertise with the inexplicable, for instance: "Hildegard of Bingen […] had talents and skills that seem to us evidence of genius because we cannot rationally account for them" (Mellers, 1989). Others have demonstrated how this romanticised, genius-focused view was passed on to critical reviews of late-20th-century, modernist composers (Piotrowska, 2007) and to myth-building in rock music (Pattison, 1987). In contemporary popular culture, genius discourse dominates 'The X Factor' reality TV concept named after a phenomenon that is defined by its ability to defy definition. In other words, if particular musical traits do not elude verbalisation, they would not be signs of X factor, or expertise for that matter.

Second, musical excellence tends to be regarded as *innate* rather than as resulting from persistent practice (Bourne, Kole, & Healy, 2014; Chaffin & Lemieux, 2004). This notion was already present in Galton's (1869) early work emphasising and documenting inherited aspects of musical intelligence. Although later music researchers have characterised this widespread presumption as "folk psychology" (Davis, 1994; Sloboda, Davidson, & Howe, 1999) and a "myth" (Howe, Davidson, & Sloboda, 1998), yet it dominates colloquial discourse. For instance, 8-year-olds already tend to believe that, in contrast to sports skills, musical skills cannot be improved (O'Neill, 1996), and 75% of adults concur that the ability to compose, sing, and play a musical instrument requires a natural talent (Davis, 1994). Moreover, when providing free responses to the open-ended statement "Musical ability is…", equally many report that it is innate (~9%) and both innate and learned (~9%), whereas fewer people consider musical ability as only learned (~1%) (Hallam & Prince, 2003). When it comes to expressive rather than technical skills, the folk-psychological belief in innate talents is even prominent amongst musicians (Sloboda, 1996). This misconception may owe partly to the etymological meaning of *genius* as "inborn nature" or "guardian deity or spirit which watches over each person from birth" (Harper, 2007).

Third, excellence has traditionally been regarded as an *all-or-nothing* issue: either you have it or you don't. Indeed, until recently, musicians were almost exclusively regarded as a homogenous group (Tervaniemi, 2009), and categorical comparisons between musicians and non-musicians dominated empirical music research both in the behavioural (e.g., Bigand, 2003; Brandler & Rammsayer, 2003) and brain sciences (e.g., Schlaug, 2001; Gaser & Schlaug, 2003; Münte, Altenmüller, &

Jäncke, 2002). Arguably, this has caused some negligence of instrument- and genre-specific expertise. An all-or-nothing view of musical excellence also places learning in a peripheral role because practice cannot be used to transcend the boundaries of novice, amateur, and expert musicianship. In this way, research studies including amateur musicians as participants have typically just treated them as 'musicians' rather than as a distinct group (Fujioka, Trainor, Ross, Kakigi, & Pantev, 2004, 2005; Tervaniemi, Castaneda, Knoll, & Uther, 2006). Admittedly, however, recent research shows a budding interest in amateurs in individualised terms (Jentzsch, Mkrtchian, & Kansal, 2014; Müllensiefen, Gingras, Musil, & Stewart, 2014) as well as in stylistic specialisation (Vuust, Brattico, Seppänen, Näätänen, & Tervaniemi, 2012a).

Fourth, musical ability is commonly referred to in positive terms as exclusively *beneficial* to its possessor. For instance, in a lexicon of core concepts in musicology, genius is described as "[a] term that invokes certain musical qualities, with the implication of greatness and a heightened sense of value" (Beard & Gloag, 2004, p. 70). In this light, the advantages of expertise overshadow the disadvantages in terms of research focus (Chi, 2006b; see, however, Frensch & Sternberg, 1989; Grigorenko, 2003; Sternberg, 1996; Sternberg & Frensch, 1992), effectively leaving novices, amateurs, aspiring talents, and music-related pathologies outside the brightest spotlight of scientific enquiry.

Fifth, musical excellence is primarily expected to enhance its owner's *creative* capability to generate music rather than his or her aptitude for perceiving and distinguishing musical qualities (e.g., Williamon, 2004). While studies of perceptual expertise are extremely commonplace in visual perception, this topic has received limited attention in auditory research (Chartrand, Peretz, & Belin, 2008). In other words, experts studied in empirical music research are typically highly skilled instrumentalists, and sometimes singers or composers. Similarly, in musicological discourse, Mozart is most famous for his compositional output whereas his alleged successful complete and verbatim transcription of Gregorio Allegri's *Miserere* after only two listenings at the Sistine Chapel is merely considered an amusing curiosity (Hochradner, 2015). This creative bias aligns well with observations that productive skills occur in 72% of free responses provided when prompted to define "musical ability" whereas this number only reaches 28-29% for receptive skills (Hallam & Prince, 2003). Moreover, etymological scrutiny reveals a relatedness of the word "genius" with the Latin and modern Italian terms for producing or generating (i.e. *gignere* and *generare*), once again biasing musicological discourse and empirical music research in an unfortunate direction.

In conclusion, it is recommended that musical ability is phrased objectively rather than succumbing to romantically charged references to genius or musical excellence. Thus, while these terms have been used somewhat interchangeably until now, the more neutral term *musical expertise* will be adopted henceforth. In the following, this decision will be substantiated with a critique of the five Romantic characteristics, paving the way for the scientific view of expertise adopted in the current work.

2.2. Casting musical expertise in scientific terms

A closer scrutiny of the romanticised concepts of genius reveals that this picture is not tenable as a scientific view of musical expertise. First of all, intensive engagement with music manifests itself in terms of concrete changes of behaviour and of brain structure and function (Herholz & Zatorre, 2012; Merrett, Peretz, & Wilson, 2013; Schlaug, 2015; Stewart, 2008). Conceiving of these dynamics as elusive and thus exempting them from systematic studies would be highly unscientific.

Likewise, empirical research has long since called into question whether genetics representative of innate musical talents can at all be identified without reference to essential interactions with environmental factors (Coon & Carey, 1989;

Simonton, 1999). In particular, researchers have not succeeded in predicting the potential for musical ability, arguably due to failures in accounting for musical training (Lehmann & Gruber, 2006). General psychological expertise research has similarly stressed the importance of accumulated practice time (Ericsson, Prietula, & Cokely, 2007) and how it is spent (Ericsson, 2006). Conversely, a recent meta-analysis surveying published research on expertise in chess and music established that factors like general intelligence, age of commencement, and working memory–some of which may have congenital components–constrain the effectiveness of expertise acquisition (Hambrick et al., 2014). Hence, a more nuanced view is needed.

The challenges faced by a leading music researcher when struggling to define musical expertise clearly exemplify the potential benefits of rejecting the all-or-nothing view. Specifically, Sloboda (1991) formulated both (a) a *relativistic definition* and (b) a *goal-oriented definition* of musical expertise. Whereas the former characterises a person solving a task better than average as an expert, the latter focuses on his or her ability to achieve a specific pre-defined goal. The author finds definition (a) limited because it refers to other people's skills, thus circumventing a purely cognitively based definition which is independent from societal norms and traditions. Definition (b), on the other hand, is regarded as problematic because it provides no guarantee that the formulated goals are sufficiently ambitious, thus risking to inflate the expertise concept itself. What the author seemingly fails to realise, however, is that both of these definitions presume a categorical distinction between experts and non-experts. If this legacy is abandoned, the average performance level loses its importance. Thus, the crux of the matter is not whether one can achieve a particular goal that enables one to cross some arbitrary boundary, but rather how supplely and parsimoniously one is capable of doing so. In principle, this problem has no upper (or lower) limit, opening up all expertise levels to meaningful scientific enquiry.

Studies of maladaptive consequences of musical training, such as dystonia (Konczak & Abbruzzese, 2013) and tinnitus (Henry, Dennis, & Schechter, 2005), directly contradict the status of expertise as unconditionally beneficial. Under some circumstances, stylistic specialisation may, furthermore, deteriorate performance in unfamiliar musical styles (Curtis & Bharucha, 2009). Thus, detaching expertise from the notion of cognitive superiority provides a more balanced view.

Because receptive skills have been regarded as a side effect of musical expertise, wholly secondary to creative skills, scientific knowledge about the specialised abilities of receptive experts remains rudimentary. Whereas piano tuners (Teki et al., 2012) and DJs (Butler & Trainor, 2015) have been subject to tentative (albeit promising) investigation, to my knowledge, few such studies (or none at all) exist for music critics, acousticians, sound technicians, audiophiles, music theorists, and musicologists. While this productive bias has some bearing in classical expertise domains like chess and bridge, which one is typically only exposed to by practising them, unintentional, passive exposure is central to music. This, in turn, renders receptive aspects paramount to musical expertise.

Increasing scientific interest in perception-action coupling (Jackson & Decety, 2004; Knoblich & Sebanz, 2006) and its relation to expertise (Farrow & Abernethy, 2003; Novembre & Keller, 2014; Rosenbaum, Augustyn, Cohen, & Jax, 2006) raises the question whether receptive and productive aspects can be meaningfully dissociated at all. Until a true synthesis is achieved, it may be worthwhile devoting comparably more attention to the understudied receptive aspects of musical expertise. In fact, such a focus would be more consistent with what musicians themselves find important. Specifically, musically trained individuals value receptive skills much higher and productive skills much lower than untrained individuals when prompted to define musical ability (Hallam & Prince, 2003).

In the light of these limitations, for the remainder of this dissertation, I will adopt a view of expertise which is dissociated from previously dominant romanticised concepts of genius and excellence (Figure 1). Specifically, musical expertise will be regarded as a non-metaphysical phenomenon which has a cognitive and neurobiological basis in the human brain, making it accessible to systematic empirical investigation with scientific methods. It will be acknowledged that expertise is acquired, but that this process may be subject to biological constraints. Following naturally from this, musical expertise not only spans a non-categorical continuum, but is in itself a multidimensional phenomenon whose composite parts are orthogonal and combine in unique ways for each individual. Thus, all levels of expertise resulting from different combinations of expertise dimensions may be relevant to study. This should solely depend on the research question. Importantly, this inclusive expertise concept also extends beyond beneficial consequences of training-induced neuroplasticity to maladaptive ones as well as beyond productive skills to receptive and recepto-productive ones.

Namely, the rejection of the innate and all-or-nothing qualities of expertise assigns hitherto unseen levels of importance to *musical learning*. In other words, systematic studies of musical expertise aim not only to understand what this phenomenon is, but also how it is acquired. In this light, research should not only aim to understand what expertise is, but also aim to develop optimal teaching and practice strategies for achieving it. The next step is to introduce a perspective on musical learning that I find especially productive when it comes to illuminating musical expertise. This is of course substantiated by an abundance of empirical and theoretical work which will also be summarised below.

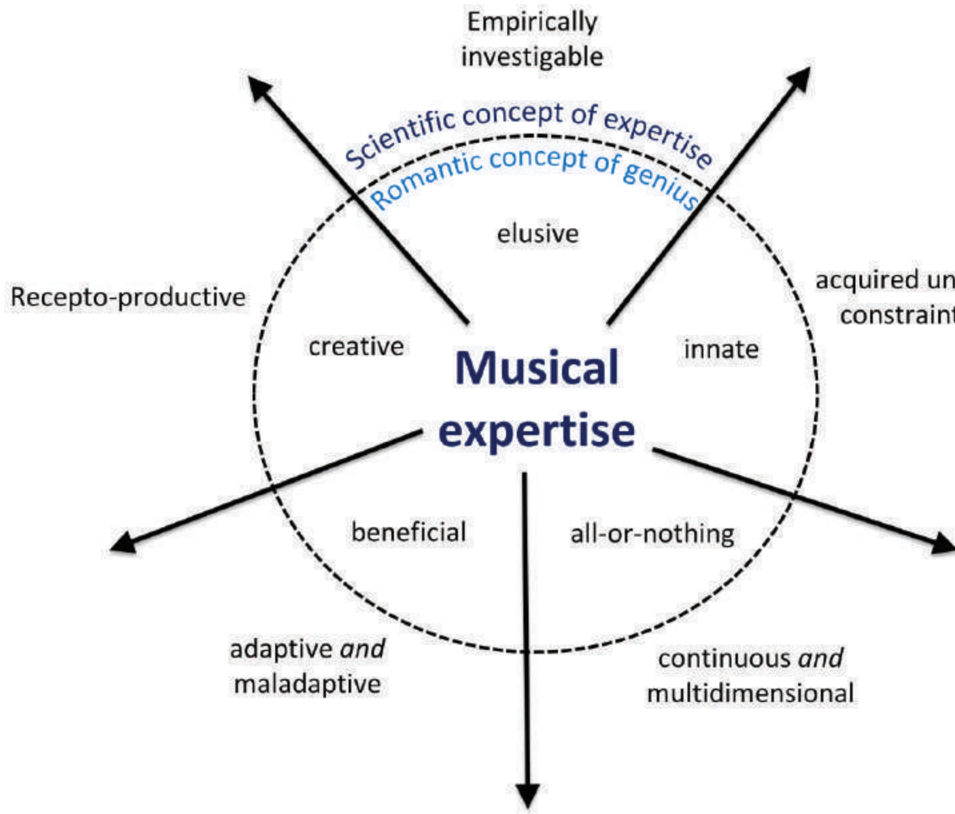

Figure 1. Concepts of musical expertise. Whereas the traditional romanticised concepts of genius and excellence tend to view musical expertise as elusive, innate, all-or-nothing, beneficial, and creative, a more modern scientific concept of musical expertise transcends this picture viewing it instead as a multidimensional phenomenon open to scientific enquiry. A Danish version of this figure appeared in Hansen (2015).

2.3. Musical learning as predictive processing optimisation

Given the multidimensionality of musical expertise described above, further delimitation is preferable before formulating specific research questions. In addition to conveying that musical learning should play a special role in this regard, I will argue that musical expertise and, in turn, musical learning should be understood in terms of optimisation of predictive processing. This predictive perspective is especially suitable due to (a) its validity across expertise domains, (b) its particular relevance in musical contexts, and (c) its potential to unify multifarious characteristics of musical expertise. Further details will be given below.

Regarding (a), the general expertise literature contains numerous examples of superior predictive processing and more refined cognitive representations in experts (Ericsson & Towne, 2010; Endsley, 2006). This applies to chess players (Klein & Peio, 1989), but also to athletes specialising, for instance, in squash (Abernethy, Gill, Parks, & Packer, 2001), rugby (Mori & Shimada, 2013), or tennis (Williams, Huys, Cañal-Bruland, & Hagemann, 2009). Enhanced prediction may, in turn, underlie experts' superiority in detection and recognition (Chi, Feltovich, & Glaser, 1981), working memory (Ericsson & Delaney, 1999), and continuous self-monitoring (Chi, 1978).

The relationship between expertise and anticipatory skills is, however, not straightforward. For instance, in cricket, accumulated hours of practice only explains a negligible proportion of variance in a player's ability to predict other player's actions (Weissensteiner, Abernethy, Farrow, & Müller, 2008). Although this possibility has not been tested formally, this may relate to the way that anticipation was assessed. Specifically, an explicit task without time constraints was applied which may differ fundamentally from more intuitive real-time processing. Similarly, educational qualification is a better predictor than clinical experience of a physician's diagnostic skills (Kundel & La Follette, 1972). This, on the other hand, may be ascribable to ceiling effects (Camerer & Johnson, 1997), especially if the formal training that the physicians had received was already delivered at a very high level. These examples aptly demonstrate the importance of ecological validity and task difficulty when designing expertise studies.

Regarding (b), perception and production of music is based on minute precision within the temporal dimension and thus imposes considerable demands concerning immensely accurate real-time processing, both on the part of the listener and the performer. These requirements are typically less prominent within the classical expertise domains. Even in *blitz games* with limited time for each chess move (Calderwood, Klein, & Crandall, 1988), the timescale is still considerably longer than in music and also not constrained by regularly repeating metrical structure. For these reasons, expectation mechanisms are considered paramount in music perception and cognition (Huron, 2006; Pearce & Wiggins, 2012; Vuust, Ostergaard, Pallesen, Bailey, & Roepstorff, 2009) where behavioural and neural measures of predictive processing efficacy relate directly to degrees of musical expertise (e.g., Vuust et al., 2012a). The notion that predictive processing is particularly relevant to music is, furthermore, consistent with the increasing consensus in general expertise research assigning varying degrees of significance to different skill components (e.g., prediction, verbalisation, speed, differentiation accuracy, and memory) within each expertise domain (Thompson, Tangen, & Searston, 2014).

Lastly, regarding (c), predictive processes are involved in most musical activities that can be enhanced through practice and experience. This includes musical performance (Gingras et al., 2015), interaction (Pecenka & Keller, 2011), improvisation (Goldman, 2013), and composition (Wiggins, Pearce, & Müllensiefen, 2009), reading musical notation (Waters et al., 1998), and listening to music (Huron, 2006). Prediction also underlies key aspects of emotional experiences to music (Huron, 2006; Juslin & Vastfjall, 2008; Meyer, 1956). Thus, optimised predictive processing may explain expertise advantages in relation to pitch memory (Williamson, Baddeley, & Hitch, 2010), deviance detection for rhythm (Vuust et al., 2005) and pitch (Besson, Schön, Moreno, Santos, & Magne, 2007) as well as for boundary perception (Neuhaus, Knösche, & Friederici, 2006) and implicit learning of novel musical material (Francois & Schön, 2011). Note that whereas the vast majority of classical studies on expertise-related enhancements in predictive processing mentioned above address higher-order decision making, music-related studies demonstrate the pertinence of this topic across all levels of action, perception, cognition, emotion, and learning.

In summary, musical learning increases the aspiring expert's ability to predict musical continuation, and this knowledge enhances processing in a multitude of ways. Given that optimised predictive processing is thought to be biologically adaptive (Bubic, von Cramon, & Schubotz, 2010), music's potential in this regard may explain why some (if not most) humans devote considerable time and resources to musical activities. This hypothesis about the driving forces of musical expertise, and thus ultimately about the origins of music itself, assumes an explicit computational formulation in predictive coding theory under the free-energy principle as expressed in cognitive neuroscience.

2.4. Predictive coding and free-energy minimisation

Recent theories of human cognition and neuroscience converge on regarding the human brain as a hierarchically structured "prediction machine" optimised for inferring the causes of sensory input, thus enabling it to generate correct predictions about the future (Bar, 2007, 2011; Bubic et al., 2010; Clark, 2013, 2015; Hohwy, 2013). This view has its roots in Hermann von Helmholtz' (1875/2011) seminal work on perception, but finds a neurobiologically plausible and explicit mathematical formulation in modern predictive coding theory (Friston, 2005, 2009). Due to its clear focus on continuous optimisation of predictive brain models, this theory offers an exceptionally adequate framework for understanding musical learning and expertise, both conceptually and computationally. Nevertheless, whereas recent studies have developed predictive coding accounts of auditory (Furl et al., 2011; Kumar et al., 2011) and music perception (Lee & Noppeney, 2014; Vuust et al., 2009; Vuust & Witek, 2014; Winkler & Czigler, 2012), the potential of this theory for addressing musical expertise questions remains largely uninvestigated.

Predictive coding theory posits that humans are biologically predisposed to adapt behaviours and strategies that minimise surprise in interactions with their environment (Friston, 2009). Surprise, in this context, corresponds to the negative log-probability of an outcome given the current generative model of the brain. Minimisation of surprise is achieved when events that the biological system represented by the brain considers to be especially likely are also the ones that actually happen. As will be evident from Sections 2.6-7 below, a predictive model that assigns high probability to a few elements from the range of theoretically possible outcomes is characterised by low uncertainty. Thus, in effect, learning through predictive coding entails a process of gradually reducing the uncertainty of one's predictions.

Importantly, the world is governed by two distinct types of uncertainty (Weber & Johnson, 2008). "Epistemic uncertainty" is the subjective type described above which we can reduce by updating and optimising our predictive models. There will, however, always be more or less random–and thus objectively unpredictable–fluctuations around us giving rise to "aleatory uncertainty" which we can never reduce, even if we were gifted with perfect knowledge. Thus, if we tune our predictive model beyond epistemic uncertainty, it becomes over-confident (cf. Section 2.10.3) and outcomes to which we have assigned low probability will indeed occur. Surprise then rises again. In other words, the potential for predictively coded learning is constrained by stochastic properties of the world.

Due to aleatory uncertainty, humans never achieve full knowledge about future states and thus cannot, in fact, minimise surprise itself. Rather, they minimise *free energy*, representing a maximum bound on surprise (Friston & Stephan, 2007). This can be done in two ways: either by updating one's generative model as previously described, or by selectively sampling sensory input that conforms to–and thus maximises the evidence for–this model (Friston, Kilner, & Harrison, 2006). The former corresponds to *perception* whereas the latter corresponds to *action*. For instance, to facilitate speech decoding in a noisy cocktail party environment, we may develop a sophisticated mental model that can predict what is being said based on the context (i.e. perception) as well as increase signal quality by moving closer to the speaker and gaining a good view of her lips (i.e. action). This means that learning (musical and otherwise) can be modelled directly with the computational principles that predictive coding formulates for perceptual inference.

One further characteristic that makes predictive coding especially relevant for modelling musical learning is the fact that this theory embodies a recent paradigm shift in theoretical neuroscience concerning the way that sensory information is thought to be represented in the human brain (Picard & Friston, 2014). Notably, previous accounts followed the so-called *compressive coding doctrine* (Redlich, 1993), emphasising how neural encoding schemes seemingly aim for a minimum description length leading to optimally efficient cognitive representations of sensory information (Simoncelli & Olshausen, 2001). Whereas this previous doctrine arose from *The Computational Theory of Mind* which dominated cognitive science in the 1960s and 1970s (Rescorla, 2015), predictive coding accommodates later critiques of computationalism referring, in particular, to the embodied nature of cognition and the ensuing importance of the organism's interaction with its environment (e.g., Chemero, 2011; Varela, Thompson, & Rosch, 1991).

Although compressive and predictive coding both promote simplicity as a fundamental cognitive principle (Chater, 1999; Pothos & Chater, 2002) and adopt information theory in their modelling strategies (Section 2.6), they differ fundamentally in terms of information processing (Barlow, 2001). Whereas compressive coding generally conceives of these processes as passive, unidirectional information passing from the external environment into the brain, predictive coding involves both feedforward and feedback connections structured hierarchically at multiple levels (red and black elements in Figure 2, respectively). Specifically, the activity on a lower level in the cortical processing hierarchy that cannot be successfully explained away by descending predictions from the next level up is passed upwards where they are subjected to further higher-level predictions (Rao & Ballard, 1999). This feedforward component of information processing is referred to as *prediction error*, giving rise to error signals in the brain which can be detected with non-invasive, neurophysiological methods (Garrido, Kilner, Stephan, & Friston, 2009; Wacongne, Changeux, & Dehaene, 2012) (Section 2.9).

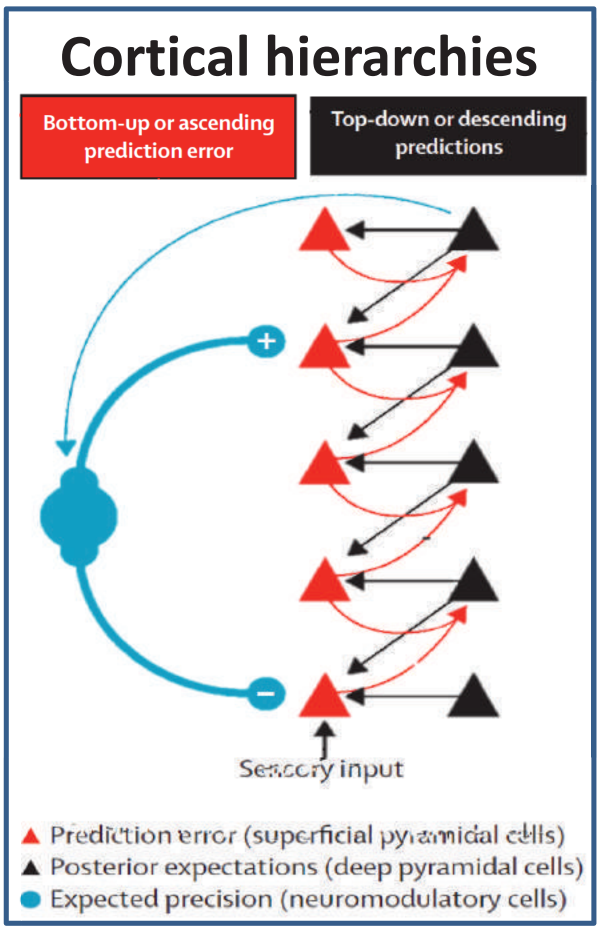

Figure 2. Information processing in predictive coding. Ascending prediction errors (red) and descending predictions (black) are elements in neural processing following computational principles of empirical Bayes. Further, neuromodulation of synaptic gain takes place according to expected precision (blue). This figure is adapted from Friston et al. (2014).

Computationally, predictive coding is based on empirical Bayes where priors are estimated directly from sensory data (Friston, 2005) and where this information is encoded as probability distributions (also referred to as the "Bayesian coding hypothesis" (Knill & Pouget, 2004; Pouget, Beck, Ma, & Latham, 2013).

Importantly, in this system, prediction errors are weighted according to their expected precision using neuromodulatory mechanisms of synaptic gain control (blue elements, Figure 2) (Friston, 2009; Ross & Hansen, 2016). In this way, the brain's generative model is assigned greater importance under conditions of deteriorated signal quality. Thus, in the aforementioned cocktail party example, we rely more strongly on our ability to infer what is being said when the volume of the background music is increased. This shows the importance of quantifying, modelling, and measuring not only surprise, but also uncertainty in the system (Sections 2.6-8).

Free-energy minimisation has been promoted as a candidate for a unified theory of human cognition and brain function (Friston, 2010). The most important argument for this proposition is constituted by its mathematical and conceptual similarities with other key theories in machine learning, computational neuroscience, and evolutionary biology (Figure 3). For this reason, predictive coding has been adopted as a framework for explaining and operationalising such diverse phenomena as attention (Brown & Friston, 2013), associative learning (Pezzulo, Rigoli, & Friston, 2015), theory of mind (Ondobaka, Kilner, & Friston, 2015), mirror neurons (Kilner, Friston, & Frith, 2007), neural migration and differentiation (Friston, Levin, Sengupta, & Pezzulo, 2015), human and animal communication (Friston & Frith, 2015), visual illusions (Brown & Friston, 2012), dreaming during REM sleep (Hobson, Hong, & Friston, 2014), reinforcement learning (Friston, Rigoli, et al., 2015), eye movements (Perrinet, Adams, & Friston, 2014), self-representation (Moutoussis, Fearon, El-Deredy, Dolan, & Friston, 2014), Freudian constructs (Carhart-Harris & Friston, 2012), and decision making (Friston et al., 2014). Moreover, deficiencies in predictive coding processes may explain a multitude of pathologies such as schizophrenia (Fogelson, Litvak, Peled, Fernandez-del-Olmo, & Friston, 2014), autism (Quattrocki & Friston, 2014), psychotic delusions (Adams, Brown, & Friston, 2015), and musical hallucinations (Kumar et al., 2014). Given this generality, predictive coding theory has potential as a computational theory for understanding expertise-related empirical findings in cognitive psychology.

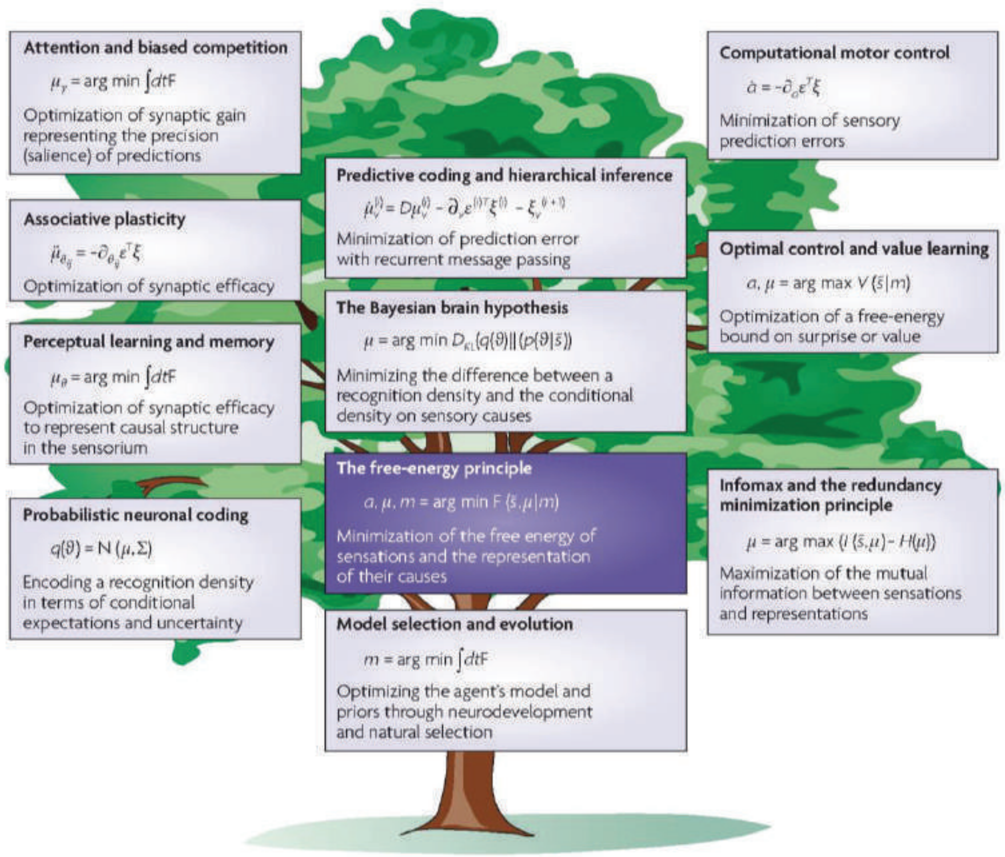

Figure 3. The free-energy principle as a unifying theory of human brain function. By way of the free-energy principle, predictive coding theory has close theoretical, computational, and empirical affiliations with other key theories in computational neuroscience, evolutionary biology, and machine learning. This figure appeared in Friston (2010).

2.5. Statistical learning

During the last two decades, research in the field of cognitive psychology has shown great interest in *statistical learning* as a key mechanism whereby humans acquire knowledge about probabilistic regularities and dependencies in their environment (Aslin & Newport, 2012). This mechanism is especially crucial in early language acquisition (Romberg & Saffran, 2010), as clearly exemplified by Saffran (2003). She describes a situation where an infant in a setting with English as a native language hears the syllable combination "pretty baby". Because word boundaries are far from unambiguously evident from the temporal structure of spoken language, the infant needs to perform word segmentation based on previous experience. Quite impressively, the transitional statistics in speech to young infants in and of themselves provide sufficient information for the infant to solve this task successfully. Specifically, it will have heard "-ba" following "tty-" much less frequently (~0.03%) than "-tty" has followed "pre-" (~80%). Consequently, "pretty" and "baby" are likely to be acquired as separate words.

Statistical learning is most commonly demonstrated in experiments comprising an initial exposure phase and a subsequent test phase (e.g., Saffran, Aslin, & Newport, 1996). After brief exposure to a continuous stimulus sequence (typically less than half an hour for adults and only a couple of minutes for infants), participants internalise transitional statistics allowing them to distinguish "words", i.e. stimulus combinations they were exposed to, from "part-words" and "non-words" which they were only exposed to in part or not at all. Learning is usually assessed using an explicit two-alternative, forced-choice task for adults and a variation of the head-turning paradigm for infants (Saffran, Johnson, Aslin, & Newport, 1999).

In addition to language, such procedures have demonstrated robust learning effects for visual sequences of abstract shapes (Fiser & Aslin, 2002) and animal pictures (Saffran, Pollak, Seibel, & Shkolnik, 2007), for visuomotor (Hunt & Aslin,

2001) and tactile tasks (Conway & Christiansen, 2005), and for musical timbres (Tillmann & McAdams, 2004) and pitches (Loui, Wessel, & Hudson Kam, 2010; Saffran et al., 1999). Statistical learning even generalises to some types of non-adjacent dependencies (Newport & Aslin, 2004). Additionally, it happens from birth (Teinonen, Fellman, Näätänen, Alku, & Huotilainen, 2009), is largely automatic and implicit (Turk-Browne, Jungé, & Scholl, 2005), applies across modalities (Kirkham, Slemmer, & Johnson, 2002; Perruchet & Pacton, 2006), and can be detected in primates (Newport, Hauser, Spaepen, & Aslin, 2004) as well as in non-primate mammals (Toro & Trobalón, 2005).

The efficacy of statistical learning is, however, affected by attention (Toro, Sinnett, & Soto-Faraco, 2005; Turk-Browne et al., 2005) as well as by domain-specific biases (Saffran, 2003), tied to perceptual properties of the input (Conway & Christiansen, 2006). Particularly for stimuli that are presented sequentially (Saffran, 2002) and characterised by high task demand (Robinson & Sloutsky, 2013), the strongest learning effects have been obtained in the auditory modality (Conway & Christiansen, 2005). Despite this apparent bias, however, the diversity of the previously summarised findings clearly indicates that statistical learning may represent a behavioural manifestation of innate and universal processing mechanisms akin to those described above for predictive coding (Section 2.4). The auditory bias only makes music an especially suitable domain for investigating predictive coding of expertise.

If predictive coding under the free-energy principle truly constitutes a generalisable computational principle characterising all levels of cognitive and neural processing, then this principle should also underlie statistical learning. Consequently, hypotheses derived from predictive coding theory should hold true for statistical learning (Fiser, Berkes, Orbán, & Lengyel, 2010). Specifically, based on predictive coding theory, we would first of all expect that model optimisation manifests itself in terms of reductions in predictive uncertainty that can be demonstrated in test data from statistical learning experiments. Second, the expectations resulting from exposure would reflect probabilistic characteristics of the particular musical style in question, and this should be the primary factor influencing what is learned. Third, this learning process would be expected to depend on the statistical decodability (i.e. the amount of epistemic uncertainty) of the stimulus material. Fourth and finally, given that predictive coding describes innate and fundamental principles of neural information processing, notable expertise-related enhancements would not be expected for the cognitive learning capabilities themselves. These are all empirical questions that can be–and will be–tested directly (Chapters 3 and 4; Study 3). This task requires the availability of computational concepts with applicability across cognitive psychology and neuroscience.

2.6. Information-theoretic models of cognition

Information theory, introduced by Claude E. Shannon (1948), offers a way of quantifying statistical learning, including the cognitive limitations and probabilistic constraints of the stimulus material which affect these processes. This field has had an immense impact on science (Brillouin, 2013), represented by disciplines as diverse as signal processing, data compression, physics, statistics, economics, computing, and, finally, the neurobiology of perception, including predictive coding (Rao & Ballard, 1999). Three information-theoretic concepts, which all play a key role in the mathematical formulation of predictive coding theory (Section 2.4), will be capitalised upon here because they aptly quantify different aspects of the listening experience relevant to musical learning and expertise.

First, *information content* (IC) models surprise, which is sometimes also referred to as "surprisal" (MacKay, 2003). Note that because surprise, in this context, depends on the probability assigned to events according to a particular observer (i.e. a subjective probability), IC constitutes a subjective property of the brain's generative model of the world rather than an objective property of the world itself. Formally, IC corresponds to the negative log probability; typically, the base-2 logarithm is used, making *bits* (i.e. binary digits) the relevant unit of measurement. Thus, for a discrete random variable, X, where $P(x_i)$ refers to the probability of the ith state of X, the information content of the outcome that X attains the value x_i equals:

$$\boldsymbol{IC(x_i) = -log_2\, P(x_i)} \qquad \text{(information content) (1)}$$

Second, *absolute entropy* (also "Shannon entropy") models the uncertainty with which predictions are being generated. In mathematical terms, for a discrete random variable, X, with n possible states, we have the probability distribution over the n states of X, $P(X)$, which will henceforth simply be referred to as P as a shorthand. The absolute entropy of P, $H(P)$, thus represents the uncertainty with which values sampled from P can be predicted, corresponding to the expected value of the information content:

$$\boldsymbol{H(P) = -\sum_{i=1}^{n} P(x_i)\log_2 P(x_i)} \qquad (2)$$

In other words, absolute entropy quantifies the shape of the probability distribution such that "flat" distributions where all possible outcomes are equally likely to occur are maximally uncertain. "Spiky" distributions, on the other hand, where one or more particular outcomes are much more likely than others enable prediction characterised by low degrees of uncertainty. Importantly, Equation 2 assumes that all events in the distribution have non-zero probabilities and sum to unity.

As evident from Equation 2, the maximum entropy of a given probability distribution depends on n, which is also referred to as the *alphabet size*. Therefore, to allow comparison across probability distributions with different alphabet size, absolute entropy is often normalised by dividing by the maximum entropy, corresponding to a uniform distribution with the relevant alphabet size, i.e. $H_{max}(P) = \log_2 n$ (see e.g., Eerola, Himberg, Toiviainen, & Louhivuori, 2006). For the remainder of this dissertation, the resulting normalised entropy measure (Equation 3) will simply be referred to as "absolute entropy":

$$\boldsymbol{H_{norm}(P) = \frac{H(P)}{H_{max}(P)} = \frac{-\sum_{i=1}^{n} P(x_i) \log_2 P(x_i)}{\log_2 n}} \qquad \text{(absolute entropy) (3)}$$

Third, the Kullback-Leibler Divergence, $D_{KL}(P||Q)$, quantifies the dissimilarity between two probability distributions which are referred to here by shorthand as P and Q (Kullback & Leibler, 1951). In detail, it designates the information lost when approximating one distribution (P, e.g. the "true" one) with another distribution (Q, e.g. a model of the true distribution):

$$\boldsymbol{D_{KL}(P\| Q) = \sum_{i=1}^{n} log_2 \left(\frac{P(x_i)}{Q(x_i)}\right) P(x_i)} \qquad (4)$$

As evident from Equation 4, the computation of Kullback-Liebler Divergence is similar to that for absolute entropy, with the sole exception that the log-probability is replaced by the log of the probability ratio, representing the two distributions in question. Because the association of distributions to numerator and denominator is not arbitrary, Kullback-Leibler Divergence is non-symmetric, and therefore not a true metric, i.e. $D_{KL}(P \| Q) \neq D_{KL}(Q \| P)$. As was also the case for absolute entropy, maximum

D_{KL} increases with alphabet size. Whereas no further normalisation was performed here because the current experimental designs did not necessitate this (see Appendix 6.3 for further details), symmetrisation was indeed implemented. In contrast to the original inventors who simply recommended adding the two divergences (Kullback & Leibler, 1951), for convenience we further divided this sum by two. Consistent with common terminology (Cover & Thomas, 2012), this symmetrised version of the Kullback-Leibler Divergence will henceforth be referred to simply as *relative entropy*.

$$symD_{KL}(P,Q) = \frac{D_{KL}(P \parallel Q) + D_{KL}(Q \parallel P)}{2} = \frac{\sum_{i=1}^{n} log_2\left(\frac{P(x_i)}{Q(x_i)}\right) P(x_i) + \sum_{i=1}^{n} log_2\left(\frac{Q(x_i)}{P(x_i)}\right) Q(x_i)}{2}$$

(relative entropy) (5)

Having formally defined information content (Equation1), absolute entropy (Equation 3), and relative entropy (Equation 5), we can now use these information-theoretic measures to quantify intrinsic aspects relevant to predictive coding of music and musical expertise. First, we let P designate the probabilistic structure of the music that a listener has been exposed to (cf. green line in Figure 4). In the context of a statistical learning paradigm, as specified in Section 2.5 above, P may describe a probability distribution over the alphabet of elements occurring in the exposure sequence; this is indeed the case in Figure 4. The ensuing Section 2.7 introduces an alternative way of estimating P if we do not have access to the exact profiles of exposure stimuli. This is particularly relevant when modelling musical learning on longer timescales outside the laboratory setting, for instance in the course of an entire life. Next, we let Q designate the subjective expectations of a given listener for different pitch continuations of the same melody (cf. the solid and dashed red lines in Figure 4). Section 2.8 describes in greater detail how empirical data representative of

Q may be obtained such that the previously described modelling attempts may be validated systematically.

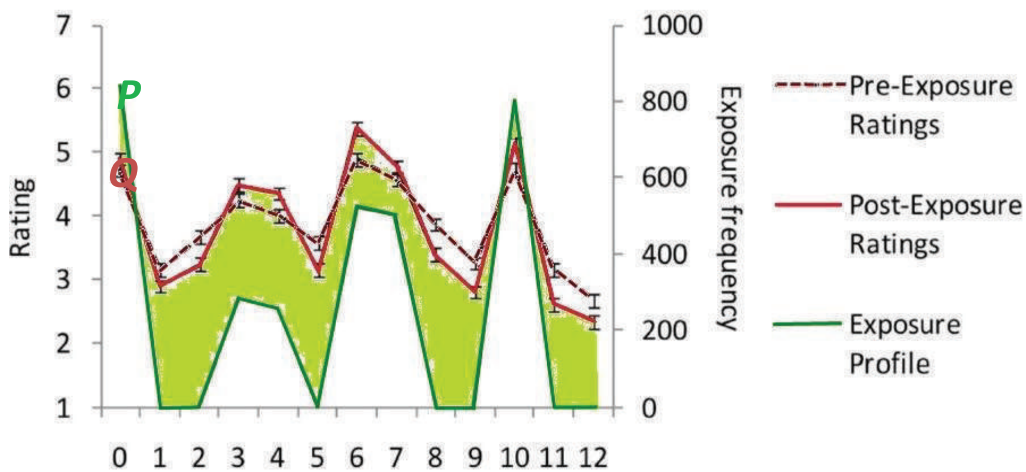

Figure 4. Information-theoretic modelling of musical listening and learning. Exemplification of experiential aspects that can be quantified with information-theoretic means. For instance, the green line, P, may represent the frequencies with which the 13 notes of a scale have occurred during exposure (e.g. in a statistical learning experiment). The red lines, Q, conversely, represent empirical data of the listener's expectations for these 13 notes before (dashed) and after (solid) exposure (Section 2.8). Information content models the surprise experienced in response to a given note. Absolute entropy models the uncertainty with which predictions about melodic continuation can be made. Relative entropy, finally, models the dissimilarity between the red and green lines, which is hypothesised to decrease with musical learning. This figure was adapted from Loui et al. (2010).

To recap, we have defined two probability distributions, P, representing the objective exposure of a given listener (green line in Figure 4), and Q, representing the subjective listening experience (red lines in Figure 4). Because statistical learning and predictive coding suggest that the listener gradually internalises characteristics of the former distribution during exposure, P, in other words, represents an idealised model of listener expectations whereas Q represents an empirical manifestation of this idealised model. Following from this, the IC of an event sampled from P constitutes a model of the *surprise* or *unexpectedness* experienced by the listener.[3] The absolute entropy of P, in turn, provides a model of the uncertainty experienced by the listener whereas the absolute entropy of Q represents its empirical manifestation. Finally, statistical learning and predictive coding also suggest that exposure decreases the dissimilarity between P and Q, thus making the relative entropy between these two distributions a model of musical expertise. In the context of Figure 4, this learning process would align the solid red line with the green line.

The cognitive validity of these measures will now be substantiated, elaborating, in particular, on their relation to predictive coding. First of all, information content constitutes a relatively well-tested model of surprise in music, accounting for a considerable proportion of the variance in expectedness ratings (~78%) and response times for such ratings (~56%) (Pearce, Ruiz, Kapasi, Wiggins, & Bhattacharya, 2010). The same study also found that notes with high and low IC produced significantly different event-related responses and oscillatory brain activity. The effect of IC on expectancy can similarly be detected using an implicit timbre judgement paradigm (Omigie, Pearce, & Stewart, 2012), and its relevance as a cognitive model has been extended to many other datasets (Pearce & Wiggins, 2006), including psychological and physiological measures of emotional experience (Egermann, Pearce, Wiggins, & McAdams, 2013).

Absolute entropy has only been used to explicitly model cognition outside the musical domain. Here, its cognitive relevance has been established for sentence comprehension (Hale, 2006), decision making (Swait & Adamowicz, 2001), psychological anxiety, physiological noradrenaline release (Hirsh, Mar, & Peterson, 2012), and for altered states of consciousness (Carhart-Harris et al., 2014). Although

[3] For the remainder of this dissertation, the terms "surprise" and "unexpectedness" will be used interchangeably. Whereas the former has a very specific meaning in information theory, the latter may be easier to relate to for participants in a listening experiment. In terms of what we model with information content, these concepts will be considered as equivalent.

reference to predictive coding and free-energy minimisation was only made explicit in the last case, the parallels are most certainly reasonable.

In the musical domain, Shannon's information theory was quickly translated by Meyer (1957) into the statement that "musical styles are internalized probability systems" (p. 414). This, in turn, inspired a whole generation of computationally minded researchers to implement absolute entropy in musical analysis and composition (Hiller & Bean, 1966; Hiller & Ramon, 1967; Siromoney & Rajagopalan, 1964; Youngblood, 1958; Zanten, 1983, as reviewed by Ames, 1987, 1989; Cohen, 1962; Margulis & Beatty, 2008), with subsequent ramifications in music information retrieval (e.g., Madsen & Widmer, 2007). However, apart from a few relatively recent exceptions (e.g., Duane, 2010, 2012; Eerola, Toiviainen, & Krumhansl, 2002), these researchers have typically estimated entropy from small music collections. This has prevented them from incorporating the schematic effects of long-term exposure which constitute a necessary requirement for a true model of melodic cognition (Huron, 2006). Also, if assessed as a cognitive model, early work ignores that probabilities change dynamically as a musical progression unfolds (Meyer, 1957), thus erroneously assuming that expectations are informed by music that the listener has not yet heard. More recent studies have used absolute entropy to quantify response consistency in a categorical rhythm discrimination task (Desain & Honing, 2003) or in an explicit betting paradigm regarding the continuation of Balinese gamelan melodies (Huron, 2006, pp. 53-55, 154, 162). Because these information-theoretic response metrics were, however, not related directly to properties of the stimuli, these studies only offer half of what is required for a cognitive model.

Relative entropy constitutes a key computational component of predictive coding theory. Specifically, free energy can be expressed as surprise plus the relative entropy between the recognition density and the conditional density on the causes of sensory data (Friston, 2010). Thus, free-energy minimisation automatically entails minimisation of relative entropy. Such parallels between relative entropy and free-energy minimisation are equally plentiful beyond cognition in optimal control theory (Theodorou & Todorov, 2012), financial mathematics (Cherny & Maslov, 2004), and neural-network classification tasks (Santos, Alexandre, & de Sá, 2004).

In cognitive disciplines, minimisation processes may manifest themselves in various ways. For instance, absolute entropy minimisation has been used both to model artificial grammar learning in visual cognition (Pothos, 2010) and perceptual grouping in auditory cognition (Smaragdis, 1997). Relative entropy modelling has, in comparison, primarily informed Bayesian research on visual perception and reward processing. This work has demonstrated that visual attention is guided by the relative entropy between prior and posterior distributions of beliefs of an observer (Itti & Baldi, 2009). Additionally, exploration and exploitation in reward behaviour can be accounted for in terms of minimisation of the relative entropy between likely and desired outcomes (Schwartenbeck, FitzGerald, Dolan, & Friston, 2013). Interestingly, despite the generality of these principles promoted by predictive coding and substantiated by empirical work in other domains, relative entropy minimisation has thus far not been demonstrated in the auditory modality.

In summary, entropy has been used for modelling objective characteristics of musical styles, revealing interesting aspects of the compositional process. Additionally, while IC represents an empirically validated model of music cognition, the absolute and relative entropy metrics have not yet been fully implemented and tested within this domain. Related work in neighbouring areas, however, alludes to the relevance of these metrics as models of predictive processing in music listening, giving rise to musical expertise. A computational model of expectation would allow researchers to take full advantage of this potential.

2.7. IDyOM: A computational model

The computational model of auditory expectation *Information Dynamics of Music* (henceforth IDyOM; Pearce, 2005) provides a much-needed bridge between neuroscience and psychology in that it allows researchers to model statistical learning with the information-theoretic concepts that play such a crucial role in predictive coding theory. Because IDyOM can combine short-term estimation of probabilities with the effects of long-term exposure on listener expectations, it, furthermore, offers an alternative approach to estimating the *P* distribution, referred to in Section 2.6 and Figure 4 above.

Based on unsupervised statistical learning, IDyOM produces a conditional probability distribution governing a pre-specified attribute of the next event given the preceding events in the sequence (Pearce, 2005). Typically, and most relevant here, the sequence comprises notes of a musical melody, and the relevant attribute (also referred to as the "target viewpoint") is absolute pitch defined in chromatic pitch space using MIDI pitch numbers (i.e. middle C4 would have the value 60). However, in principle, the basic modelling procedure could be applied to any type of sequence, thus paving the way for future applications of IDyOM to verbal and non-verbal languages, dance, etc.

The generated probability distributions are normalised such that they sum to unity across the complete alphabet, normally comprising the union of pitch values occurring in the test and training corpora (further details below). Moreover, zero probabilities are bypassed using so-called *smoothing* techniques (Pearce, 2005; Witten & Bell, 1991). As pointed out in Section 2.6 above, these two conditions enable the computation of absolute entropy values (Equations 2 and 3) for each point in the sequence, providing a dynamic model of predictive uncertainty experienced by the listener and/or characterising the predictions that he or she would make at that point in the melody.

IDyOM is a variable-order Markov model based on *n*-gram methods (Manning & Schütze, 1999). Thus, model predictions are conditional probabilities for events given a preceding context, which rely on the most informative length of prior context. In practice, fixed-order *n*-gram models for all possible context lengths below a certain maximum bound, which can be optionally specified by the user, are computed and subsequently combined using a weighted average favouring higher-order *n*-grams which occurred in the training corpus (Pearce, 2005).

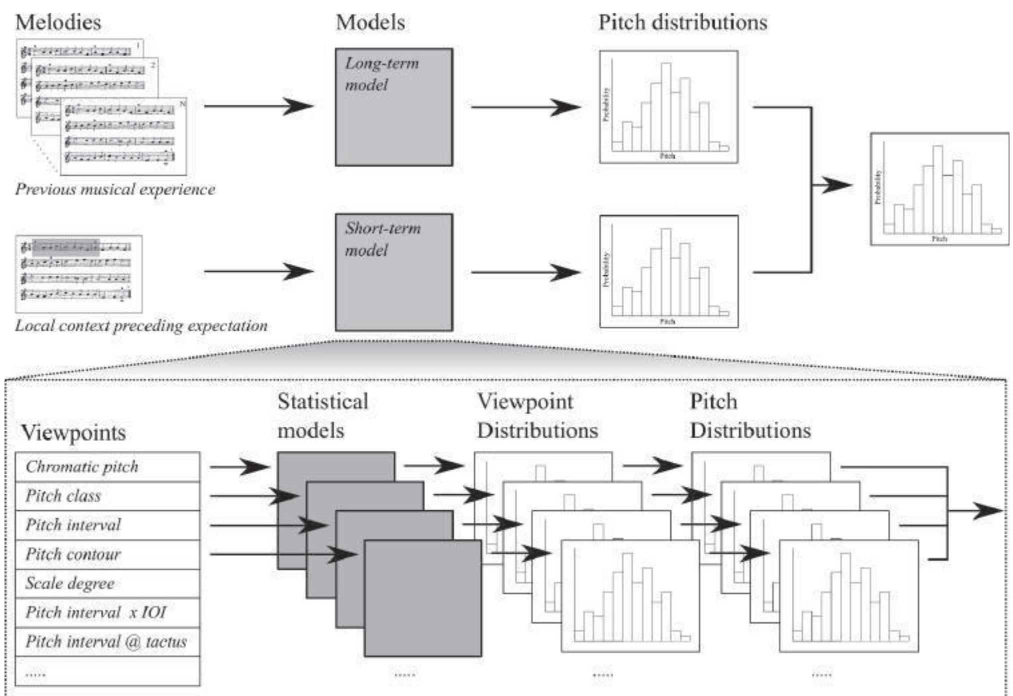

Figure 5. Information Dynamics of Music (IDyOM). This computational model uses unsupervised statistical learning and variable-order Markov modelling to generate probability distributions over properties (e.g., absolute pitch) of the next note in a melodic sequence. Most commonly, IDyOM mathematically combines a long-term sub-model (LTM) trained on large musical corpora with a short-term sub-model (STM) acquiring statistics from the local context. One or more viewpoints (e.g., scale degree and pith interval) are used to represent musical structure. This figure is printed with permission from Marcus Pearce and also appeared in Hansen (2015).

As evident from Figure 5, IDyOM comprises two model components: a short-term sub-model (STM) and a long-term sub-model (LTM). STM is an initially empty model acquiring knowledge from the current composition only. It is designed to capture *dynamic expectations* (Huron, 2006), resulting from local repetitions of motivic structure within a piece of music. LTM, on the other hand, is trained on a pre-specified training corpus and models *schematic expectations* (Huron, 2006), resulting from long-term exposure.

Importantly, depending on what the user aims to model, STM and LTM can be used in isolation or in combination (BOTH). Moreover, the LTM component can be set to update incrementally based on the test set (LTM+, BOTH+). For the BOTH and BOTH+ configurations, probability distributions generated by STM and LTM(+) are combined using a weighted geometric mean (Pearce, 2005).

In addition to, or instead of, being trained on a training set, LTM can be trained on the test dataset itself using *k*-fold cross-validation. In that case, the test dataset is partitioned into *k* subsets, and LTM(+) is trained on the *k*-1 subsamples whereas the remaining one is used as test data. This process is then repeated *k* times (resulting in *k* folds), such that the IC of each event is estimated only once.

IDyOM represents musical structure using a multiple viewpoint system (Conklin & Witten, 1995) (Figure 5). This implies that each event in the sequence is characterised by one (or more) numeric values representing the specific feature(s) which the user has pre-specified. This could, for instance, be absolute pitch, scale degree, pitch interval, note duration, or inter-onset interval. Note that some of these are *basic viewpoints* (e.g., absolute pitch, note duration) whereas others are *derived viewpoints* (e.g., scale degree derived from the modulo-12 pitch interval from the tonic; and inter-onset interval derived from the difference in onset for the current and previous notes). Multiple viewpoints can be linked together, such that each event is represented by a pair of values instead of a single value.

IDyOM requires both a (set of) basic target viewpoint(s) whose members it generates probability distributions over as well as a (set of) source viewpoint(s) to use in prediction. Because source viewpoint distributions are converted into target viewpoint distributions as part of the modelling procedure (Figure 5), source viewpoints need to be meaningfully related to the target viewpoint in order to be considered (e.g., note duration alone cannot be used to predict absolute pitch). Alternatively to pre-specification, source viewpoints can also be selected using an automated selection procedure picking the (combination of) viewpoint(s) leading to the lowest average IC (i.e. the model that is least "surprised" on average by what it experiences).

Typically, better prediction performance is obtained with variable-order models compared to fixed-order models and for combined short- and long-term sub-models compared to each component used in isolation (Pearce, 2005; Chapter 6). However, combined, variable-order models are not always cognitively relevant. For instance, it would be irrelevant to include LTM if the music uses a scale that the listener has never heard before. Similarly, configuring the long-term component to learn incrementally across pieces (i.e. LTM+) would only be suitable if the listener is indeed exposed to the musical pieces in that particular order.

To recap, when running IDyOM (e.g., Chapter 3), the user typically specifies:

[1] a **target dataset** to generate predictions about;

[2] **target viewpoint(s)** specifying which musical feature(s) to be predicted;

[3] **source viewpoint(s)** to use in prediction;

[4] an **order bound** setting the upper limit for context length;

[5] **sub-model configuration** (i.e. STM, LTM, LTM+, BOTH, or BOTH+);

[6] **training dataset(s)** for the LTM component (if this is used); and

[7] the number of **resampling folds** (if cross-validation is applied).

IDyOM writes output to a data file containing probability, IC, and absolute entropy for each event in the sequence comprising the target dataset. In addition, probabilities for all possible target viewpoint values that did not occur at the present point (i.e. the complete probability distribution from which entropy was computed) is available in the output as well as information concerning the model order and relative STM and LTM weights applied for each event. Various basic viewpoint sequences (e.g., absolute pitch, duration, key signature, and mode) are also printed to facilitate identification of events in the output. This provides all the material needed to estimate unexpectedness and predictive uncertainty as indicated by the P distribution plotted in green in Figure 4. A method for obtaining empirical data regarding listener expectations will now be introduced. This corresponds to the Q distribution, plotted in red in Figure 4.

2.8. Expectation in behaviour: The Predictive Uncertainty Paradigm

Different behavioural paradigms have been developed for assessing expectations in music listening (reviewed by Huron, 2006, pp. 41-57). Due to the nature of the work presented in this dissertation, the main focus here will be on paradigms that enable the collection of data pertaining to uncertainty and expectedness experienced by listeners in relation to the pitch of notes in a melodic sequence. This can be investigated with implicit as well as explicit approaches which will be reviewed below. Broadly speaking, the main methodologies can be categorised into: (a) *production paradigms* where the participants provide expected continuations in one form or another; and (b) *perception paradigms* providing data concerning the participants' experience (usually retrospectively).

In *production paradigms*, participants are typically exposed to a melodic sequence and asked to sing (Carlsen, 1981; Carlsen, Divenyi, & Taylor, 1970; Unyk & Carlsen, 1987), compose or improvise (e.g., on a piano keyboard) either a single continuation tone (Abe & Hoshino, 1990; Povel, 1996) or a full completion of the melody (Larson, 1997; Schmuckler, 1989; Thompson, Cuddy, & Plaus, 1997). Importantly, these methods often only provide expectedness data regarding a single continuation tone (i.e. the most expected one). With data from multiple participants, however, between-participant expectedness distributions can be computed from response frequencies (Carlsen, 1981), potentially giving rise to uncertainty data on the group level.

Speaking against the applicability of production paradigms for studying musical expertise, they pose considerable task demands because response methodologies tend to rely on familiarity with singing, musical notation, or specific musical instruments. This may exclude non-musicians from participation (Tillmann, Poulin-Charronnat, & Bigand, 2014). Moreover, these tasks tend to call for highly explicit processing, involving intellectual considerations that are unlikely to be prominent in real-time music listening. In this regard, perceptual paradigms may be more ecologically valid.

Probe-tone tasks, where participants rate the perceived goodness-of-fit for different continuations on the basis of a tonal context (Krumhansl & Shepard, 1979), represent some of the most widely used *perceptual paradigms* for investigating melodic expectation. Although the first version of this paradigm restricted itself to scales (Krumhansl & Shepard, 1979), contexts were quickly extended to include chords and harmonic cadences (Krumhansl, 1990; Krumhansl & Kessler, 1982), and ultimately melodies (Schmuckler, 1989). Using this methodology to collect probe-tone ratings for multiple continuations of each melody, within-participant expectedness distributions have been obtained for simple implicative intervals (Cuddy & Lunny, 1995) as well as for a range of musical styles, including Finnish spiritual hymns (Krumhansl, Louhivand, Toiviainen, Jarvinen, & Eerola, 1999), North-Sami yoiks (Krumhansl et al., 2000), and British folk songs, atonal Webern songs, and

Chinese folk songs (Krumhansl, 1995; Schellenberg, 1996). Since these data pertain to individuals, they can easily be associated with measures of musical experience, altogether making probe-tone paradigms better suited for expertise research than production paradigms, especially when prioritising a receptive focus.

Critics have, however, pointed out that, due to interruption of the musical flow, probe-tone ratings may reflect expectations specific to tonal closure (Aarden, 2003). Pearce et al. (2010) accommodated this concern by continuing the melody beyond the probe tone, but displaying a clock that silently counted down to its position. This visually-cued paradigm is especially suitable for isochronous stimuli, facilitating unambiguous interpretation of the clock countdown. With more ecologically valid, rhythmically diverse melodies, however, the clock steps either become non-isochronous or need to rely on underlying metrical structure, thus complicating the task for participants with limited musical training. Other uninterrupted paradigms exist, e.g. using continuously sampled predictability ratings (Eerola et al., 2002) or goodness-of-fit ratings in relation to a concurrently sounded probe tone (Toiviainen & Krumhansl, 2003). Continuous paradigms may be suboptimal for assessing unexpectedness for different continuations of the same melody, in that notes beyond the first continuation tone may affect ratings retrospectively. In other words, manipulating the probe-tone, in effect, changes two intervals, while transposing the whole continuation causes tonal instability. Paradigms that use continuous response methodologies, in particular, entail methodological challenges, including difficulties in matching responses unambiguously to discrete events (Schubert, 2010). Since modelling at the event level is at the crux of the Markovian procedures applied here (Section 2.7), continuous response sampling overall seems unsuitable. Hence, despite the clear advantage of continuous probe-tone paradigms for many other purposes, the stimuli used here need to be interrupted to obtain valid uncertainty data.

It has, furthermore, been argued that even probe-tone paradigms disadvantage non-musicians because explicit verbalisation leads to psychophysical rather than to music-syntactic responses (Bigand & Poulin-Charronnat, 2006). Although such differences could in fact be a hallmark of musical expertise itself, priming methodologies offer a gateway into non-expert implicit processing.

Priming paradigms, a subgroup of perception paradigms, capitalise on the fact that expected events facilitate more general aspects of cognitive processing (Neely, 1991). Specifically, the relationship between a prime and a target is manipulated systematically, and the response time in an unrelated task is then taken as a measure of expectedness. In the musical version of this paradigm (reviewed by Tillmann, 2005), stimuli have mostly comprised chord sequences. Melodic experiments have, however, also been conducted with speeded judgement tasks pertaining to melodic contour (i.e. rising, falling, or same) (Aarden, 2003), intonation (i.e. in-tune vs. out-of-tune) (Marmel & Tillmann, 2009; Marmel, Tillmann, & Dowling, 2008), or timbre (Marmel & Tillmann, 2009; Marmel, Tillmann, & Delbé, 2010; Omigie et al., 2012). Despite their potential relevance for expertise questions, implicit paradigms will not be applied here (apart from neurophysiological measures, see Section 2.9). This decision reflects that probe-tone methods may reveal expertise-related differences in the conscious availability of predictive processing knowledge. This may complement previous work focusing on similarities rather than differences between musicians and non-musicians (e.g., Bigand, 2003; Bigand & Poulin-Charronnat, 2006).

To this end, in addition to unexpectedness data obtained with the classical probe-tone paradigm, explicit ratings pertaining to uncertainty would also be relevant. This suggestion has precursors in terms of data on perceived tension or stability (Bigand, 1997), completeness of the phrase (Bigand, 1993; Krumhansl, 1987), expectancy specificity or strength (Schmuckler, 1989), or melodic predictability (Eerola et al., 2002), typically obtained using a 7-point Likert-type scale or continuously sampled response devices. Although these tasks have not referred to uncertainty as such, exceptionally high correlation between some measures (e.g., r = .96 for expectancy specificity and strength in Schmuckler, 1989) suggests that they could be capturing related aspects of a common underlying psychological phenomenon.

Next, the question arises how unexpectedness distributions should be quantified and related to probability distributions resulting from models of musical exposure. Different ways of inferring uncertainty from distributional expectedness data exist in the literature. For instance, using data from a production paradigm, Carlsen (1981) computed a coarse measure, simply characterising implicative intervals producing low maximum frequencies as uncertain. That is, in practice, only the most expected event was taken into account. Schmuckler's (1989) difference score between minimum and average unexpectedness ratings obtained in a perceptual task only slightly improved this method. That these scores remained insensitive to distributional properties is evident from their lack of correlation with expectancy specificity/strength for melodic stimuli (Schmuckler, 1989).

Similar limitations apply to previous ways of comparing distributions representative of subjective listener expectations and objective exposure. Specifically, previous studies have applied Pearson and partial correlation measures (Eerola, Louhivuori, & Lebaka, 2009; Krumhansl et al., 1999, 2000; Krumhansl, 1990; Loui et al., 2010). In contrast to information-theoretic measures which were originally cast as probabilistic measures (Section 2.6) and later re-cast as models of cognition (Section 2.4), correlational measures were first of all designed to assess linear dependence between two numerical variables. Thus, absolute (Equation 3) and relative entropy (Equation 5) are expected to outperform earlier approaches, both in terms of cognitive validity and sensitivity to distributional information.

Summing up, to test the predictive coding theory of musical expertise presented here, there is a need for distributional data concerning listeners' unexpectedness and predictive uncertainty which can be directly related to computational model estimates using information-theoretic measures (Sections 2.6-7). The Predictive Uncertainty Paradigm (Figure 6) is an explicit, perceptual paradigm that meets these requirements. Specifically, it comprises two experimental phases where participants first listen to incomplete melodies, providing explicit ratings of perceived uncertainty, using a 9-point Likert-type scale ranging from "highly uncertain" to "highly certain" (Phase A). Subsequently, the melodies are heard again multiple times, each time followed by one of nine different probe-tone continuations to which participants provide explicit unexpectedness ratings on a similarly designed scale (i.e. "highly unexpected" to "highly expected") (Phase B). The probe tones span a chromatic set centred on either the median pitch of the context (Study 1) or on the pre-probe-tone pitch (Study 2) and are presented in direct continuation of the context. All stimuli are randomised within each phase. Importantly, explicit uncertainty ratings (Phase A) are always collected before unexpectedness ratings (Phase B) to ensure that perceived levels of uncertainty are not influenced by hearing a set of actual continuations. Potential closure effects are, furthermore, alleviated by asking participants explicitly not to think of the last note as the final note in the phrase. From the distribution of unexpectedness ratings obtained in Phase B, yet another measure of uncertainty is inferred, simply by normalising the distribution such that it sums to unity and computing its absolute entropy. After having introduced an elegant behavioural paradigm for obtaining data for the Q distribution in Figure 4, neurophysiological measures of musical expectations will now be introduced.

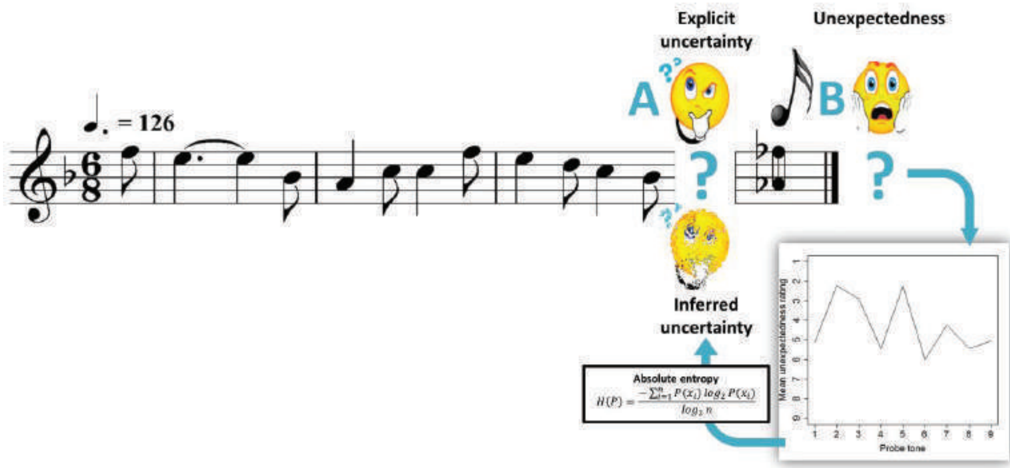

Figure 6. The Predictive Uncertainty Paradigm. In Phase A, participants provide 9-point Likert-type ratings of explicit uncertainty about the immediate pitch continuing an interrupted melodic context. In Phase B, similar ratings are provided regarding perceived unexpectedness in response to nine different chromatically distributed probe-tone continuations. Another uncertainty measure is finally inferred by computing the absolute (Shannon) entropy of the distribution of unexpectedness ratings.

2.9. Expectation in neurophysiology: Mismatch Negativity (MMN)

In neurophysiological research, aspects of predictive music processing, including its expertise-related correlates, have been studied in terms of the Mismatch Negativity response (MMN) (Trainor & Zatorre, 2015). This response, representing a negative deflection in the event-related potential (ERP), was first discovered and reported in electroencephalography (EEG) research by Näätänen, Gaillard, and Mäntysalo (1978). They used a classical oddball paradigm where deviant stimuli, differing on frequency or intensity, were infrequently and unpredictably inserted into a sequence of constantly repeating, isochronous standard tones. The MMN emerged as a difference wave peaking in the 150-250 ms post-stimulus range when subtracting the averaged response to standards from the averaged response to deviants (cf. Figure 7).

Since its original discovery within the auditory modality, MMN responses have been found in all sensory modalities, including vision (Kimura, Schröger, & Czigler, 2011; Pazo-Alvarez, Cadaveira, & Amenedo, 2003), somatosensory perception (Butler et al., 2011), nociception (Hu, Zhao, Li, & Valentini, 2013), and olfaction (Pause & Krauel, 2000). Furthermore, it can be used as a marker of different neurological and neuropsychiatric diseases (Näätänen et al., 2011) and of musical expertise (Vuust et al., 2011). In the following, further characteristics of this brain response will be summarised, including a few practicalities entailed in measuring it, previous expertise-related findings will be introduced, and theories will be discussed regarding which types of neural computations underlie the response and how all this relates to predictive coding. Finally, it will be proposed that MMN paradigms can be adopted to study expertise effects on cognitive representations in music.

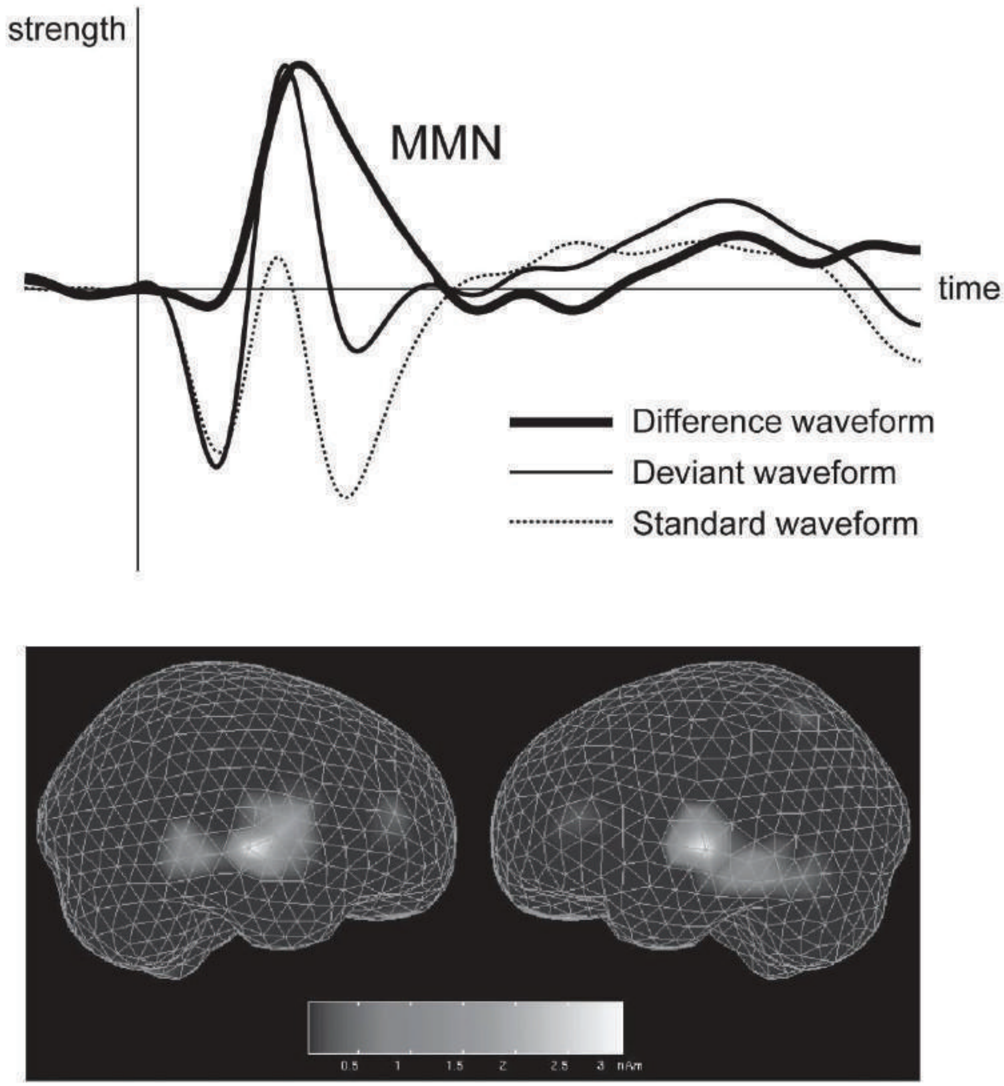

Figure 7. Neurophysiological profile of the MMNm. (A) Similar to its electrophysiological counterpart (not depicted here), the magnetic mismatch negativity response MMNm (bold) appears in the 150-250 ms post-stimulus time range when subtracting the average time-locked MEG response to standards (dashed) from that to deviants (solid), differing from the standards on one or more stimulus features (e.g., frequency, intensity, duration, location). This plot depicts the typical MMNm signal recorded from a supratemporal gradiometer sensor (cf. Study 4). (B) As evident from this panel, based on source reconstruction using minimum L1 norm estimation, the neural generators of the auditory MMNm are typically located in the primary and secondary auditory cortices as well as in the inferior frontal cortices. This figure was adapted from Tervaniemi and Brattico (2004).

Although the MMN was first discovered using EEG, it can also be reliably detected with magnetoencephalography (MEG) where its magnetic counterpart is referred to as the MMNm, a supratemporal deflection of the event-related field (ERF). MEG is a neurophysiological method measuring the magnetic fields arising from the minute electrical currents in the brain that are measured with EEG (Papanicolaou, 2009). More specifically, the MEG system used in the present research is the Elekta Neuromag TRIUX which has 102 magnetometers, measuring the magnetic field, and 204 planar gradiometers measuring the magnetic field gradients (i.e. the rate of change in magnetic fields over distance). Because these magnetic fields are perpendicular to the underlying electrical currents generating them, MEG is most sensitive to neural sources that are tangentially aligned with the scalp surface. Compared to magnetometers which may pick up subcortical activity, the planar gradiometers used in the present work (Study 4) are particularly sensitive to superficial sources.

These sensitivity characteristics are especially important in the context of the auditory MMN(m) response whose neural generators (cf. Figure 7) are distributed between sources in the primary and secondary auditory cortices (bilaterally) and sources in the inferior frontal gyrus (predominantly right-laterally) (Schönwiesner et al., 2007). Notably, due to the orientation of these neuronal assemblies, MEG sensors are primarily sensitive to the supratemporal MMNm source (Hämäläinen, Hari, Ilmoniemi, Knuutila, & Lounasmaa, 1993), making this method superior to EEG for research where these two sources need to be dissociated. As evident below, this may be highly beneficial, for instance, when assessing signal additivity which tends to differ between these sources (Paavilainen, Mikkonen, et al., 2003).

The frontal MMN(m) generator is involved in involuntary attention switching mechanisms (Näätänen, Paavilainen, Rinne, & Alho, 2007). The MMN(m) itself, on the other hand, is primarily viewed as a pre-attentive response in that it is also elicited in the absence of attention, e.g. in comatose patients (Fischer, Morlet, & Giard, 2000; Näätänen et al., 2007; see, however, Sussman, 2007, for a review of different attentional influences on standard formation and deviance detection). For this reason, participants are usually asked to watch a silent movie during an MMN(m) experiment while ignoring the presented stimuli. This process serves to circumvent attentional components like the N2b response which sometimes overlaps with the MMN(m) (Folstein & Van Petten, 2008; Näätänen & Gaillard, 1983).

MMN(m) measurements may also be enhanced by refining and extending the classical oddball paradigm itself. This is exemplified by the optimum multi-feature paradigms where multiple deviant types (e.g., frequency, intensity, duration, location, and tone omission) are included in the same experimental block separated by as few as one standard stimulus (Näätänen, Pakarinen, Rinne, & Takegata, 2004), or none at all (Pakarinen, Huotilainen, & Näätänen, 2010). Because deviants in these paradigms contain invariant features on all other parameters, they function as standards for the other deviants. Thus, more multifaceted data can be obtained in shorter time, making this method especially suitable for diagnosis and for monitoring a multitude of medical conditions (Näätänen et al., 2012). This extends beyond clinical contexts to investigations of neurodevelopment (Lovio et al., 2009) and skill-related individual differences (Pakarinen, Takegata, Rinne, Huotilainen, & Näätänen, 2007).

The optimum multi-feature paradigms have inspired developments along these lines in the musical domain. For instance, adopting one of the first multi-feature paradigms described above (Näätänen et al., 2004), somewhat surprisingly, Tervaniemi, Castaneda, Knoll, and Uther (2006) only obtained musical expertise effects for location deviants. This could be due to either limited ecological validity of the stimuli or to the inclusion of amateur musicians, engaging in practise to a lesser extent than most professional musicians.

The importance of musically relevant stimuli is supported by the considerable context-dependency of expertise as demonstrated by psychological research (Ericsson & Towne, 2010; de Groot, 1978). This has been accommodated by musical MMN paradigms incorporating melodic material (e.g., Brattico, Tervaniemi, Näätänen, & Peretz, 2006). Those of these studies that have demonstrated greater MMN amplitudes in musicians, have, however, also typically included amateurs rather than professional musicians (Fujioka et al., 2004, 2005).

Studies by Vuust and colleagues (2011; 2012a; 2012b; 2015), introducing a musical multi-feature paradigm (Figure 8), accommodate the needs for both ecological validity and sufficiently high expertise levels. Specifically, this paradigm is based on repetitions of a characteristic four-note pattern corresponding to chord arpeggiations in the order "lowest-highest-middle-highest". This pattern, named after the Italian composer Domenico Alberti (1710–1740) who used it extensively in early 18th-century keyboard music, is widely used for accompaniment across historical eras, musical instruments, and genres (Fuller, 2015). Most typically, in this musical multi-feature paradigm, every second occurrence of the third note in the pattern (the one termed "middle" above) serves as standard whereas the remaining occurrences deviate in terms of e.g. pitch,[4] intensity, perceived location, timbre, timing, or by introducing pitch slides (Petersen et al., 2015; Timm et al., 2014; Vuust et al., 2011, 2012a, 2012b, 2015). The fact that the pitch level of the pattern changes each time all deviant types have appeared just further contributes to stimulus variability (Figure 8).

[4] Note that the term "pitch" is used here, and henceforth, instead of "frequency". Whereas many classical MMN studies (e.g. Näätänen et al., 1978) have used pure-tone stimuli and manipulated the frequency of the sine wave (in units of Hz), the studies by Vuust and colleagues have used complex tones and have manipulated the frequency of the fundamental pitch in units of cents, which have a more direct interpretation in terms of perceived pitch. This is in particular necessary when using modulating stimuli (as in Vuust et al. and in Study 4 included here).

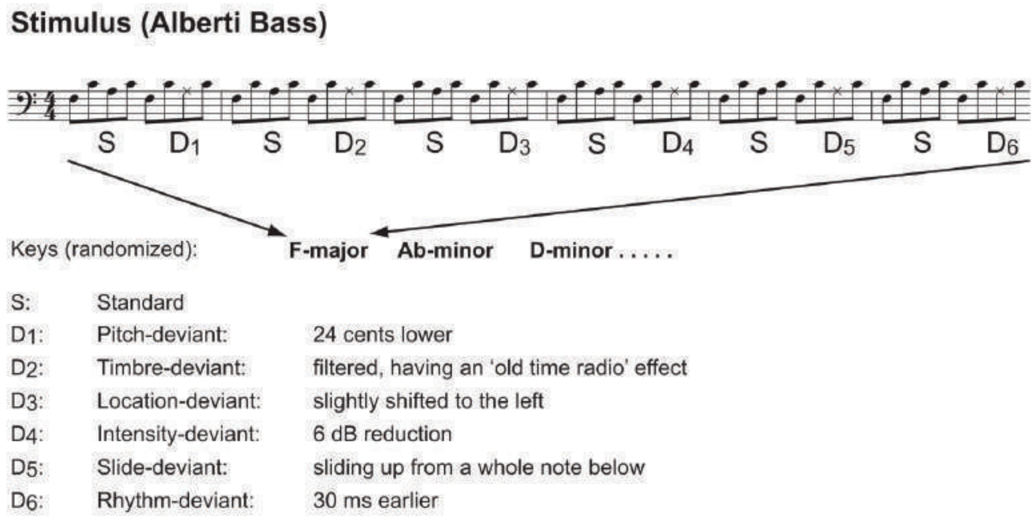

Figure 8. The musical multi-feature paradigm. This paradigm uses the Alberti-bass figure, well-known from various musical repertoires, to assess MMN(m) responses time-locked to standards and deviants coinciding with the third note in the pattern. Multiple deviant types can be incorporated into a single stimulus block, enabling the experimenter to quickly obtain a multidimensional, neurophysiological profile of the receptive expertise of individual participants. A version of this figure appeared, for instance, in Vuust et al. (2011, 2012a, 2012b).

Despite recent efforts to increase ecological validity in musical MMN(m) paradigms even further, e.g. resulting in melodic multi-feature paradigms capable of quickly distinguishing between folk musicians and non-musicians (Tervaniemi, Huotilainen, & Brattico, 2014) and between classical, jazz, and rock musicians (Tervaniemi, Janhunen, Kruck, Putkinen, & Huotilainen, 2015), to my knowledge, no direct comparisons of expertise effects across paradigms have thus far been conducted within the same experimental session. Such studies would be necessary to fully investigate the context-dependency of expertise effects on musical prediction capabilities, as demonstrated by the MMN.

In this regard, an acknowledgement of previous findings relating to expertise enhancements of the MMN response is justified. This work overall capitalises on the fact that increasing the salience of deviants or, alternatively, increasing the discrimination accuracy of participants, may lead to increased amplitude and decreased peak latency of the MMN response (Näätänen et al., 2007). By extension, adjustments in the opposite direction may have contrasting effects. This principle generalises to stimuli presented in musical paradigms (Vuust et al., 2015).

Following the same logic, increased MMN(m) amplitudes, and sometimes shorter peak latencies, have been found in musicians compared to non-musicians in response to deviants in pitch and contour (Fujioka, Trainor, Ross, Kakigi, & Pantev, 2004, 2005; Lopez et al., 2003), rhythm (van Zuijen, Sussman, Winkler, Näätänen, & Tervaniemi, 2005; Vuust et al., 2009), and for unexpected tone omissions (Rüsseler, Altenmüller, Nager, Kohlmetz, & Münte, 2001). Again, however, context matters, in that expertise advantages are sometimes restricted to relevant cases where pitch mistunings are embedded in musical chords (Koelsch, Schröger, & Tervaniemi, 1999) or are preceded by a musical context (Brattico, Näätänen, & Tervaniemi, 2001). Long-term musical training may even increase the potential for short-term plasticity, as demonstrated by within-session increases in MMNm amplitude elicited by deviants in abstract regularities (Herholz, Boh, & Pantev, 2011). Recent findings of enhanced MMN amplitudes in jazz musicians compared to classical and rock/pop musicians further attest to the great potential of multi-feature paradigms for investigating stylistic specialisation in music (Vuust et al., 2012b).

A greater theoretical understanding of the neural representations underlying the MMN response would be conducive to pursuing this goal. Traditionally, the MMN has been interpreted as a change detection mechanism, evident of 'sensory intelligence' in the auditory cortex (Näätänen, Tervaniemi, Sussman, Paavilainen, & Winkler, 2001), which automatically and pre-attentively compares incoming sensory input to an echoic-memory trace (Näätänen, Paavilainen, & Reinikainen, 1989). Whereas this may be the explanation that most naturally emerges from the initial findings reported by Näätänen, Gaillard, and Mäntysalo (1978), later demonstrations of MMN effects for more abstract environmental regularities challenge this account in ways that will now be described (reviewed by Paavilainen, 2013). Such abstract features include patterns resulting from feature conjunctions (Gomes, Bernstein, Ritter, Vaughanm, & Miller, 1997; Sussman, Gomes, Nousak, Ritter, & Vaughan, 1998), ascending or descending pitch motives (Saarinen, Paavilainen, Schöger, Tervaniemi, & Näätänen, 1992) or scales (Tervaniemi, Maury, & Näätänen, 1994), or from consistent alternations between presenting sounds to the right and the left ear (Takegata, Paavilainen, Näätänen, & Winkler, 2001). Because each of the constituent features contributing to a rare conjunction in Gomes et al. (1997) occurred no less frequently than other features overall, the MMN response could only be ascribed to an abstract representation of specific feature conjunctions rather than of the features themselves. Similarly, because the pitch level of the two-note motives used by Saarinen et al. (1992) varied for each new presentation of a standard or deviant motif, the standard representation must have pertained to the pitch relationship between notes rather than to the notes themselves. Also speaking against the interpretation of the MMN as resulting from a simple sensory memory trace, MMN-like responses have been found for notes in a melody that deviate from the scale or are slightly out of tune (Brattico et al., 2006). Taken together, these studies suggest that the underlying representations giving rise to MMN responses sometimes rely both on abstract relationships and long-term memory outside the immediate context, e.g. relating to musical scales and tuning systems. In other words, not unlike the accounts of cognition and neuroscience previously presented with reference to statistical learning (Section 2.5) and predictive coding (Section 2.4), MMN representations appear to retain the complete history of auditory stimulation (Winkler, 2007).

Yet other critics have questioned the traditional memory-based explanation by formulating an Adaptation Hypothesis (May & Tiitinen, 2010). According to this view, the MMN simply results from latency and amplitude modulations of the N1 response due to activation of fresh afferents that were not yet adapted (see Näätänen, Jacobsen, & Winkler, 2005, for a response to this criticism).

With interesting implications for the perspective on musical expertise proposed in the current dissertation (Sections 2.3-6), predictive coding has been promoted as an explanatory framework that has the potential to resolve the controversy between memory-based and adaptation-based approaches to understanding the MMN(m) response (Garrido et al., 2009; Winkler & Czigler, 2012). Amongst other things, this suggestion gains support from the apparent generality of MMN(m) processes, as exemplified by some of the previously mentioned findings; specifically that it occurs in conditions without increased afferent input, such as sound omissions (Raij, McEvoy, Mäkelä, & Hari, 1997) and decreases in intensity (Schirmer, Simpson, & Escoffier, 2007) and duration (Näätänen et al., 1989), across sensory modalities, and across levels of stimulus complexity and representational abstraction. The predictive coding-based account has, furthermore, been validated by promising computational models of MMN data on a trial-by-trial basis, capitalising on empirical Bayes and free-energy minimisation (Lieder, Daunizeau, Garrido, Friston, & Stephan, 2013; Wacongne et al., 2012). Preliminary theoretical efforts have, moreover, been made to relate this updated view of MMN to other types of early electrophysiological responses (e.g., P50, N1, N2b, early anterior negativity, and evoked gamma-band responses) in a wider framework of predictive processing in audition (Bendixen, SanMiguel, & Schröger, 2012). Although it is beyond the scope of this dissertation to review this work in further detail, it suffices to conclude that evidence accumulates for the MMN(m) as reflecting predictive optimisation of cognitive representations.

2.10. A novel framework for scientific studies of musical expertise

In the previous sections, it has been argued that romanticised concepts of musical excellence and genius should be discarded and replaced with a scientific concept of musical expertise understood in terms of predictive processing optimisation. Predictive coding and statistical learning have been presented as unifiable neuroscientific and cognitive-scientific theories regarding these processes, which can be formalised using well-established measures from information theory. This renders the presented theory of predictive coding of musical expertise available to empirical investigation using computational, behavioural, and neurophysiological methods.

As substantiated above, however, musical expertise constitutes a highly complex and multidimensional phenomenon. In acknowledgement of this complexity, the current analytical framework breaks down musical expertise into six perspectives (Table 1). Each of these perspectives generates an overall research question which can be related to findings in psychological expertise research and be addressed empirically in the specific context of musical expertise, using a distinct subset of approaches from the methodological battery presented above (Sections 2.5-9).

Table 1. An analytical framework for studying musical expertise. Each of the six perspectives can be characterised by an overall research question which can be addressed with approaches from the methodological battery described in Sections 2.5, 2.6, 2.7, 2.8, and 2.9.

Perspectives	Research questions	Methods
Origin	How does expertise arise?	IDyOM: Unsupervised statistical learning Behaviour: Probe-tone ratings before vs. after statistical learning Neurophysiology: MMN(m)
Cognitive representations	How does expertise affect cognitive representation of musical structure?	IDyOM: Viewpoints, order bound, sub-model configurations Behaviour: Statistical learning Neurophysiology: MMN(m)
Predictive uncertainty	How does expertise affect the uncertainty of listener expectations?	IDyOM: Entropy Behaviour: Explicit and inferred uncertainty
Predictive flexibility	How does expertise affect the ability to specify, access, and prioritise competing predictive models?	IDyOM: Training corpora Behaviour: Expectedness, explicit and inferred uncertainty Neurophysiology: MMN(m)
Conscious availability	How does expertise affect the availability of predictive models to conscious introspection?	Behaviour: Explicit and inferred uncertainty expectedness
Neural correlates	How does expertise affect brain function?	IDyOM: Information content, entropy Neurophysiology: MMN(m)

2.10.1. Origin

The first analytical perspective, *origin*, relates to the question about where musical expertise arises from. To reiterate, the classical emphasis on innate giftedness (e.g., Galton, 1869) was already called into question by early cognitive expertise research demonstrating highly domain-specific, and thus, plausibly, acquired, pattern recognition skills in chess experts (Chase & Simon, 1973; de Groot, 1966). Subsequent empirical work in music and beyond has only consolidated this criticism (Howe & Davidson, 2003; Howe et al., 1998). Consequently, the doctrine on innate talents unique to the individual has been replaced by one on individualised expertise acquisition under (more or less) universal cognitive constraints. In the musical domain such constraints have indeed been found for music listening and composition (Huron, 2001; Lerdahl, 1992; London, 2002; McAdams, 1989; McDermott & Hauser, 2005; Parncutt, 1999; Thompson & Schellenberg, 2002; Tierney, Russo, & Patel, 2011). Generalising this principle to musical learning processes seems like a natural step. Yet, important questions remain regarding whether specific cognitive capacities constitute immutable constraints or are themselves subject to expertise-induced plasticity. For instance, can the mechanisms for statistical learning, or those for auditory feature processing, be optimised through experience?

Having established that musical expertise is predominantly acquired, understanding the nature of this acquisition process becomes paramount. This is likely to entail both implicit learning (cf. Section 2.5) and explicit instruction. In addition, *deliberate practice* has been proposed as a path to expert performance that incorporates elements from both (Ericsson, 2006, 2008; Ericsson, Krampe, & Tesch-Römer, 1993). Specifically, deliberate practice designates a highly structured iterative process whereby aspiring experts continuously monitor their own performance, correcting inaccuracies accordingly with the explicit goal of improving performance.

IDyOM directly models implicit aspects of musical skill acquisition, thus making it highly suitable for testing the view of predictively coded expertise as acquired through passive exposure. Effects of explicit instruction and deliberate practice, on the other hand, are much more challenging to model over longer timescales, namely because all three types of skill acquisition tend to go hand in hand. Although specialist populations like musical savants with little explicit instruction exist, linguistic and general cognitive deficits sometimes compromise the generalisability of results obtained from these groups (Hermelin, O'Connor, & Lee, 1987; Ockelford & Pring, 2005; Young & Nettelebeck, 1995; Sloboda, Hermelin, & O'Connor, 1985). Thus, designing short-term experiments with systematic control of both implicitly internalisable musical structure and access to explicit knowledge seems like a fruitful path to pursue. To this end, probe-tone ratings and/or neurophysiological measurements collected before and after exposure in a statistical learning paradigm can be compared.

2.10.2. Cognitive representations

The second analytical perspective, *cognitive representations*, relates to how expertise affects the way in which musical structure is cognitively represented. Cognitive representation (also "mental representation"), in this context, refers to specific memory for objects and events which can be used to determine whether or not a percept is representative of a given category (Stuart-Hamilton, 1996).

Although psychological research provides abundant evidence that experts benefit from more sophisticated cognitive representations than non-experts (Chi, 2006a), the specific manifestations and underlying mechanisms of this sophistication process are far from unequivocally understood. The overall consensus appears to be that general working memory capacity is relatively constant (Cowan, Chen, & Rouder, 2004; Miller, 1956), but that experts represent knowledge in larger chunks (Simon & Gilmartin, 1973) that are both more functional, abstract, and hierarchically structured than non-experts' typically more superficial representations (Chi et al., 1981; Feltovich, Prietula, & Ericsson, 2006; Johnson & Eilers, 1998; Mayfield, Kardash, & Kivlighan Jr, 1999; Shafto & Coley, 2003; Tanaka, 2001; Tanaka & Taylor, 1991). Expert perception is, furthermore, enhanced by the ability to direct attention towards especially pertinent aspects of the sensory input (Endsley, 2006).

In a musical context, for instance, these characteristics emerge in terms of musicians' superiority in distinguishing melodic variations maintaining the original underlying harmonic structure from those that deviate from it (Bigand, 1990). Non-musicians, in this task, were sometimes deceived by surface characteristics and thus unable to decode hierarchical structure. Summing up, findings in music and beyond support the hypothesis that cognitive representations in experts are characterised by greater complexity, efficiency, and domain-specific relevance.

One key aspect of representational complexity pertains to the integration and segregation of composite stimulus features within a single sensory modality. While many theories exist regarding feature integration in the visual system (Grill-Spector & Weiner, 2014; Marr, 1982; Nassi & Callaway, 2009; Treisman & Gelade, 1980), this topic has not been studied as thoroughly in the auditory modality (Shamma, 2008). Arguably, expertise questions are somewhat more pertinent in audition than in vision due to the existence of highly specialised individuals like musicians engaging in extensive daily practice throughout their lives from an early age (Ericsson, 2006).

Two competing theories make mutually incompatible predictions about skill-related effects on expert feature processing (in music as well as in other domains). Specifically, either (a) expertise causes separate processing of features further up in the processing hierarchy, thus giving rise to an *independent processing hypothesis*, or (b) expertise causes integrated processing by shared neural resources at an earlier stage, thus giving rise to a contrasting *dependent processing hypothesis*. While the general expertise research reviewed above as well as findings of decreased neural activity sometimes associated with perceptual learning (Jäncke, Gaab, Wüstenberg, Scheich, & Heinze, 2001; Zatorre, Delhommeau, & Zarate, 2012) would speak in favour of the latter hypothesis, other findings and theories support the former hypothesis. For instance, an influential theory proposes that perceptual learning provides access to lower-level representations with higher relevance for particular contexts (Ahissar & Hochstein, 2004; Ahissar, Nahum, Nelken, & Hochstein, 2009). Moreover, more independent processing could enable experts to better track simultaneous progressions within individual features, which, in turn, would allow them to more accurately dissociate violated expectations and attribute them to the relevant feature in question. This seems especially relevant in the musical domain where the covariance of acoustic features provides informative structural cues on segmentation boundaries (Hansen, 2011; Lerdahl & Jackendoff, 1983; Prince & Schmuckler, 2014). The contrasting hypotheses regarding more dependent or independent processing of acoustic features in musical experts can be resolved with neurophysiological methods in terms of the additivity of the MMN(m) response (Section 2.9).

IDyOM offers a number of computational modelling procedures facilitating, specifically, the study of cognitive representations. First, the option to specify different source viewpoints enables the experimenter to contrast expectations resulting from different representations of musical structure. Such viewpoints can, furthermore, be linked to model the integration of multiple features. This procedure may be used to test hypotheses regarding expertise-induced increases in representational complexity. Second, restricting the maximum order bound (i.e. context lengths used in Markov modelling) may be used to model limitations in non-experts' ability to chunk elements together. Third, different sub-model configurations allow the experimenter to test expertise-enhanced weighting of local and global aspects of musical structure according to contextual relevance. Finally, the statistical learning paradigm (Section 2.5) offers a systematic way of assessing which cognitive representations are more conducive to the learnability of musical material. Future work along these lines may shed further light on the nature of the sophistication process that cognitive representations undergo.

2.10.3. Predictive uncertainty

The third analytical perspective, *predictive uncertainty*, relates to how expertise affects the uncertainty of the predictions that listeners make about musical continuation. Previous research on expectations in music has focused almost exclusively on the expectedness perceived by listeners retrospectively in response to events (e.g., Huron, 2006; Krumhansl, 1990; Tillmann, 2005). This is the case for most studies using behavioural perception paradigms entailing the collection of explicit probe-tone ratings or implicit reaction time data (Section 2.8) as well as neurophysiological paradigms assessing expectedness, e.g. in terms of the MMN(m) response (Section 2.9). By comparison, very few studies have investigated the uncertainty with which musical predictions are generated (e.g., Schmuckler, 1989), and none of these have applied cognitively justified, probabilistic measures like the ones introduced here (Section 2.6).

Psychological expertise research has studied uncertainty in terms of how realistic and adequate people's view of their own predictive capabilities is. This has also been termed "calibration", referring to the match between confidence in and accuracy of one's own predictions (Glenberg & Epstein, 1987). The results are, however, somewhat inconsistent. Specifically, over-confidence (i.e. unrealistically high confidence in one's own predictions) has been demonstrated for chess players (Chi, 1978), clinical psychologists (Oskamp, 1965), and experts in physics and music theory (Glenberg & Epstein, 1987), whereas better calibration in terms of lower over-confidence is sometimes found in weather forecasters (Hoffman, Trafton, & Roebber, 2006). Although these findings suggest that predictive uncertainty is highly context-dependent, such dynamics are very likely to behave differently outside the realm of complex, higher-order decision making where demand characteristics may also be less prominent.

As presented above, IDyOM models predictive uncertainty with absolute entropy (Sections 2.6-7). The generated entropy estimates can readily be compared to explicit uncertainty ratings as well as to uncertainty inferred from probe-tone ratings (Section 2.8). Furthermore, it is hypothesised that musical expertise entails uncertainty reduction in terms of gradual minimisation of the relative entropy between objective probabilities and subjective uncertainty data, but this process is constrained by the statistical decodability of the musical material (Section 2.6). This prediction is consistent with results from psychological expertise research suggesting that expertise effects should only arise in contexts characterised by high certainty, or, in other words, a high proportion of epistemic (and thus reducible) uncertainty (Farrington-Darby & Wilson, 2006).

2.10.4. Predictive flexibility

The fourth analytical perspective, *predictive flexibility*, relates to how expertise affects the ability to specify, access, prioritise between, and maybe even suppress multiple stylistic models of musical expectation. To investigate this question, research is needed that systematically contrasts two or more types of specialised expertise, preferably within the same participants. Despite preliminary advances relating to bimusicalism (Wong, Chan, & Margulis, 2012; Wong, Chan, Roy, & Margulis, 2011; Wong, Roy, & Margulis, 2009) and stylistic specialisation within individuals (Münte, Kohlmetz, Nager, & Altenmüller, 2001; Münte, Nager, Beiss, Schroeder, & Altenmüller, 2003; Pantev, Roberts, Schulz, & Engelien, 2001; Proverbio, Calbi, Manfredi, & Zani, 2014; Strait, Chan, Ashley, & Kraus, 2012; Vuust et al., 2012a), musical expertise research is still largely dominated by categorical comparisons between musicians and non-musicians (Tervaniemi, 2009).

Psychological expertise research, on the other hand, has addressed the question of predictive flexibility by assessing how quickly and successfully experts and novices adjust to sudden changes in the rules of the game. For instance, in these contexts, high-ranking bridge players initially show more deteriorated performance than novices, although they relatively quickly regain their initial superiority (Frensch & Sternberg, 1989). This suggests that a certain degree of conservatism characterises the rejection of predictive models. The experts' inclination to stick with their original internal model may, in turn, be justified by its greater sophistication (and thus predictive power).

The theory on “cognitive firewalls” also provides an interesting perspective on predictive flexibility grounded in evolutionary biology. Specifically, this theory posits that while acquisition of new knowledge through statistical learning can increase chances of survival, failure to limit the scope of this knowledge to relevant contexts may conversely result in dangerous or fatal situations (Cosmides & Tooby, 2000). Although Huron (2006, pp. 203-18) has proposed the application of this framework to stylistic knowledge in music, its predictions have not yet been tested within this domain. If multiple predictive models specific to musical styles do indeed give rise to different expectations within the same listener in varying contexts, then it remains unknown which cues trigger different models and if and how such mechanisms are affected by expertise. The option to specify different training datasets for IDyOM strongly facilitates this endeavour.

2.10.5. Conscious availability

The fifth analytical perspective, *conscious availability*, relates to how expertise affects the availability of the brain’s predictive models to conscious introspection. The general expertise literature seems to be split regarding this question, adhering to views of expertise acquisition as comprising either a process whereby knowledge becomes increasingly explicit (*explication theories*) or one whereby it becomes increasingly implicit (*implication theories*).

Exemplifying the implication theories, Fitts and Posner (1967) proposed a *Multi-Stage Theory* of motor skill learning according to which learning progresses through three specific stages. First, in the *cognitive stage*, the learner takes steps to understand the overall goal of the task and works consciously following specific instructions, typically needing external feedback to correct errors. Second, in the *associative stage*, the constituent parts of the skills are put together, thus allowing refinement of the skill, but still following conscious strategies. Third, in the *autonomous stage*, the skill is mastered and cognitive resources are therefore liberated for other purposes. Anderson's (1982) model of cognitive skill acquisition contains similar elements, describing instead an advancement from a *declarative stage* to a *procedural stage* through a process characterised as *knowledge compilation*.

Dreyfus (1996) devised a related model applicable to acquisition of both motor skills and cognitive skills. This model comprises: (1) *the novice*, who uses context-free, experience-independent rules in an algorithmic fashion; (2) *the advanced beginner*, who also incorporates some situational rules; (3) *the competent*, who uses hierarchical problem solving and takes responsibility for wrong decisions; (4) *the proficient*, who uses intuitive behaviour to achieve specific goals, but still relies on conscious decisions; and (5) *the expert*, who, given more subtle and refined discrimination ability, tends to respond immediately and intuitively.

In contrast, explication theories describe an expertise-induced development towards more explicit processing. For instance, the *bottom-up model of skill learning* proposes that declarative knowledge develops from procedural knowledge (i.e. an implicit-to-explicit development) (Sun, Merrill, & Peterson, 2001; Sun, Slusarz, & Terry, 2005; Sun, Zhang, Slusarz, & Mathews, 2007). Along these lines, Chaffin's work on memorisation strategies in a professional pianist (Chaffin & Logan, 2006; reviewed by Geeves et al., 2014) describes how explicit processing serves as a hallmark of expert musicianship.

Again, work on deliberate practice provides a somewhat unifying perspective in the sense that musical experts are characterised by remaining longer in Fitts and Posner's associative stage, where their actions can be consciously monitored, whereas expertise acquisition reaches a plateau once entering the autonomous stage (Ericsson & Towne, 2010). This account acknowledges both the importance of explicit processing in practise and skill enhancement and the importance of intuitive processes in the creative act of performance itself.

Summing up, once again, the vast majority of the psychological expertise literature, including music-related work emerging from this tradition, focuses on decision-making or production of specific motor acts. Some of these processes could be notably different for musical expertise, especially if adopting a receptive rather than productive stance (cf. Section 2.2). Thus, it remains unknown whether enhancement of perceptual capabilities for music follows the trajectory of the explication or implication theories.

The issue of conscious availability may be addressed in the framework of the Predictive Uncertainty Paradigm by collecting explicit as well as inferred measures of predictive uncertainty (Section 2.8). Potentially, more directly implicit measures such as reaction time data and/or neurophysiological responses, like the MMN(m) obtained in a passive listening task, could be conducive to this goal.

2.10.6. Neural correlates

The sixth and final analytical perspective, *neural correlates*, relates to how expertise influences the structure and functioning of the human brain. This perspective views musical expertise in terms of neuroplasticity, which may, however, manifest itself in various ways that can be detected with different neuroimaging techniques. For clarity and simplicity, such changes will here be categorised broadly into issues of (1) sensitivity, (2) temporality, (3) metabolism, (4) localisation and connectivity, and (5) anatomical structure.

First, changes in the *sensitivity* to musical stimuli may be reflected in greater amplitude of neural activity, as detected, for instance, in terms of the MMN(m) response described above (Section 2.9) (Fujioka et al., 2004) or the Early Anterior Negativity (EAN) typically observed in relation to syntactic violations in music (e.g., Koelsch, Schmidt, & Kansok, 2002). Second, as similarly described above, the time course, i.e. *temporality*, of neural responses may also be enhanced as evident from shorter latencies of various ERP or ERF components (e.g., Besson & Faïta, 1995). Third, studies using functional Magnetic Resonance Imaging (fMRI) have shown expertise-related decreases or increases in cerebral blood flow associated with differences in *metabolism* in that musicians and non-musicians require varying amounts of blood oxygenation for neural processing of music. For instance, evident of more efficient motor processing, professional pianists have lower metabolic demands in the primary and secondary motor cortices when performing bimanual tapping task in comparison with non-musicians (Jäncke, Shah, & Peters, 2000). Fourth, differences in *localisation and connectivity* of brain activity may indicate that musical experts recruit other, potentially more sophisticated, neural networks for music processing (Fauvel et al., 2014; Grahn & Rowe, 2009; Vuust et al., 2005). Generally greater recruitment of cortico-subcortical rather than just cortico-cortical networks (Lehmann, 2002) is, for instance, consistent with some of the implication theories reviewed above regarding expertise effects on the conscious availability of predictive knowledge (Section 2.10.5). Fifth, musicianship is associated with increases in both grey (e.g., Bermudez, Lerch, Evans, & Zatorre, 2009; Gaser & Schlaug, 2003) and white matter (e.g., Bengtsson et al., 2005; Schlaug, Marchina, & Norton, 2009) in the brains of practising musicians.

Methodologically, the indices of expertise-induced neuroplasticity just summarised can be related to information-theoretic measures estimated by IDyOM to investigate predictive processing of music in the brain. This promising line of work is still in its infancy, but has already been preliminarily pursued for information content (Pearce et al., 2010) and entropy (Lindsen, Pearce, Wiggins, & Bhattacharya, 2012). Also, very importantly, the sixth and final perspective constitutes a meta-perspective whose methodologies can be used to address pertinent questions raised by the previous five analytical perspectives. This potential receives further exemplification in the following.

In Section 2.10.2, two hypotheses were proposed in relation to training-induced effects on cognitive representation. To recap, musical expertise was hypothesised to cause either more dependent processing or more independent processing of stimulus features. Although overlaps in neural processing have previously been investigated in terms of signal additivity of the MMN(m) response, such neurophysiological work has not framed this topic in the context of expertise. Specifically, earlier studies have compared an *empirical* MMN(m) resulting from double or triple deviants, differing from the standard on two or three features, to a *modelled* MMN(m) corresponding to the sum of responses for the relevant single deviants. Full correspondence between these two MMNm responses has been taken to indicate independent neural processing, whereas under-additive responses, where the modelled MMNm exceeds the empirical one, have been interpreted as signs of overlapping (i.e. dependent) processing.

Using this method, MMN(m) additivity has been established for simple acoustic features like frequency, intensity, stimulus onset asynchrony (SOA), and duration (Levänen, Hari, McEvoy, & Sams, 1993; Paavilainen, Mikkonen, et al., 2003; Paavilainen, Valppu, & Näätänen, 2001; Schröger, 1995; Wolff & Schröger, 2001). Further source reconstruction studies have corroborated that separate neural populations process these features (Giard et al., 1995; Levänen, Ahonen, Hari, McEvoy, & Sams, 1996; Molholm, Martinez, Ritter, Javitt, & Foxe, 2005; Rosburg, 2003). Independent processing of inter-aural time and intensity differences (Schröger, 1996), phoneme quality and quantity (Ylinen, Huotilainen, & Näätänen, 2005), as well as attack time and even-harmonic attenuation in timbre perception (Caclin et al., 2006) have similarly been demonstrated in terms of MMN additivity. Additivity also shows that MMN responses to infrequent feature conjunctions are separable from MMNs in response to deviants in simple (Takegata, Paavilainen, Näätänen, & Winkler, 1999) or abstract features (Takegata, Paavilainen, et al., 2001). This is similarly corroborated by source reconstruction (Takegata, Huotilainen, Rinne, Näätänen, & Winkler, 2001).

Lack of MMN(m) additivity also provides important information about feature processing mechanisms. For instance, this method has demonstrated that abstract-feature MMN responses relating to changes in the direction of frequency and intensity changes (Paavilainen, Degerman, Takegata, & Winkler, 2003), timbral changes (Caclin et al., 2006), or vowel and pitch information when listening to sung stimuli (Lidji, Jolicœur, Moreau, Kolinsky, & Peretz, 2009) are processed in combination. Overall, these trends for under-additivity are stronger for triple than for double deviants (Caclin et al., 2006; Paavilainen et al., 2001). Moreover, in contrast to the temporal MMN generator, the frontal MMN generator is characterised by underadditivity, thus suggesting that it reflects more integrated processing (Paavilainen, Mikkonen, et al., 2003; see, however, Wolff & Schröger, 2001, for feature-specific variations in this pattern). In the light of this work, MMN(m) paradigms focusing on signal additivity offer a highly adequate means of investigating expertise-related effects on cognitive representation hypothesised by the second analytical perspective using the methods of the sixth perspective.

2.11. Research questions and hypotheses

The remaining part of this dissertation comprises four studies aiming to realise a small, but significant, selection of the potential research agendas outlined thus far. Specifically, two overall research questions will be addressed:

A) To what extent may key aspects of musical expertise, including its manifestation, specialisation, and acquisition, be captured by the Predictive Coding of Musical Expertise Theory (which emerges from the preceding literature review and is depicted in Figure 9)?

B) Are neural mechanisms for auditory feature processing subject to expertise-related neuroplasticity, and if so, how do these effects manifest themselves?

Two behavioural experiments using the Predictive Uncertainty Paradigm (Studies 1-2) and a systematic re-analysis of data from previous experiments (Study 3) were designed to address the former question. To address the latter question, an MEG experiment combining a classical oddball paradigm with a musical multi-feature MMNm paradigm was designed (Study 4). Before proceeding to introduce these studies one by one, the aforementioned theory will be briefly summarised.

The Predictive Coding of Musical Expertise Theory (Figure 9) offers a framework for rationalising experiential aspects of musical expertise acquisition and for modelling this process in the context of predictive coding theory. At the centre of this theory as it is depicted in Figure 9, one finds the musical event. In fact, each musical event evokes a cycle of surprise, learning, and uncertainty in the listener. In other words, before an event, the listener generates predictions based on an internal generative model taking relevant aspects of the musical context into account. These predictions are characterised by a level of uncertainty that can be quantified in terms of absolute entropy. The musical event itself evokes surprise in the listener, which is a manifestation of prediction error and may be quantified in terms of information content. This, in turn, triggers a process of learning, entailing optimisation of the listener's internal model, with the aim of minimising the relative entropy between model predictions and future sensory input.

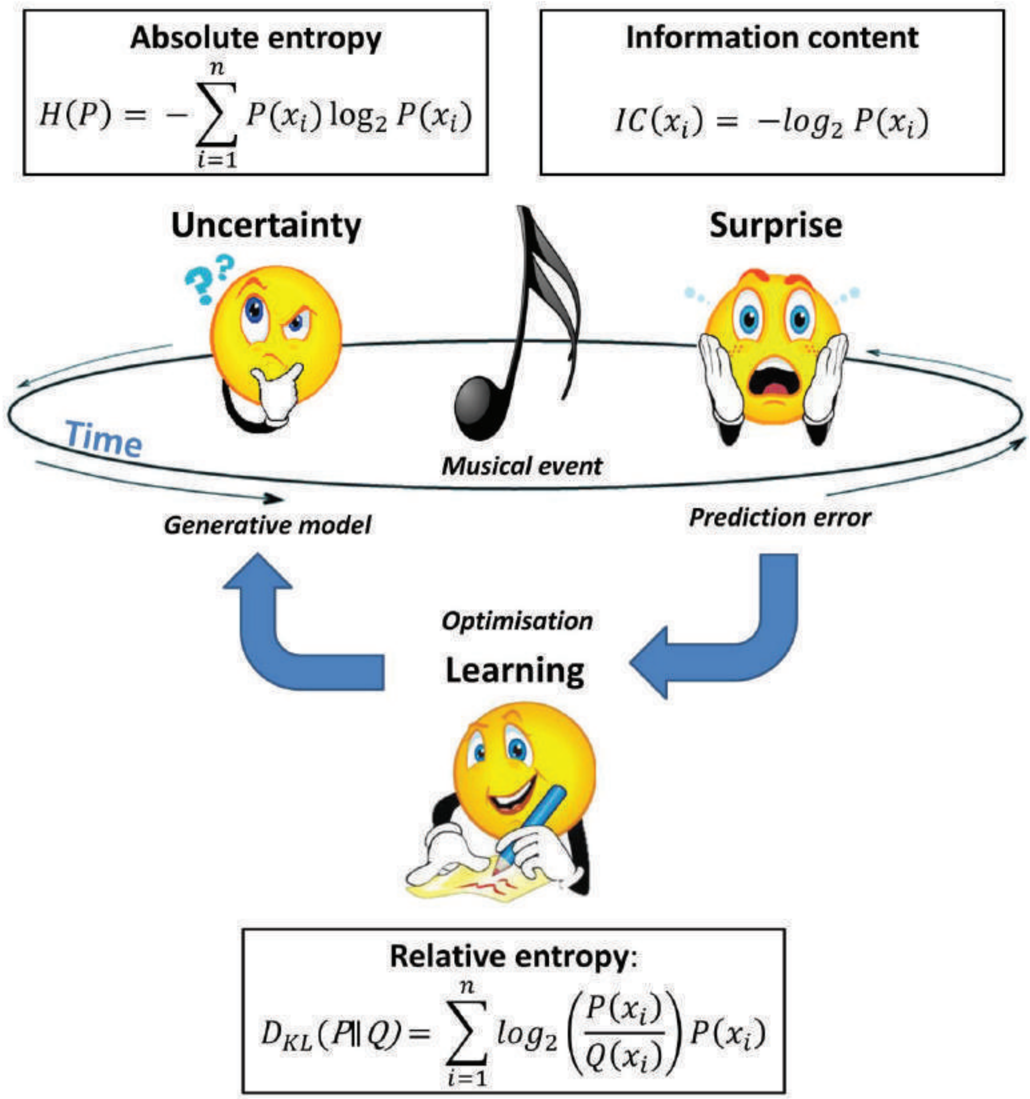

Figure 9. The Predictive Coding of Musical Expertise Theory. This theory posits that musical expertise is acquired through a process where every musical event is associated with a cycle comprising surprise, learning, and uncertainty phases. In the context of predictive coding theory, this corresponds to prediction error causing optimisation of the listener's internal generative model giving rise to new predictions. The predictive processing involved in these phases can be quantified in terms of information content, relative entropy minimisation, and absolute entropy.

2.11.1. Study 1: Predictive uncertainty

Study 1 aimed to test absolute entropy as a model of predictive uncertainty in melodic pitch expectation. Musicians and non-musicians listened to melodic contexts selected by IDyOM to afford expectations with either high or low levels of absolute entropy. Ratings of explicit uncertainty and unexpectedness for different continuations were collected. Four hypotheses were tested. First, absolute entropy was expected to model predictive uncertainty, resulting in main effects of entropy on explicit and inferred uncertainty. Second, musicians would predict with lower degrees of uncertainty than non-musicians, resulting in main effects of expertise on inferred and explicit uncertainty. Third, expertise would be selectively advantageous in low-entropy contexts where musicians would more correctly identify low-probability continuations as such, thus experiencing larger prediction error on average than non-musicians. This would result in an entropy-by-expertise interaction on unexpectedness ratings. Fourth, information content was hypothesised to model unexpectedness and this relationship would increase with expertise.

2.11.2. Study 2: Stylistic specialisation

Study 2 aimed to contrast the effects of stylistically specialised expertise with those of general musical expertise. Following a procedure similar to that for Study 1, non-musicians and professional musicians specialising in either jazz or classical music rated unexpectedness and explicit uncertainty for improvised bebop solos by Charlie Parker. The stimuli were selected by IDyOM to either afford high-entropy expectations in the context of bebop jazz and simultaneously low-entropy expectations in the context of general tonal music or, alternatively, afford low bebop entropy and high general entropy. Effects of generalised musical expertise would emerge from classical vs. non-musician comparisons whereas those of specialised expertise would emerge from comparisons of jazz vs. classical musicians. Differences between explicit and inferred measures would, furthermore, provide support for either implication or explication theories of musical skill acquisition.

2.11.3. Study 3: Entropy minimisation

Study 3 aimed to test relative entropy as a cognitively justified model of uncertainty reduction in statistical learning of musical tone sequences. To this end, data from previous statistical learning experiments (Loui & Wessel, 2008; Loui et al., 2010) (i.e. Experiments A1-A3) as well as data from Study 1 (i.e. Experiment B) were subjected to re-analysis. Relative entropy minimisation was hypothesised to take place on the short and long timescales, and more so in low-entropy contexts. This presumably universal learning mechanism was, however, not expected to depend on musical expertise or on differences in the size of the exposure corpus.

2.11.4. Study 4: Feature processing

Study 4 aimed to test whether musical expertise influences neural mechanisms for auditory feature processing, and if so, to determine whether such changes follow the dependent or independent processing hypotheses. This was done by assessing the additivity of the MMNm response to single, double, and triple deviants in pitch, perceived location, and intensity presented in classical oddball and musical multi-feature paradigms.

3. Methods

In this section, a brief overview will be provided of the methods applied in Studies 1-4. Complete methodological descriptions are found in the manuscripts (see Appendices).

Table 2. Descriptive statistics for participants in Studies 1-4.

Study	Group	n	Gender	Age Mean (SD)	Musical expertise	
					Measure	Value Mean (SD)
1	Musicians	17	9F, 8M	26.7 (5.7)	❶	53.1 (7.8)
	Non-musicians	17	8F, 9M	28.9 (6.4)	❶	13.9 (3.6)
2	Jazz musicians	22	4F, 18M	35.4 (12.1)	❷, ❸	42.5 (4.7), 213 (18)
	Classical musicians	20	14F, 6M	29.4 (8.7)	❷, ❸	44.0 (2.2), 130 (15)
	Non-musicians	20	8F, 12M	32.0 (10.0)	❷, ❸	10.6 (3.2), 99 (14)
3 (A1)	Musically trained	20	17F, 3M	19.4 (1.3)	❹	9.2 (2.2)
3 (A2)	Musically trained	24	12F, 12M	19.5 (1.3)	❹	9.5 (3.1)
3 (A3)	Musically trained	24	13F, 11M	19.5 (1.3)	❹	9.6 (2.6)
	Musically untrained	24	13F, 11M	19.8 (1.2)	❹	0.1 (0.2)
3 (B)	Musicians	17	9F, 8M	26.7 (5.7)	❶	53.1 (7.8)
	Non-musicians	17	8F, 9M	28.9 (6.4)	❶	13.9 (3.6)
4	Musicians	25	10F, 15M	25.0 (3.9)	❷	42.4 (3.1)
	Non-musicians	25	11F, 14M	24.7 (2.9)	❷	10.9 (7.3)

Self-report measures of musical expertise:
❶ Gold-MSI, v0.9, "musical training" subscale. ❷ Gold-MSI, v1.0, "musical training" subscale.
❸ Composite jazz experience. ❹ Years of musical training.

3.1. Study 1: Predictive uncertainty

3.1.1. Participants

Musicians and non-musicians were recruited, primarily from the graduate student population at Goldsmiths College, University of London (Table 2). Participants' self-declared group membership was confirmed by scores on the musical training subscale from *Goldsmiths Musical Sophistication Index* (Gold-MSI) v0.9 that were either below the 33rd or above the 67th percentile of scores from a sample of 488 individuals representative of the general British population (Müllensiefen, Gingras, Stewart, & Musil, 2011). Groups were matched on age and gender.

3.1.2. Materials

A total of 24 monophonic melodic contexts were selected for four experimental conditions (i.e. six contexts in each condition) containing *simple* or *complex* stimuli affording continuations with *high* or *low* entropy. Simple stimuli originated from a corpus of 120 English hymns isochronised by a skilled musicologist (Nicholson, Knight, & Dykes Bower, 1950) whereas complex stimuli originated from 35 "Selected Songs" by Franz Schubert (Max Friedländer/C.F. Peters, Frankfurt).

Stimulus selection followed the procedure outlined in Figure 10 with two separate runs of IDyOM (Section 2.7) using the configurations specified in Table 3. Specifically, chromatic pitch was predicted using source viewpoints linking pitch interval and scale degree for simple stimuli and pitch interval, scale degree, and the Parsons code for inter-onset-intervals for complex stimuli. Both sub-models were used with the long-term sub-model trained on chorale melodies and German and Canadian folksongs (Creighton, 1966; Fink, 1893; Riemenschneider, 1941).

The first model runs identified 72 candidate contexts, corresponding to the notes with the highest and lowest absolute entropy values from the simple and complex corpora preceded by their original context. The segmented candidate contexts always started with a phrase beginning and contained minimum eight notes and four distinct pitches. The second model runs modelled these candidates when listened to in isolation, using updated key signatures from Temperley's (1999) version of the Krumhansl-Schmuckler algorithm (Krumhansl, 1990, pp. 77-110). The final stimulus contexts were selected based on the absolute entropy of normalised probability distributions for nine chromatically distributed probe tones surrounding (and including) the median pitch of each context.

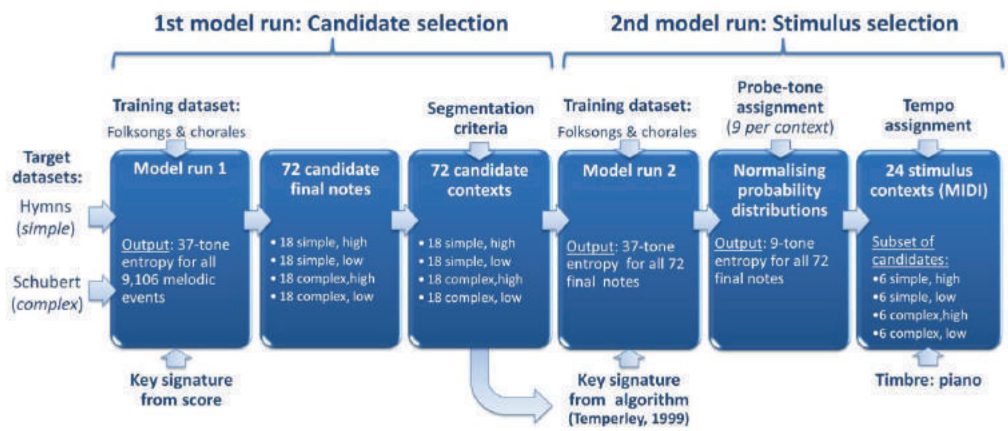

Figure 10. Stimulus selection for Study 1. Twenty-four stimulus contexts with high or low entropy were selected from hymns (*simple*) and Schubert songs (*complex*) using two runs of IDyOM.

Table 3. IDyOM configurations for Study 1.

	Target dataset	Target viewpoint	Source viewpoint	Order bound	Sub-model(s)	Training dataset(s)	Resampling folds
1st	Hymns	cpitch	cpint⊗cpintfref	none	BOTH	Folksongs & Bach chorales	N/A
1st	Schubert	cpitch	cpint⊗cpintfref ⊗bioi-contour	none	BOTH	Folksongs & Bach chorales	N/A
2nd	36 hymn candidates	cpitch	cpint⊗cpintfref	none	BOTH	Folksongs & Bach chorales	N/A
2nd	36 Schubert candidates	cpitch	cpint⊗cpintfref ⊗bioi-contour	none	BOTH	Folksongs & Bach chorales	N/A

Viewpoints: *cpitch*: chromatic pitch; *cpint*: chromatic pitch interval; *cpintfref*: chromatic scale degree; *bioi-contour*: Parsons code (i.e. up, down, or repeat) for inter-onset intervals.

3.1.3. Procedure

The experimental procedure followed the Predictive Uncertainty Paradigm (Section 2.8, Figure 6). First, explicit uncertainty ratings (1-9) and dichotomous familiarity judgements (yes/no) were collected for the incomplete melodic contexts presented with a piano timbre. Next, expectedness ratings (1-9) were collected for the nine probe tones for each context. Stimulus presentation was randomised and lasted 60-90 mins in total. Data from familiar contexts were excluded from further analysis.

3.2. Study 2: Stylistic specialisation

3.2.1. Participants

Jazz musicians, classical musicians, and non-musicians resident in the Greater London area, UK, were recruited for this study (Table 2). Whereas non-musicians had never received regular one-on-one music tuition and not performed music in public after the age of 12, musicians were professionally active, either earning the majority of their income from teaching and/or performing music or being full-time performance degree students. The three groups were matched on age, but not on gender. Jazz and classical musicians were matched on self-report measures of musical sophistication, but jazz musicians outperformed classical musicians on listening tests relating to genre sorting and melodic memory (Müllensiefen et al., 2014).

3.2.2. Materials

A total of 20 monophonic melodic contexts were selected for the two conditions referred to as "high bebop entropy" and "low bebop entropy". All stimuli originated from a subset of transcribed solos from Charlie Parker's *Omnibook* (Parker, 1978) deemed as "unfamiliar to the average jazz musician" by two independent jazz experts.

Stimulus selection took place over two model runs and was based on the difference between absolute entropy estimates from two implementations of IDyOM referred to as the "bebop" model and the "general" model (Figure 11; see Table 4 for configurations). Both models predicted pitch from pitch interval linked with scale degree. However, whereas the "general" model was trained on folksongs and hymns (Böhme, 1897; Creighton, 1966; Nicholson et al., 1950), http://www.dva.uni-freiburg.de/sammlungen/Deutsches_Volksliedarchiv), the "bebop" model used 10-fold cross-validation to predict from the Omnibook dataset itself in the first model run and was trained on the Omnibook dataset excluding candidate contexts in the second model run. The 72 candidate contexts (all in a major key) were segmented to begin with phrase beginnings, contain at least 12 events and six pitches with no overlaps with the song theme or with other candidate contexts. Final selection relied on normalised probability distributions for nine chromatically distributed probe tones surrounding and including the pre-probe tone pitch.

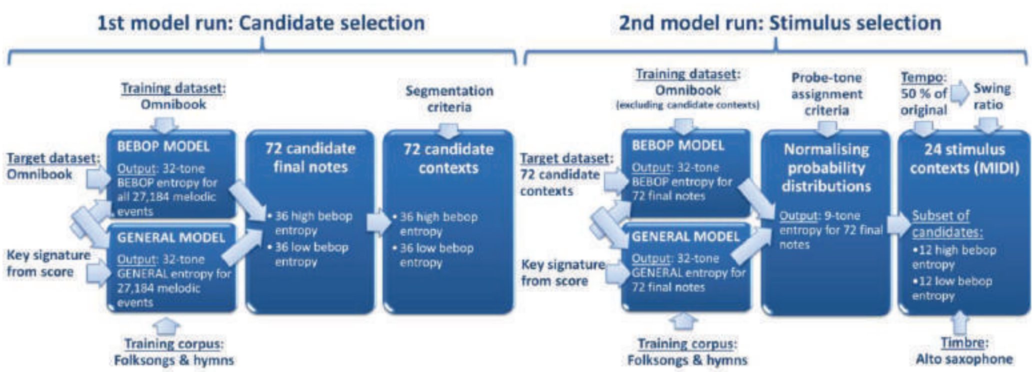

Figure 11. Stimulus selection for Study 2. Twenty stimulus contexts with high or low bebop entropy (and simultaneously low and high general entropy, respectively) were selected from Charlie Parker's *Omnibook* of transcribed saxophone solos, using two runs of IDyOM.

Table 4. IDyOM configurations for Study 2.

	Target dataset	Target viewpoint	Source viewpoint	Order bound	Sub-model(s)	Training dataset(s)	Resampling folds
1st (B)	Omnibook	cpitch	cpint⊗ cpintfref	none	BOTH	Omnibook	10
1st (G)	Omnibook	cpitch	cpint⊗ cpintfref	none	BOTH	Folksongs & hymns	N/A
2nd (B)	72 Omnibook candidates	cpitch	cpint⊗ cpintfref	none	BOTH	Omnibook (-candidates)	N/A
2nd (G)	72 Omnibook candidates	cpitch	cpint⊗ cpintfref	none	BOTH	Folksongs & hymns	N/A

Models: B: Bebop; G: General. **Viewpoints:** *cpitch*: chromatic pitch; *cpint*: chromatic pitch interval; *cpintfref*: chromatic scale degree.

3.2.3. Procedure

The experimental procedure followed the Predictive Uncertainty Paradigm (Section 2.8, Figure 6). First, ratings of explicit uncertainty (1-9) and liking (1-5, not analysed here) were collected for the incomplete melodic contexts. Next, expectedness ratings (1-9) were collected for nine chromatically distributed probe tones surrounding the final pitch of the context. Stimuli were presented using an alto saxophone timbre at half the original tempo with an added swing feel based on preferred durational ratios (Friberg & Sundström, 1997). All contexts were preceded by a piano cadence (ii^7-V^7-I^{Δ}) to enforce underlying meter (always 4/4), metrical position, key (always major), and harmonic style (seventh chords typical for jazz). Presentation order was randomised, and sessions typically lasted 90 mins in total.

To assess influences of specialised and generalised expertise, model-fit values were computed in terms of Pearson correlations between IDyOM model estimates (i.e. absolute entropy or information content) and empirical data (i.e. explicit/inferred uncertainty or expectedness), separately for the bebop and general models.

3.3. Study 3: Entropy minimisation

3.3.1. Experiment A: Participants

Musically trained and untrained undergraduate students were recruited at the University of California at Berkeley, USA. Musical training received was less than one year for untrained participants and between 5 and 16 years for trained participants.

3.3.2. Experiment A: Materials and procedure

Experiment A comprised three sub-experiments (A1-A3), each of which contained an exposure phase (cf. Section 2.5) preceded as well as succeeded by a probe-tone task. Exposure phases lasted 25-30 mins during which participants listened to pure-tone sequences with note durations of 500 ms played at 70dB over headphones while drawing on paper to pass time. Each sequence consisted of randomised and concatenated 8-tone melodies separated by 500 ms of silence. Participants heard either 5 melodies played 100 times (A1), 15 melodies played 27 times (A2), or 400 melodies played once (A3). A subset of six pitches from the artificially constructed Bohlen-Pierce (BP) scale was used. This scale divides the tritave, corresponding to an octave and a fifth, into 13 logarithmically even subdivisions, thus mirroring the construction of the 12-tet equal-tempered scale, but evading the culturally embedded listening schemata that this familiar scale evokes in a typical Western listener (Mathews, Pierce, Reeves, & Roberts, 1988). In each sub-experiment (A1-A3), two distinct finite-state grammars were used to generate exposure sequences with comparable zeroth-order probabilities, but dissimilar first-order transition probabilities. Before and after exposure, probe-tone ratings for all 13 notes of the BP scale were given on a scale ranging from 1 ("poor") to 7 ("well").

3.3.3. Experiment B: Participants, materials, and procedure

Participants, materials, and procedure for Experiment B were identical to those reported for Study 1 (Section 3.1.1-3). Relative entropy values between normalised distributions of expectedness ratings and normalised probability distributions estimated by IDyOM were computed (as specified in Section 2.6, Equation 5). These data were subjected to 2x2x2 ANOVA with style (hymn vs. Schubert), entropy (high vs. low), and expertise (musicians vs. non-musicians) as factors.

3.4. Study 4: Feature processing

3.4.1. Participants

Twenty-five non-musicians and 25 musicians, matched on age and gender, were recruited for this study (Table 2). Musicians were full-time conservatory students or professional musicians receiving their main income from performing and/or teaching music. Non-musicians did not regularly play a musical instrument and had received less than one year of music tuition beyond mandatory school lessons.

3.4.2. Materials

Standard and deviant tones for the experiment were generated from sampled piano sounds with 200 ms duration including 5 ms rise time and 10 ms fall time. Seven types of deviants resulted from modification in Adobe Audition v3.0 (Adobe Systems Inc.) of the notes from the pitch range A#2-A3. Specifically, pitch deviants (P) were shifted down 35 cents, intensity deviants (I) were decreased by 12 dB, and location deviants (L) were produced by delaying the right track by 200 µs compared to the left one. Double and triple deviants combined these modifications in this particular order (i.e. PI, IL, LP, and PIL).

3.4.3. Procedure

The experiment lasted ~100 mins in total and comprised seven blocks (M1-C1-M2-C2-M3-C4-M4), each of 11-14 mins duration (Figure 12). M blocks used Vuust et al.'s (2011) musical multi-feature paradigm with a constant SOA of 205 ms (Section 2.9, Figure 8); however, the standard pattern occurred three times between each deviant to accommodate the lack of independence between double and triple deviants and their constituent single deviants (Näätänen et al., 2004). As a control, O blocks used an oddball paradigm with a SOA of 400 ms and 3-5 standards between each deviant. For both paradigms, pitch level changed within the range A#2-A3 for each presentation of the seven deviants; deviant types and pitch levels were permuted (Figure 12). Three iterations of this procedure constituted an M block whereas four iterations constituted a C block, resulting in 144 samples of each deviant type for each paradigm.

Participants were instructed to stay still throughout blocks while watching a silent movie with the soundtrack disabled. During the 1-2 mins breaks between blocks, participants remained seated inside the magnetically shielded room, but were allowed to stretch, move, and talk with the experimenter. Sounds were presented binaurally at 50 dB above individual hearing threshold through Etymotic ER•2 earphones using the Presentation software (Neurobehavioral Systems, San Francisco, USA).

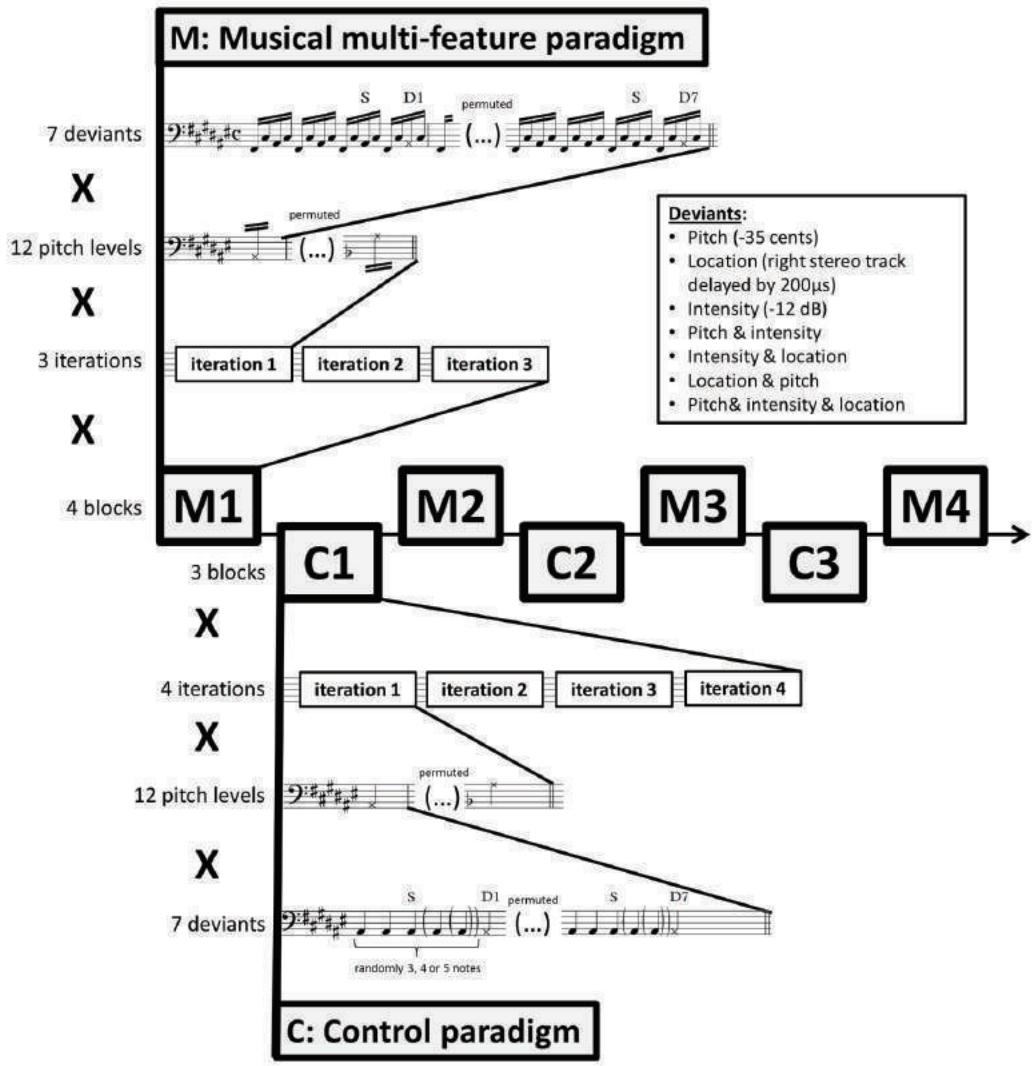

Figure 12. Experimental paradigm for Study 4. Alternating musical multi-feature (M1-M4) and control blocks (O1-O3) were presented. Each block comprised three of four iterations of full permutations over pitch levels A#2-A3, which, in turn, contained all seven deviant types.

3.4.4. *MEG acquisition and analysis*

MEG data were sampled at 1000 Hz using the 102 magnetometers and 204 planar gradiometers of the Elekta Neuromag TRIUX system. Concurrently, four continuous Head Position Indicators (cHPI) and surface electrodes monitored horizontal and vertical EOG, ECG, and movements. Pre-processing used Elekta's MaxFilter software (Version 2.2.15), configured to temporal signal source separation (tSSS) (Taulu, Kajola, & Simola, 2004; Taulu & Simola, 2006) and down-sampling to 250 Hz. EOG and ECG artefacts were removed with independent components analysis (ICA), as implemented in MNE Python (Gramfort et al., 2013, 2014) and as validated by visual inspection. Using Fieldtrip (Oostenveld, Fries, Maris, & Schoffelen, 2010), http://www.ru.nl/neuroimaging/fieldtrip), data coinciding with "S" and "D1-D7" in Figure 12 were epoched with 100 ms pre-stimulus and 400 ms post-stimulus intervals and band-pass filtered at 1-40 Hz (using data padding). Planar gradiometers were combined, and baseline correction performed based on the 50 ms pre-stimulus interval.

Non-parametric, cluster-based permutation tests (Maris & Oostenveld, 2007), using maximum value of the summed t values as cluster-level statistic and 10,000 random permutations of the group or condition labels, were run on data from the nine combined gradiometers surrounding and including the sensor with the highest MMNm signal in each hemisphere (i.e. 18 sensors in total) recorded within the 100-300 ms post-stimulus time range. First, MMNm effects were established by comparing standard and deviant responses. Next, potential additivity was established by comparing MMNms for triple and double deviants with those for their constituent single or double deviants. Finally, as recommended for testing interaction effects within the permutation framework[5], expertise effects on under-additivity were assessed by comparing the difference between empirical double and triple MMNms

[5] http://www.fieldtriptoolbox.org/faq/how_can_i_test_an_interaction_effect_using_cluster-based_permutation_tests.

and modelled MMNms corresponding to the sum of relevant empirical single MMNms across musicians and non-musicians. Bonferroni correction was applied to this main analysis.

4. Results

4.1. Study 1: Predictive uncertainty

4.1.1. Explicit uncertainty

For explicit uncertainty, different patterns of the hypothesised effects were found for *simple* (i.e. hymns) and *complex* (i.e. Schubert) stimuli (Figure 13A). Specifically, for simple stimuli, explicit uncertainty was lower in low-entropy contexts compared to high-entropy contexts, and musicians generally experienced lower uncertainty than non-musicians. No such entropy or expertise effects were present for the complex stimuli. When averaged across participants within groups, explicit uncertainty did not generally correlate with absolute entropy, and the extent of this fit for individual participants did also not correlate with measures of musical experience.

4.1.2. Inferred uncertainty

For inferred uncertainty, as hypothesised, the analysis of data from simple stimuli showed lower uncertainty in low-entropy contexts and lower uncertainty for musicians compared to non-musicians (Figure 13B). For complex stimuli, however, entropy effects were only present in musicians, and the expertise effects were more prominent for low-entropy contexts. Additionally, when averaged across participants, inferred uncertainty increased with absolute entropy (Figure 13C), but individual model-fit did not correlate with musical experience.

4.1.3. Relationship between explicit and inferred uncertainty

When averaged across participants, explicit and inferred uncertainty measures were correlated. This relationship was slightly stronger in musicians than in non-musicians.

4.1.4. *Unexpectedness*

For mean unexpectedness ratings, entropy interacted with expertise, such that musicians experienced low-entropy contexts as more unexpected on average than did non-musicians (Figure 13D). In other words, expertise effects were less prominent when entropy was high. As hypothesised, average unexpectedness increased with information content (Figure 13E), and the strength of this relationship further increased with musical training (Figure 13F).

4.1.5. *Model comparisons*

Model comparison analysis revealed that absolute entropy was generally superior to Schmuckler's difference scores (Section 2.8) in modelling predictive uncertainty from the IDyOM output (cf. appendix for Manuscript 1, Section 6.1). IC based on IDyOM also vastly outperformed Schellenberg's (1997) implementation of the rule-based *Implication-Realization Model* (Narmour, 1990, 1992) as a model of unexpectedness. Moreover, in configuring IDyOM, simple first-order Markov models were sufficient to predict unexpectedness whereas longer contexts of three or more notes offered a slight advantage for modelling uncertainty. For these short excerpts, the short-term sub-model did not increase model performance.

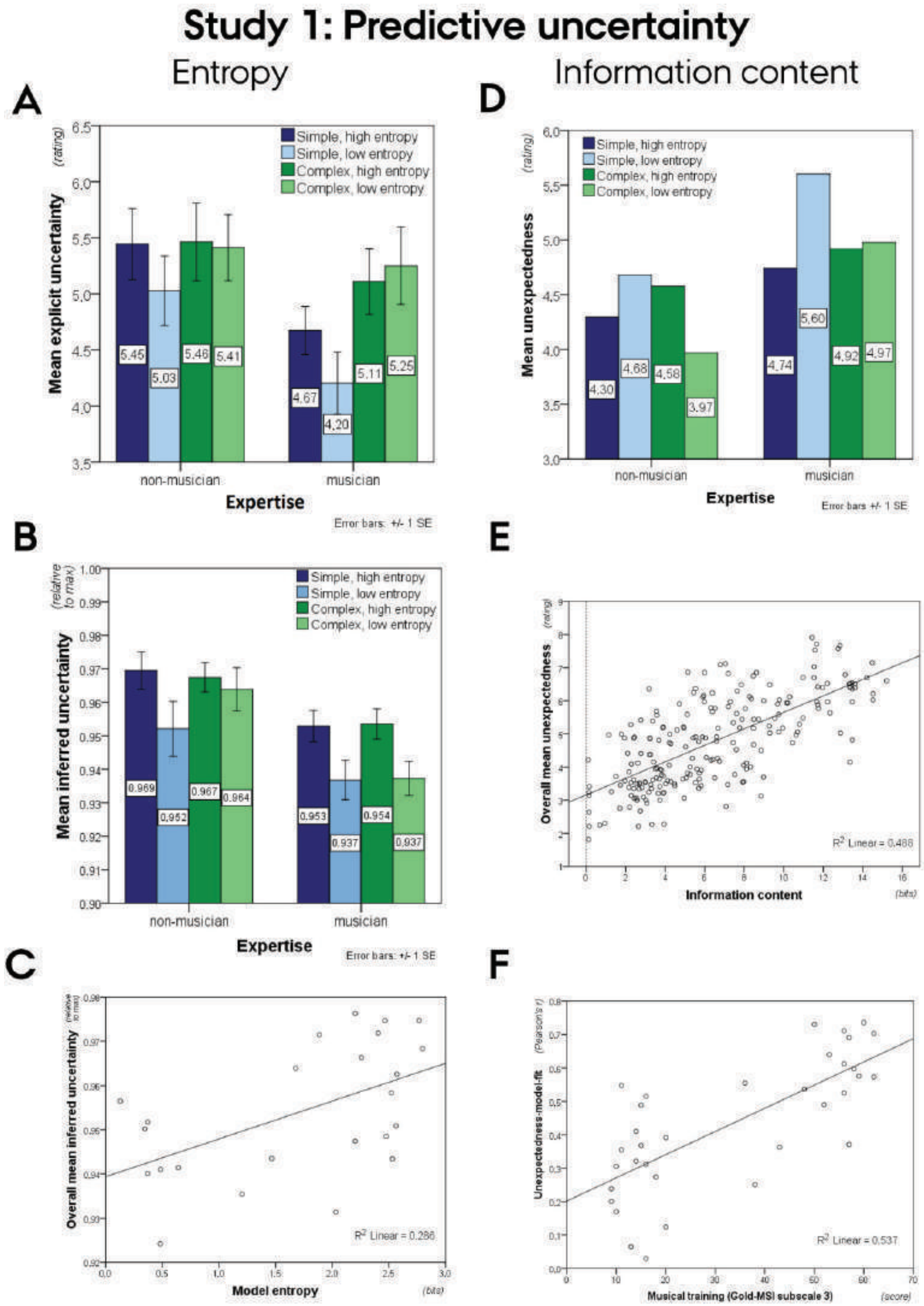

Figure 13. Models of predictive uncertainty and unexpectedness. (A) Mean explicit uncertainty ratings; (B) Mean inferred uncertainty; (C) Inferred uncertainty increases with absolute entropy; (D) Mean unexpectedness ratings; (E) Unexpectedness increases with information content; (F) Unexpectedness-model-fit increases with musical training.

4.2. Study 2: Stylistic specialisation

4.2.1. Model-fit

For expectedness, bebop model-fit was higher in musicians than in non-musicians with no significant differences between specialists in jazz and classical music (Figure 14A). For inferred uncertainty, only marginally non-significant differences were found between classical and non-musicians, but jazz musicians did obtain significantly higher bebop model-fit than non-musicians. For explicit uncertainty, jazz musicians achieved higher bebop model-fit than both classical and non-musicians. Participants without jazz-specific expertise did, however, not differ from one another.

These findings were confirmed in terms of correlations between measures of general and jazz-specific experience and bebop model-fit. Specifically, both types of experience explained unique proportions of variance in model-fit for expectedness whereas general experience was sufficient to explain that for inferred uncertainty; for explicit uncertainty, on the other hand, only jazz-specific experience explained bebop model-fit. There were no expertise differences in fit with the stylistically irrelevant model trained on general tonal music.[6]

4.2.2. Mean expectedness and uncertainty

Condition effects, indicative of following the bebop model, were only found in jazz and classical musicians for mean expectedness and mean inferred uncertainty (Figure 14B). For mean explicit uncertainty, these effects only appeared for jazz experts. Expertise-related decreases in expectedness and uncertainty were, furthermore, only present for low-entropy contexts.

[6] Note that weak general model-fit for expectedness is due to covariance between IDyOM estimates of probability from the bebop and general models, which were not contrasted by design; similarly, reverse general model-fit for uncertainty is due to the way that stimuli were selected (i.e. based on difference scores).

4.2.3. Relationship between explicit and inferred uncertainty

Consistent with the just established importance of specialised expertise in explicit uncertainty processing (Section 4.2.1), the relationship between explicit and inferred measures of uncertainty only reached significance for jazz musicians (Figure 14C).

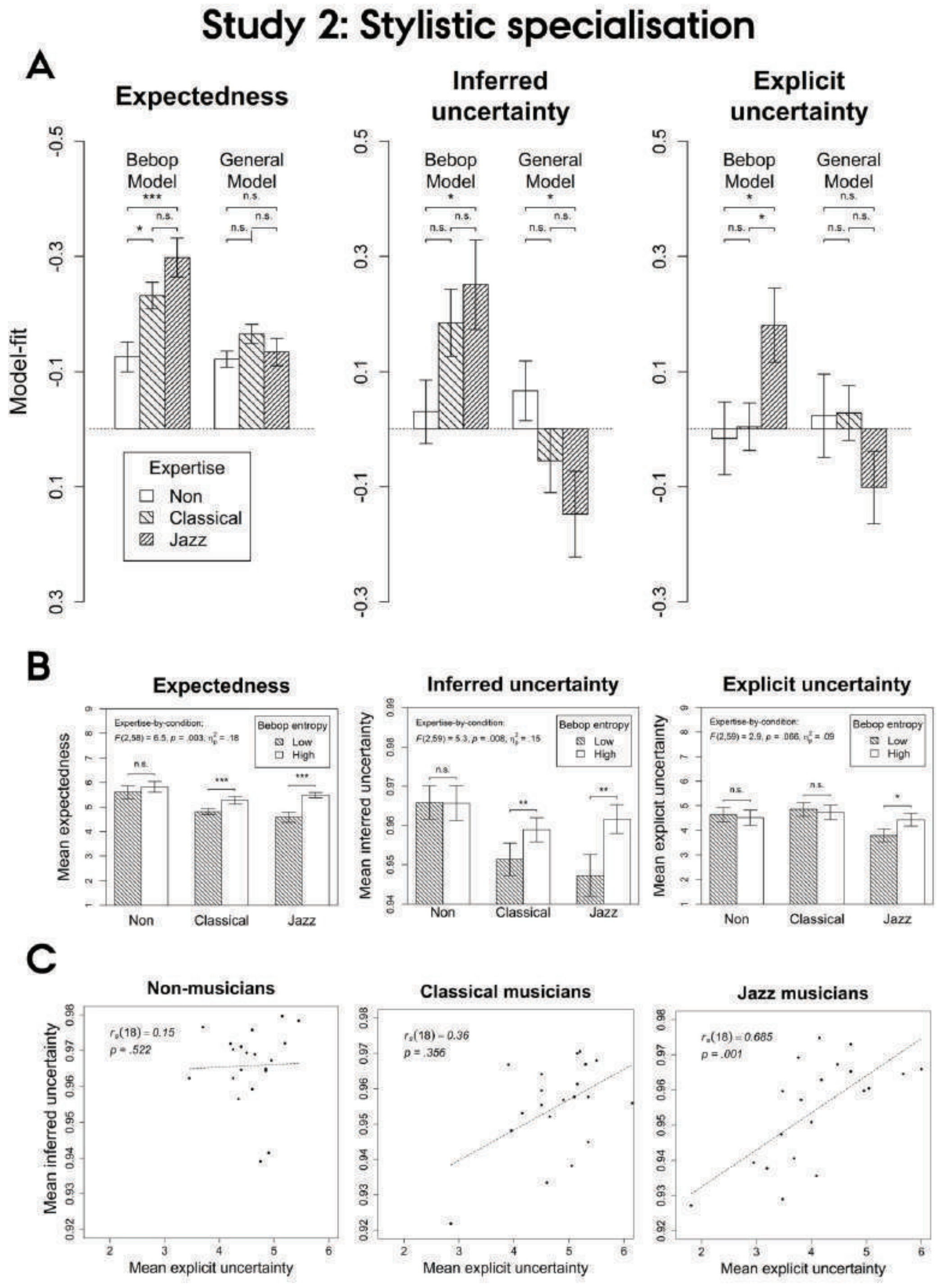

Figure 14. Results from Study 2. (A) Model-fit[7]; (B) Means of expectedness and uncertainty; (C) Relationship between inferred and explicit uncertainty. * $p < .050$, ** $p < .010$, *** $p <. .001$.

[7] Note that negative values designate good model-fit for expectedness.

4.3. Study 3: Entropy minimisation

4.3.1. Experiment A: Short-term learning

Entropy minimisation took place in all experimental conditions, as evident from lower relative entropy after exposure compared to before (Figure 15A). As hypothesised, this effect did not interact significantly with expertise or with the number of exposure melodies. Additional comparative analyses using alternative correlational and information-theoretic measures confirmed the superiority of relative entropy as a model of uncertainty reduction (further details in the appendix for Manuscript 3, Section 6.3).

4.3.2. Experiment B: Long-term learning

Entropy minimisation was found in terms of expertise effects in all four conditions (Figure 15B). As hypothesised, this effect was, furthermore, stronger for low- than for high-entropy contexts, regardless of musical style. Again, relative entropy generally picked up these effects better than alternative measures (cf. appendix for Manuscript 3, Section 6.3).

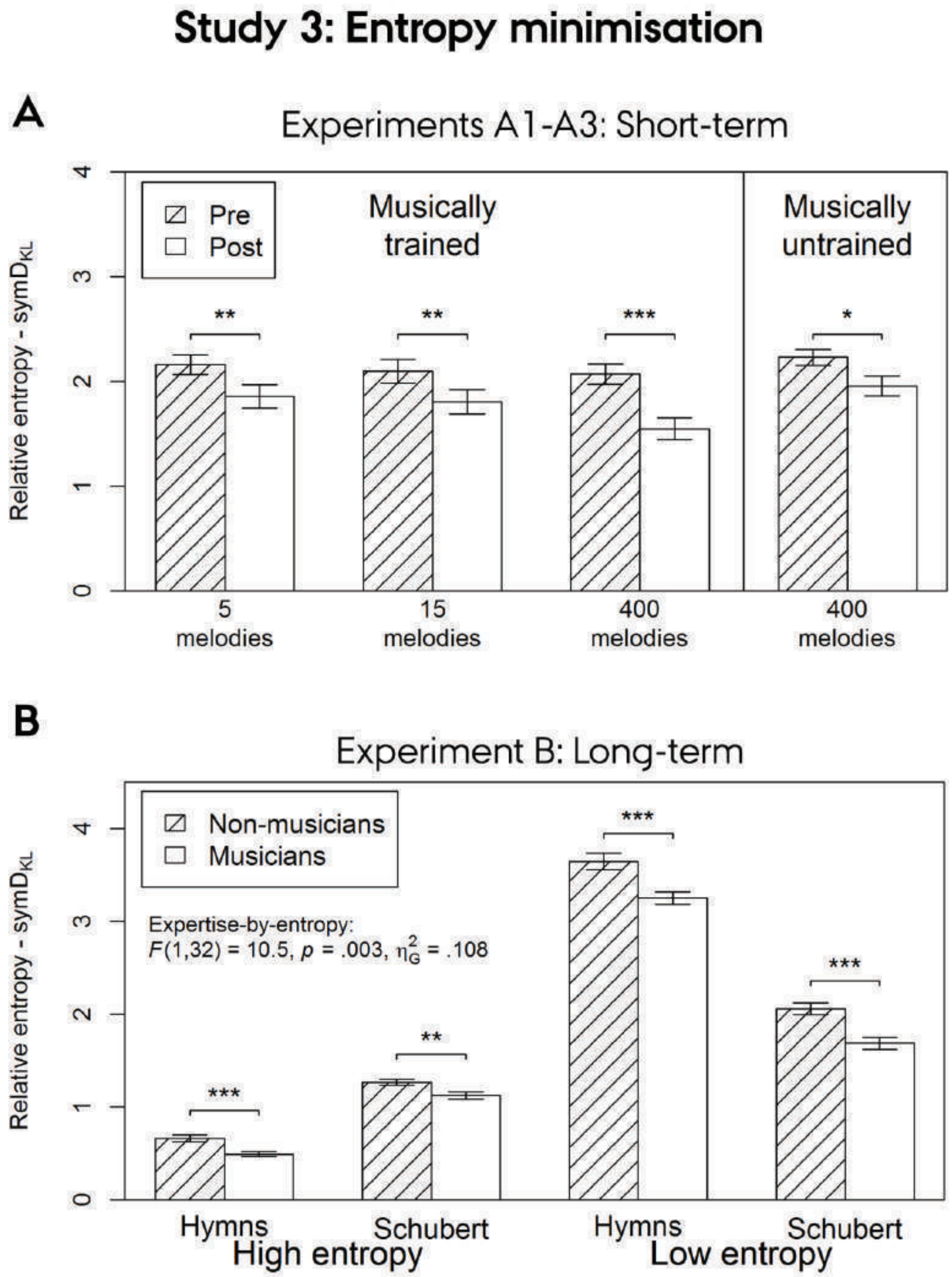

Figure 15. Entropy minimisation in short-term and long-term experiments. (A) The relative entropy between probe-tone ratings and exposure frequencies decreases after exposure. (B) The relative entropy between probe-tone ratings and probability estimates of IDyOM is smaller in musicians compared to non-musicians; this expertise effect is greater for low-entropy contexts than in high-entropy contexts. * $p < .050$, ** $p < .010$, *** $p < .001$.

4.4. Study 4: Feature processing

Significant MMNm effects were present for all deviant types in both paradigms. In the musical multi-feature paradigm, MMNms for double and triple deviants were generally larger than those for constituent single or double deviants. The only exception was that adding pitch deviance to a single deviant only resulted in non-significant (LP vs. L) or weakly significant (PI vs. I) MMNm increases. The main analysis confirmed that this suggested under-additivity for pitch in the musical paradigm was absent in non-musicians, but present in musicians, as evident from significant interaction effects for PI and LP, but not for IL (Figure 16). For PIL, non-musicians showed an under-additivity which was not significantly smaller than that for musicians when Bonferroni-correction was applied. In the control paradigm, on other hand, double and triple deviants were always significantly larger than constituent single or double deviants, and the extent of additivity did not differ between musicians and non-musicians (Figure 17).

Study 4: Musical multi-feature paradigm

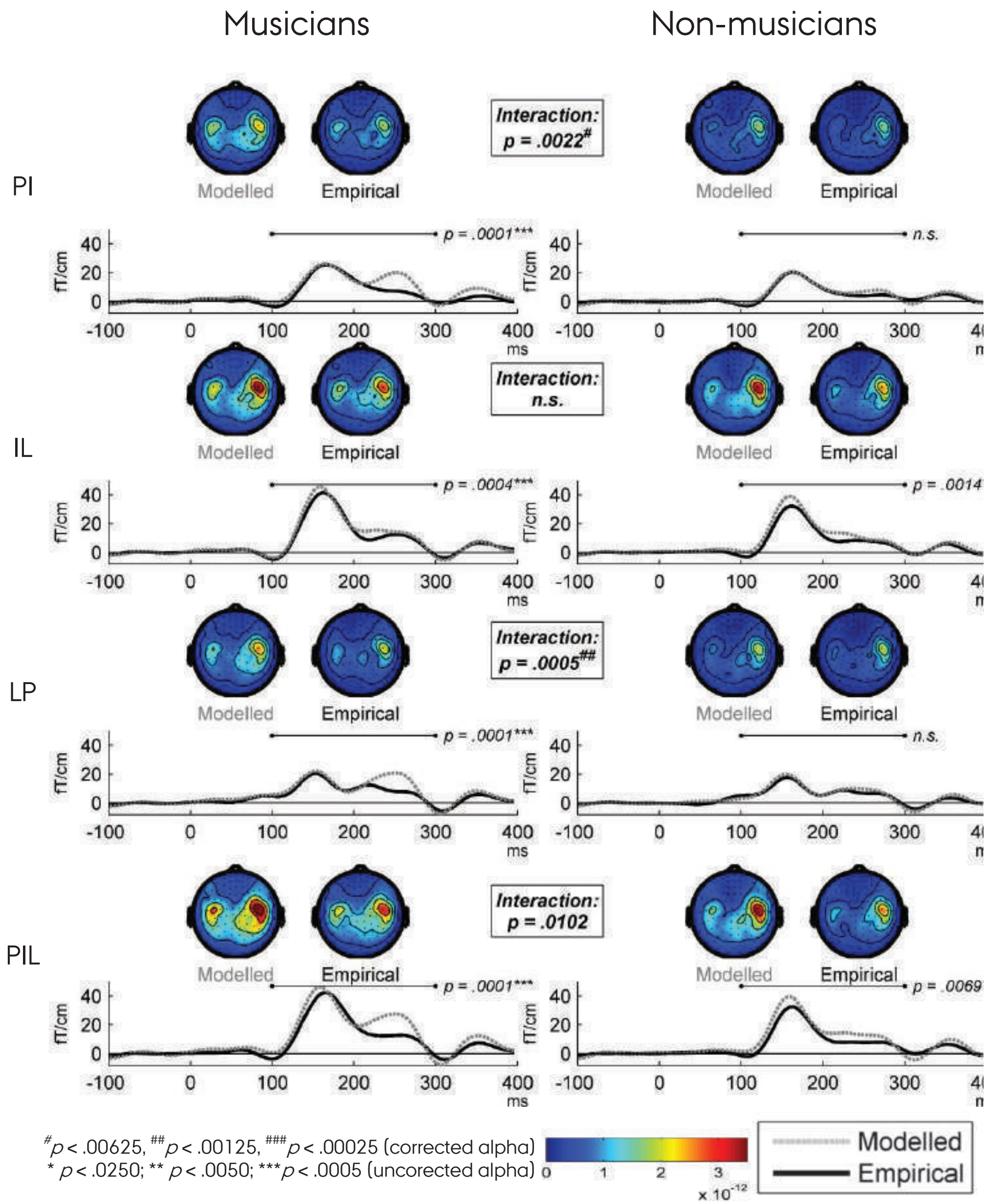

Figure 16. MMNm additivity in the musical multi-feature paradigm. Empirical and modelled MMNms to double and triple deviants differing in pitch (P), intensity (I), and/or location (L). Greater under-additivity was present in musicians compared to non-musicians for PI and LP. Data from 18 combined gradiometers, low-pass filtered at 20 Hz for visualisation purposes. Topographies depict MMNm effect in the 100-300 ms post-stimulus time range.

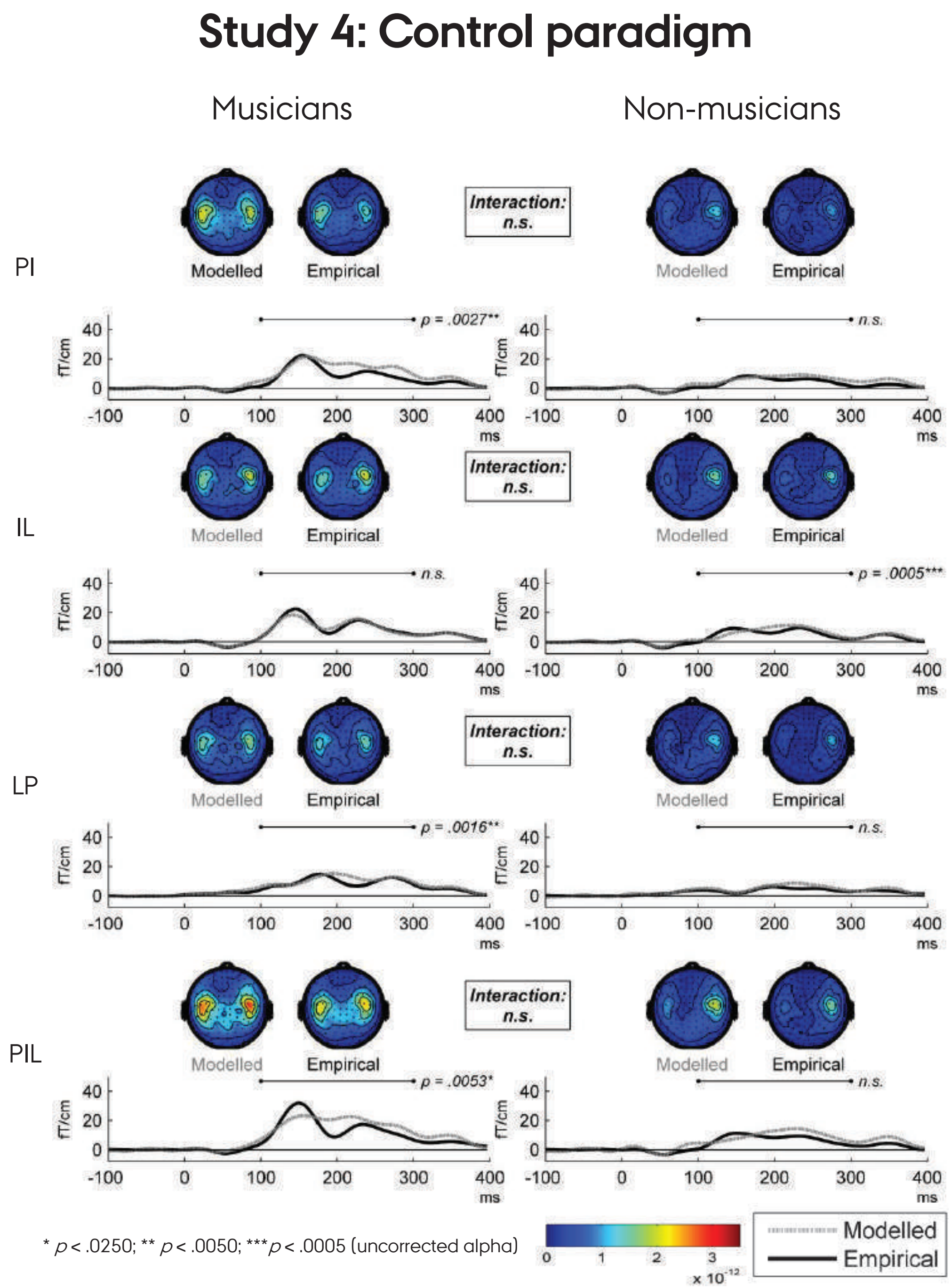

Figure 17. MMNm additivity in the control paradigm. Empirical and modelled MMNms to double and triple deviants (cf. Figure 16 for details). No significant differences in MMNm additivity was found between musicians and non-musicians.

5. Discussion

5.1. Main findings

The work presented here set out to investigate two overall research questions regarding, first, to what extent musical expertise as a phenomenon is consistent with the Predictive Coding of Musical Expertise Theory (Section 2.11), and, second, whether and how neural mechanisms for auditory feature processing are subject to expertise-induced plasticity. Four experiments were designed and carried out (Chapters 3-4). Whereas detailed discussions of each of these studies may be found in the appendices (Sections 6.1-4), the focus here will be on how the findings as a whole inform the previously presented analytical framework (Section 2.10) and, ultimately, how they reflect back on the scientific expertise concept that was introduced at the outset of this dissertation (Sections 2.2-3). First, however, the main results will be summarised along with bracketed cross-referencing pointers to the subsequent discussion.

5.1.1. Entropy as a model of predictive uncertainty

The first study demonstrated how predictive uncertainty can be characterised in terms of the absolute entropy of conditional probability distributions acquired through long-term exposure to music. This emphasises the key importance of statistical learning and uncertainty processing in expertise acquisition, which will be further discussed below (cf. Sections 5.2.2 and 5.2.5). Specifically, both when operationalised as explicit ratings of perceived uncertainty and as the actual uncertainty with which predictions were made about melodic continuation, predictive uncertainty was generally lower for melodic excerpts that IDyOM had estimated to be low in entropy in the context of Western tonal music. While this sensitivity to probabilistic structure could be detected with explicit and inferred measures in musicians and non-musicians alike using the structurally simple hymn stimuli, it was absent from the explicit ratings when using the tonally and rhythmically more complex melodies by Schubert. This inability to introspect about the uncertainty of melodic continuation was particularly noteworthy in the case of musicians whose experience of surprise to different continuations clearly reflected that they possessed knowledge of the underlying probability distributions. These results reveal an intriguing dissociation between predictive processing of surprise and uncertainty (cf. Section 5.2.4), including differences in the conscious access to such processing (cf. Section 5.2.6).

Next, it was established that the extent of correlational fit between melodic expectations and probabilistic structure in music was a linearly increasing function of expertise. This led to lower perceived uncertainty and to more specific expectations in musicians compared to non-musicians. Expertise was also associated with higher mean unexpectedness specifically for continuations of low-entropy contexts. We later interpret this as indicative of greater prediction error due to more specific expectations, particularly when probabilistic decodability is afforded by the stimuli (cf. Section 5.2.4). Higher precision-weighting of prediction error may further magnify this effect by means of synaptic gain control, as suggested by predictive coding theory (Friston, 2010).

Despite the significant advances of this first study, it remained unknown whether the identified expertise effects could be ascribed to internalisation of probabilistic musical material or merely to advantages associated with musical expertise in more general terms. For instance, musical training may enhance pitch processing (Besson et al., 2007; Schön, Magne, & Besson, 2004), attentional focus (Strait & Kraus, 2011), sensitivity to local statistics (Francois & Schön, 2011), motivation (McAuley, Henry, & Tuft, 2011), or indeed the ability to comply with task demands (Bigand & Poulin-Charronnat, 2006). Contrasting experts specialising in distinct musical styles provided a means of addressing this potential criticism.

5.1.2. Specialised stylistic expertise

The second study found distinct effects of generalised and specialised musical expertise on predictive processing of melodic improvisations by Charlie Parker. The former were assessed by comparing classical vs. non-musicians whereas the latter were assessed by comparing jazz vs. classical musicians. Using a paradigm similar to that for Study 1, generalised expertise effects emerged in terms of correlational model-fit for expectedness and inferred uncertainty measures as well as condition effects on the means of these two measures. As for Study 1, condition effects in the case of inferred uncertainty reflect that participants made predictions that were consistent with the model whereas, in the case of expectedness, they reflect greater prediction error on average in response to low-entropy contexts (cf. Section 5.2.4).

Effects of specialised musical expertise, conversely, emerged as model-fit for explicit uncertainty and model-consistent effects of experimental condition on the means of this measure. Furthermore, a significant relationship between explicit and inferred uncertainty was only observed for expert jazz musicians. This last finding may seem inconsistent with Study 1 where the explicit-to-inferred relationship was found in both musicians and non-musicians, albeit more prominently so in the former group. However, Study 2, in fact, refines this picture by demonstrating that stylistic familiarity is required for this relationship to emerge and, moreover, that explication of implicitly acquired knowledge may play a role in receptive aspects of musical expertise (cf. Section 5.2.6).

Lastly, beyond expected artefacts, no notable extent of correlational model-fit with the general model was found. General model-fit was not affected by expertise either. Thus, although Study 1 indicated that musicians and non-musicians possess a generative model for melodic continuation in general tonal music, they refrained from misapplying this knowledge in the stylistically irrelevant contexts introduced in

Study 2. This finding will be discussed in the context of cognitive firewalls (cf. Section 5.2.5).

Important to mention, the findings of Study 2 suffer from the possible limitation that, despite considerable efforts during recruitment, jazz experience was slightly higher in classical musicians than in non-musicians. Although this may mildly complicate the interpretation of generalised expertise effects, it does not compromise the key finding that specialised expertise expresses itself in terms of knowledge explication (cf. Section 5.2.6). Superior melodic memory and genre recognition skills in jazz compared to classical musicians represent another potential limitation. This may, however, be ascribed to the higher perceived importance of listening skills amongst jazz musicians (Wopereis, 2013), thus representing a characteristic of the population rather than of the sample. Yet, a truly counterbalanced design, also exposing jazz musicians to an unfamiliar, classical sub-genre, would admittedly have been preferable in this regard.

A final limitation shared by Studies 1-2 is the use of correlational measures of model-fit. As pointed out in Section 2.8, information-theoretic measures are altogether more plausible models of human cognition. Whereas absolute entropy as a cognitive model ignores the fact that statistical learning is constrained by context entropy, as established in Studies 1-2, relative entropy has greater potential as a cognitive model of learning.

5.1.3. Statistical learning as entropy minimisation

The third study established that relative entropy minimisation successfully models statistical learning taking place on short and long timescales. Although Studies 1-2 already contributed substantially by showing expertise effects on absolute entropy, the superiority of relative entropy as a model of cognitive learning processes, both in comparison to correlational and alternative information-theoretic measures was confirmed by model comparisons carried out in Study 3 (cf. Section 5.2.4).

For practical reasons, relative entropy for the short-term experiments (Study 3A) was computed from zeroth-order statistics. Because the Predictive Coding of Musical Expertise Theory posits that uncertainty is context-dependent (Section 2.11), this practice seems suboptimal. Thus, in planned and ongoing work, IDyOM is trained on the BP exposure corpora from Loui et al. (2010) to estimate variable-order conditional probability distributions, similarly to what was done for the long-term experiments (Study 3B).

Whereas relative entropy minimisation was stronger for low-entropy contexts, it neither interacted with musical expertise nor with the size of the exposure corpus. The lack of expertise advantages regarding statistical learning efficacy is consistent with predictive coding theory, thus making statistical learning a candidate for a general mechanism of human cognition and learning (cf. Section 5.2.1-2), potentially offering a perspective for reconciling theories from cognitive psychology with those from cognitive neuroscience (cf. Section 5.2.7). These results were only possible by meticulously controlling prior familiarity with the use of an artificially constructed musical scale (i.e. the BP scale). This procedure offers promising perspectives for the study of cognitive constraints for representations of musical structure (cf. Sections 5.2.2-3). In modelling melodic expectations with IDyOM, Studies 1-3 presumed that scale degree and pitch intervals constitute key factors in this regard. Although this assumption is indeed strongly supported by empirical research (e.g., Deutsch & Feroe, 1981; Dowling & Bartlett, 1981), neurophysiological methods offer a path towards a yet more refined understanding of cognitive representation.

5.1.4. Feature processing in musicians

Using magnetoencephalography (MEG), the fourth and final study found greater under-additivity of the MMNm response in musicians compared to non-musicians specifically for the pitch component when sounds were presented in a musical context. This evidence in support of the *dependent processing hypothesis* indicates that neural mechanisms for auditory feature processing are subject to expertise-induced plasticity (cf. Section 5.2.2), expressed as more integrative processing in musical experts (cf. Section 5.2.3), already at a pre-attentive stage (cf. Section 5.2.6). The fact that such expertise effects were absent in the non-musical oddball control paradigm, furthermore, suggests that these processes are flexible and context-dependent (cf. Section 5.2.5). Lastly, selective dependent processing for pitch advocates that this feature plays a privileged role in music perception which may be ascribed to its intrinsic significance in musical practice and syntax (cf. Section 5.2.3).

5.2. Predictive coding of musical expertise

The presented results will now be evaluated in relation to the *Predictive Coding of Musical Expertise Theory* (Section 2.11). Subsequently, it will be discussed what has been revealed in relation to each of the six analytical perspectives of the scientific expertise framework (Table 1).

5.2.1. The Predictive Coding of Musical Expertise Theory

The first three studies generally substantiate the *Predictive Coding of Musical Expertise Theory* (Figure 9). This is evident from the fact that the hypotheses regarding statistical learning processes that were derived directly from predictive coding theory (Section 2.5) were all supported by the empirical data. Summing up the support for this theory, it was first established that absolute entropy models prospective uncertainty before the occurrence of a musical event. However, the listener's access to this knowledge on a conscious level either emerges from accumulated implicit knowledge or, alternatively, depends on prior familiarity with the specific musical style in question. Additionally, IC models retrospective surprise or unexpectedness in response to musical events. For the first time, to our knowledge, it was further demonstrated that the strength of this relationship increases with musical experience. The prediction error giving rise to this surprise subsequently optimises the listener's internal generative model for predicting future events. This learning process involves uncertainty reduction constrained by statistics of the context and can be modelled with relative entropy minimisation on longer timescales as well as for short-term experiments when comparing melodic pitch expectations before and after exposure. Importantly, when controlling for prior learning the learning mechanism itself was not subject to considerable expertise effects.

The steps of uncertainty, surprise, and learning that were just outlined are thought to repeat for each new musical event. This cyclic nature of the *Predictive Coding of Musical Expertise Theory* is particularly interesting in the context of recent work on reward processing according to which pleasure arises from iterated phases of wanting, liking, and learning (Berridge & Kringelbach, 2015; Kringelbach, Stein, & van Hartevelt, 2012). The fact that this line of work already makes considerable references to predictive coding with implications for music perception (Gebauer, Kringelbach, & Vuust, 2012) suggests that the present work may also be favourably coupled with predictive coding-based accounts of reward behaviour and reward processing (e.g., Friston, Daunizeau, & Kiebel, 2009).

Importantly, however, the present work only demonstrates what happens after multiple spins of the cycle. When it comes to modelling learning on an event-by-event basis, predictive coding theory offers a well-established Bayesian framework for doing so (Friston & Stephan, 2007; Pouget et al., 2013), and promising studies along these lines have already succeeded in modelling single-trial MMN responses to non-musical stimuli (Lieder, Daunizeau, et al., 2013; Lieder, Stephan, Daunizeau, Garrido, & Friston, 2013; Wacongne et al., 2012). Pursuing in this direction would be a natural next step for musical expertise research.

5.2.2. Origin:

The research presented here strongly supports that key aspects of receptive musical expertise arise from an exceptionally strong human capacity for statistical learning (Studies 1-3; Conway & Christiansen, 2006; Perruchet & Pacton, 2006; Romberg & Saffran, 2010; Saffran et al., 1999). The fact that listener expectations are based on general probabilistic properties of tonal music rather than on the statistics of the local context was further substantiated by IDyOM model comparisons (Study 1). In particular, fit to empirical data was much higher when using the LTM than when using the STM sub-model (at least for the short melodic contexts used here).

This learning mechanism is largely automatic (Kim, Seitz, Feenstra, & Shams, 2009; Turk-Browne et al., 2005) and highly general. The latter is particularly evident from the present demonstration that it operates (and can be modelled with relative entropy minimisation) across different timescales and exposure corpora, including those using artificial and familiar pitch material, belonging to distinct musical styles, and of different levels of complexity (Studies 1-3).

When controlling for long-term exposure, statistical learning was not notably enhanced by prior musical training. This is consistent with neurophysiological findings (Paraskevopoulos, Kuchenbuch, Herholz, & Pantev, 2012b) and aligns well with existing views highlighting the musical sophistication of non-musicians (Bigand & Poulin-Charronnat, 2006). However, others have found that musical training improves statistical learning (Schön & François, 2011; Shook, Marian, Bartolotti, & Schroeder, 2013). These seemingly contradictory findings can be resolved with reference to expertise advantages mediated by other factors. For instance, training may optimise feature processing (Study 4) or increase attention, which could, in turn, enhance the processing of pitch (Jones, Johnston, & Puente, 2006) or indeed statistical learning itself (Toro et al., 2005). It has also been proposed that sounds provide an "auditory scaffold" facilitating processing of sequential structure in general (Conway, Pisoni, & Kronenberger, 2009). Statistical learning capacities may thus be innate (as suggested by PC), but experts excel in making optimal use of them. Unfamiliar scale systems offer a promising way in which future research can circumvent some, albeit not all, of the factors mediating expertise effects (cf. Loui et al., 2010; Study 3).

Contributing to previous work using correlational measures (Eerola et al., 2009; Krumhansl et al., 1999, 2000; Krumhansl, 1990; Loui et al., 2010; Study 1), empirical support was here obtained for an information-theoretic dissimilarity measure for modelling statistical learning (Study 3). Given its demonstrated relevance in wider aspects of cognitive (neuro-)science (Chater, Tenenbaum, & Yuille, 2006; Knill & Pouget, 2004; Simoncelli & Olshausen, 2001; Theodorou & Todorov, 2012), relative entropy arguably has greater bearing than correlational measures as a genuinely cognitive model of expertise (cf. Section 2.6). Information-theoretic models may thus still have a somewhat underused potential to inform music cognition with reference to wider currents in cognitive science (Abdallah, Ekeus, Foster, Robertson, & Plumbley, 2012; Abdallah & Plumbley, 2009).

Although some influential work in the visual modality has traditionally considered sensory feature processing mechanisms to be innate or acquired through normal neurodevelopment (e.g., Quinlan, 2003; Treisman & Gelade, 1980), the present work pertaining to auditory feature processing showed considerable training-induced plasticity (Study 4). This finding expands upon a currently growing line of research revealing training-induced effects on multimodal integration of audiovisual and audiomotor stimuli (Bishop & Goebl, 2014; Pantev, Paraskevopoulos, Kuchenbuch, Lu, & Herholz, 2015; Paraskevopoulos & Herholz, 2013;

Paraskevopoulos, Kuchenbuch, Herholz, & Pantev, 2012a, 2014; Proverbio, Attardo, Cozzi, & Zani, 2015; Proverbio et al., 2014). The present findings establish that expertise also influences unisensory feature processing in the auditory modality.

The emphasis on acquisition promoted here when accounting for the origins of musical expertise renders efforts to develop efficient teaching and practicing methodologies very essential. This, in turn, requires a refined understanding of the cognitive constraints for representing music.

5.2.3. Cognitive representations

The neurophysiological work presented here supports general expertise research demonstrating cognitive representations with greater complexity, efficiency, and domain-specific relevance in experts (Study 4; cf. Section 2.10.2). Specifically, musical expertise increased the extent of processing overlap for auditory features. If this indicates more sophisticated, holistic representations, it may explain expertise-related enhancements in verbal and visual memory (Chan, Ho, & Cheung, 1998; Jakobson, Lewycky, & Kilgour, 2008), as suggested by feature-based theories of visual short-term memory (Curby, Glazek, & Gauthier, 2009). More dependent feature processing in musicians is similarly consistent with decreased neural activity associated with perceptual learning in audition (Berkowitz & Ansari, 2010; Jäncke et al., 2001; Zatorre et al., 2012) and vision (Kourtzi, Betts, Sarkheil, & Welchman, 2005; Schiltz et al., 1999; van Turennout, Ellmore, & Martin, 2000; Yotsumoto, Watanabe, & Sasaki, 2008). Such decreases are sometimes accompanied by enhanced effective connectivity (Büchel, Coull, & Friston, 1999), just like musical expertise has been found to alter connectivity patterns observed for audiovisual integration tasks (Paraskevopoulos, Kraneburg, Herholz, Bamidis, & Pantev, 2015). This suggests that connectivity analysis could be a fruitful next step in revealing the mechanisms underlying the present findings.

Observations from musical practice may be informative in explaining why processing overlap was specific to the musically relevant pitch component whereas intensity and location seemed to be processed more independently. Whereas pitch is essential for determining melodic identity, intensity and location may be varied more freely, e.g. in the context of expressive performance (Palmer, 1996; Widmer & Goebl, 2004), without compromising the recognisability of a tune. For this reason, perception and production of pitch constitute key disciplines in most music teaching (Besson et al., 2007). Dedicated pitch rehearsal in musicians may thus manifest itself not only as superior decoding and production of linguistic prosody (Besson et al., 2007; Lima & Castro, 2011; Pastuszek-Lipińska, 2008), but also as enhanced feature processing as demonstrated here (Study 4).

Evaluation of the fit between behavioural data and model estimates from different implementations of IDyOM (Study 1) provided contrasting results to those obtained in the MEG study. Specifically, no clear differences were found between experts and non-experts in terms of the context length taken into account or the weighting of local and global structure when generating melodic predictions. For both groups, expectations primarily seemed to arise from schematic knowledge and to be based on relatively short contexts (i.e. approximately one event for expectedness and three events for inferred uncertainty). Although this is consistent with previous findings of comparable overall working memory capacities in experts and non-experts (Cowan et al., 2004; Miller, 1956; cf. Section 2.10.2), it cannot be concluded whether this pattern generalises beyond the short, monophonic excerpts used here.

Hence, more controlled studies are needed to draw more refined conclusions concerning expertise effects on cognitive representations of music. For instance, IDyOM could be used to select auditory stimuli that are specifically tailored to study this question. Additionally, optimising configurations of source viewpoints, sub-models, and/or order bounds directly to empirical data would be potentially useful.

By contrast, most current procedures for automatic model configuration currently implemented in IDyOM (Section 2.7) follow the principles of compressive coding (Section 2.4), albeit mostly with convincing cognitive justification (Pearce, 2005). The alternative path outlined here more strongly emphasises how cognitive limitations constrain the prediction of musical structure.

5.2.4. Predictive uncertainty

The first three studies first of all established that predictive uncertainty constitutes an important aspect of predictive processing that is clearly separable from unexpectedness. Not only was it shown that uncertainty and unexpectedness can be controlled separately using IDyOM in the process of stimulus selection (Studies 1-2). More importantly, these two aspects showed clearly distinct patterns of expertise effects. For instance, although internalised probabilistic knowledge gave rise to conscious experience of surprise corresponding to the information content of events in melodic sequences, this did not always translate into an ability to introspect about the uncertainty associated with these same events before they occurred (Studies 1-2). Also, stylistic specialisation emerged in terms of explicit processing, but it did so specifically for uncertainty processing whereas expectedness processing did not differ notably between musicians specialising in classical music or jazz (Study 2). Taken together, these results substantiate the necessity of modelling both prospective uncertainty and retrospective unexpectedness in order to understand predictive processing.

Having first established the key importance of predictive uncertainty as an aspect of listener expectations, the overall research question concerning how musical expertise affects this phenomenon was addressed. In the context of general expertise research introduced above (Section 2.10.3), the present findings may be interpreted such that musical expertise leads to lower uncertainty with maintained calibration.

Specifically, the findings that stylistic experts experience lower explicit uncertainty than non-musicians (Studies 1-2) are consistent with previous research suggesting that experts have greater confidence in their own predictions (Chi, 1978; Glenberg & Epstein, 1987; Oskamp, 1965). However, unlike previous studies, the musical experts in the present experiments were not subject to over-confidence, but actually did predict more accurately than non-musicians. This is evident from the co-occurring expertise effects on inferred and explicit uncertainty.[8]

In addition to expertise effects on inferred and explicit uncertainty, it was also established that expertise minimises the relative entropy between listener expectations and the probabilistic structure of music. Importantly, however, this effect was constrained by the amount of epistemic (i.e. reducible) uncertainty inherent in the musical context. Expertise was thus most advantageous in low-entropy contexts, as evident from expertise effects on mean expectedness and uncertainty that were restricted to these particular stimuli (Studies 1-2). This suggests that low levels of expertise are characterised by default predictions with high uncertainty. In other words, in lack of better evidence, the listener presumes equiprobability of all possible outcomes. This has also been referred to as the *Principle of Maximum Entropy* (Jaynes, 1957; Keynes, 1921) according to which the least biased estimate given the available information is the probability distribution with the highest possible entropy value. In the hypothetical case of a complete novice where prior information is fully absent, this reduces to the uniform distribution. Thus, the potential for learning through relative entropy minimisation is a direct function of the amount of decodable structure in the environment. If all uncertainty in the stimulus is aleatory, then the expert is at no advantage.

[8] Note that because inferred uncertainty is not a measure of accuracy *per se*, conclusions regarding greater accuracy presume that lower inferred uncertainty in experts is associated with better alignment with statistics in music. Study 3 suggests that this is a fair assumption to make.

The *Principle of Maximum Entropy* in fact has vast implications for musical composition, practising, and teaching. For instance, the reason for the limited success of aleatoric music (and perhaps for the displeasure sometimes elicited by it) might be the limited potential for uncertainty reduction inherent in such music rather than to its initial degree of unexpectedness. Related limitations may apply to dodecaphonic and serial music where decodable structure, although present, may not always be tailored to the cognitive constraints of the listener (Dienes & Longuet-Higgins, 2004). Bebop jazz, by comparison, may seem unpredictable at first, but contains vast amounts of decodable structure, for instance in terms of pattern repetition as demonstrated here and elsewhere (e.g., Finkelman, 1997; Norgaard, 2014; Study 2). In the light of research showing that learners automatically seek out information sources yielding high degrees of statistical regularity (Creel, Newport, & Aslin, 2004; Fiser & Aslin, 2001; Gómez, 2002), it could be relevant to investigate whether greater satisfaction is derived from listening to low-entropy stimuli compared to high-entropy stimuli.

Moreover, the importance of context entropy as well as of dissociating uncertainty from unexpectedness has repercussions on the way that expertise experiments are designed. For instance, in an experiment of expectations in musicians and non-musicians, Bigand et al. (1999) varied the context preceding a major chord progression ascending a fourth. In the "expected" condition, the context ensured that the final progression was heard as V-I whereas in the "unexpected" condition it was heard as I-IV. Importantly, however, this is not merely a manipulation of surprise, but also one of uncertainty. Specifically, the "unexpected" resolution is preceded by a state of higher context entropy; for this reason alone, expertise may be less advantageous than in the "expected" condition. This is just one example of how future research on predictive processing of music could benefit from appreciating the distinction between uncertainty and surprise.

5.2.5. Predictive flexibility

In answer to the research question concerning expertise-related effects on the ability to specify, access, and prioritise between competing predictive models, the present work established that musical experts are characterised by possessing highly specialised stylistic schemata optimised through exposure (Studies 1-3). Furthermore, both musicians and non-musicians alike seemed to possess an ability to suppress the influence of contextually irrelevant models (Study 2).

The general psychological construct of *cognitive firewalls* provides a candidate explanation for this latter observation. In short, cognitive firewalls are "systems of representational quarantine and error correction" that limit the scope of contexts where particular cognitive schemata can be applied (Cosmides & Tooby, 2000). They are erected to avoid maladaptive situations resulting from misapplication of schematic knowledge in contexts where it would be irrelevant or unreliable, and therefore potentially harmful. Although erroneous predictions about musical continuation are usually not dangerous *per se*, Huron (2006) has proposed that this same principle applies to music cognition. In other words, cognitive firewalls are thought to underlie common notions of musical works and genres. This would explain why non-musician participants in Study 2 apparently applied a very underdeveloped–and thus highly uncertain–predictive model of the bebop style rather than the relatively well-developed model of general tonal music that they possessed according to the findings of Study 1. Although this latter stylistically irrelevant model would have enabled expectations with high certainty to be formed, contextual relevance seemed to be of higher priority. This interpretation is substantiated by previous findings that North-American listeners refrained from misapplying Western pitch schemata when listening to Indian music (Castellano, Bharucha, & Krumhansl, 1984).

Importantly, in order for cognitive firewalls to work as intended, the listener needs to be able to quickly and efficiently detect the musical genre in order to determine contextual relevance of competing predictive models. Evidence of spectrally based musical genre identification after a mere 250ms suggests that this is indeed the case (Gjerdingen & Perrott, 2008). That this mechanism is not flawless is evident from examples of irrelevant model misapplication for twelve-tone music (Krumhansl, Sandell, & Sergeant, 1987) and Nort-Sami yoiks (Krumhansl et al., 2000). In the context of expertise research, this naturally raises the question whether mechanisms for stylistic model selection or cognitive firewall construction are prone to expertise effects. Additionally, more basic questions still remain to be addressed concerning, for instance, which cues trigger model selection in the first place and how these processes relate to individual differences in cognitive flexibility (Deak, 2004). In Study 2, saxophone timbre, seventh chord cadences, and realistic swing rhythms were applied to evoke bebop schemata, but it is unknown whether this process was always successful in all participants and which one of these factors was in fact the determining one.

The fact that expertise-related enhancements in auditory feature processing was restricted to musically relevant contexts and deviants involving pitch indicates that these neural adaptations may also be subject to cognitive firewalls (Study 4). In other words, musical relevance may in effect trigger more complex representations of musical structure. This may, in turn, help explain why, irrespective of expertise levels, shorter latencies and greater amplitudes of the MMN have been found for complex tones compared to pure tones (Tervaniemi et al., 2000) and when using a musically complex paradigm compared to a classical oddball paradigm (Lappe, Lappe, & Pantev, 2015; Study 4). By adding an expertise dimension to such research designs, others have found expertise effects on MMNm amplitudes (Fujioka et al., 2004) and on cortical representations measured with fMRI (Pantev et al., 1998) only when using complex piano notes and not when using pure tones. Such context-dependence indeed suggests that some expertise effects are housed behind cognitive firewalls.

Lastly, on the methodological level, the need for research testing two stylistically contrasting models of expectation within the same participants was accommodated by training IDyOM to two separate repertoires (Study 2). Additionally, comparisons of experts specialising in different musical styles transcended the dichotomous bias dominant in previous musical expertise research (Study 2; cf. Section 2.10.4). Because the present work did, however, not recruit experts with bimusical specialisation (cf. Wong et al., 2009), the potential for extending the current predictive coding framework to this population yet remains.

5.2.6. Conscious availability

Interestingly, full correspondence between explicit uncertainty and uncertainty inferred from expectedness ratings was not always found. This inconsistency was present for musicians in Study 1 and for classical musicians in Study 2 and corresponds to previous observations that acquired knowledge of nonlocal rules in a musical grammar could only be detected using indirect liking ratings and not by using direct grammaticality judgements (Kuhn & Dienes, 2005). Taken together, these findings emphasise the importance of investigating aspects of predictive processing with a diverse range of methods.

Following this lead, the present experiments provided an answer to the research question regarding how musical expertise affects the availability of predictive models to conscious introspection. In particular, the finding that stylistic specialisation in music was characterised by better explicit access to one's own uncertainty processing (Study 2) supports explication theories of expertise acquisition (Sun et al., 2001, 2005, 2007; also see Chaffin & Logan, 2006; Section 2.10.5). Expertise researchers have framed this process in terms of training-induced perceptual facilitation such that lower-level mental operations become more efficient, thus releasing higher-order cognitive resources for conscious planning and self-monitoring (Endsley, 2006; Logan, 1985). In the musical domain, this explication process may manifest itself, for instance, as more abstract cognitive representations for familiar musical styles (Ayari & McAdams, 2003; Castellano et al., 1984; Kessler, Hansen, & Shepard, 1984), or indeed as enhanced introspection (Study 2). The more sophisticated cognitive representations in musicians, demonstrated in Study 4, may also facilitate expertise-related explication of knowledge. Finally, given that the current findings pertain to receptive aspects of musical expertise, they, furthermore, supplement previous work which has mainly studied expertise-related implication and explication in the context of decision-making or motor processing (cf. Section 2.10.5).

All in all, it was particularly interesting that the difference in explicit access to schematic knowledge emerged specifically for uncertainty processing. Although truly implicit tasks, such as those in priming paradigms (Bharucha & Stoeckig, 1986; Bigand & Poulin-Charronnat, 2006; Bigand, Tillmann, Poulin, D'Adamo, & Madurell, 2001; Bigand, Tillmann, Poulin-Charronnat, & Manderlier, 2005; Omigie et al., 2012; Tillmann & Bharucha, 2002; Tillmann, Janata, & Bharucha, 2003), would be needed to assess expertise differences in the conscious availability of expectedness processing, the present results do suggest that uncertainty processing constitutes a more cognitively demanding aspect of predictive processing where experts could be at an advantage, in particular, by having better explicit access to cognitive processes.

5.2.7. Neural correlates

Lastly, by showing expertise-induced changes of auditory feature processing, the included neurophysiological study added further evidence to the relatively well-established point that musical expertise expresses itself in terms of neuroplasticity

(Study 4). This, moreover, provided a good exemplification of the meta-perspective of the sixth and final analytical perspective in that it can be used to investigate questions raised by some of the previous perspectives (in this case, the second one relating to cognitive representation, as discussed above, cf. Section 5.2.3). Study 3 further made a contribution to this endeavour by taking steps towards bridging theories in cognitive psychology (represented by statistical learning) with those in cognitive neuroscience (represented by predictive coding). Future work along these lines may fruitfully investigate the neural correlates of short-term expertise acquisition in the context of statistical learning experiments where factors like context entropy and the availability of cognitive representations, competing predictive models, and explicit knowledge are skilfully manipulated.

5.2.8. Conclusions

In conclusion, the preceding discussion has established how, in various ways, the empirical research presented here has addressed the research questions raised by each of the six analytical perspectives presented in the introduction (Table 5). Specifically, musical expertise can be viewed in scientific terms as (1) primarily acquired under universal cognitive constraints. This entails optimisation of internal predictive models through (2) sophistication of cognitive representations and (3) relative entropy minimisation with respect to environmental statistics. In this way, (4) the expert's predictive models are refined and his or her ability to delimit relevant models as well as suppress irrelevant ones appears to be increased. Expertise facilitates these optimisation processes (5) by gradually explicating predictive, schematic knowledge. On a neural level, all these changes are expressed in terms of (6) considerable plasticity of the human brain. These are merely preliminary answers with a potential for driving future research along the analytical expertise framework;

yet, the fundamental processes of expertise acquisition outlined here constitute key elements in the predictive coding of musical expertise.

Table 5. Six scientific view of musical expertise. Based on the empirical studies presented here (Studies 1-4), six scientific views of musical expertise emerged as answers (albeit preliminary ones) to the research questions raised by the analytical framework of musical expertise (Table 1).

Perspectives	Research questions	Scientific views of musical expertise
Origin	How does expertise arise?	Acquired under universal constraints
Cognitive representations	How does expertise affect cognitive representation of musical structure?	Sophistication of cognitive representations
Predictive uncertainty	How does expertise affect the uncertainty of listener expectations?	Relative entropy minimisation
Predictive flexibility	How does expertise affect the ability to specify, access, and prioritise competing predictive models?	Specification of relevant models and suppression of irrelevant ones
Conscious availability	How does expertise affect the availability of predictive models to conscious introspection?	Explication of predictive knowledge
Neural correlates	How does expertise affect brain function?	Neuroplasticity

5.3. Future directions for the expert(ise) researcher

Summing up on the discussion section above, several research questions with relevance to future work emerged. These are mere examples of the range of issues that could potentially be addressed within this scientific expertise framework:

- Predictive Coding of Musical Expertise: To what extent can predictive coding of expertise acquisition be modelled on an event-by-event basis using Bayesian modelling?
- Origin: How may computational modelling of expertise acquisition be extended to include explicit instruction and deliberate practice? Which other information-theoretic measures capture pertinent aspects of expert and non-expert predictive processing? How does the plasticity of neural mechanisms leading to more dependent auditory feature processing in musical experts develop longitudinally?
- Cognitive representations: What are the cognitive constraints on statistical learning? Which IDyOM viewpoints best model listener expectations? How does this vary with musical expertise? Which musical structures are most easily internalised? How is this reflected in musical universals?
- Predictive uncertainty: How do the established effects of context entropy on expertise acquisition over longer time spans manifest themselves in the context of short-term statistical learning?
- Predictive flexibility: What does it take to cross the cognitive firewalls in music perception–i.e. how are predictive model changes triggered? Does musical expertise make these walls thinner or thicker?
- Conscious availability: How can musical teaching and practising methodologies be developed to facilitate expertise-related explication of probabilistic knowledge? How does explicit instruction best support implicit acquisition of musical expertise?
- Neural correlates: What are the neural correlates of predictive uncertainty and the reduction hereof in statistical learning of musical structure? How does uncertainty reduction in music relate to reward processing?

5.4. A coda for the romanticised genius

During the course of this dissertation, I hope to have convinced the reader that musical expertise as a phenomenon is by far elusive. It is not entirely innate, and it cannot be reduced to a simple question of all or nothing. Moreover, expertise is not only beneficial and creative in its nature. By contrast, the research conducted here clearly establishes that musical expertise can be studied empirically when cast in scientific terms. Such investigations reveal that it is primarily acquired and is subject to cognitive constraints, some of which (but not necessarily all) may indeed be innate. This acquisition process happens gradually and requires persistent dedication over considerable timespans during which expertise is moulded by sensory input. In the case of music, this gives rise to fascinating phenomena like stylistic specialisation. Musical expertise is highly multidimensional and entails optimisation of predictive processing which, in turn, may be parcelled into specific sub-processes pertaining to, for instance, expectedness and uncertainty. Although I argue that expertise may sometimes be maladaptive, evidence is provided that listeners possess sophisticated cognitive machinery preventing confusion of schematic models that would lead to contextually irrelevant expectations. Lastly, musical expertise characterises not only the generation of music, but also the perception of it, as demonstrated most clearly here for bebop jazz.

Importantly, the scientific framing of musical expertise endorsed here does not take away anything from the mesmerising powers of musical excellence. On the contrary, a deeper and more multifaceted understanding of this phenomenon only increases its lure. Hence, although the romanticised genius lives on, he may have to put up with scientists picking his brain to understand their own fascination with his excellence.

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7. Appendices

The four appendices will be published as separate journal articles elsewhere and are thus not included in the present online version of the thesis.