Monitoring and Modelling Swim Performance

Sian Victoria Allen

Primary Supervisor: Professor Will G. Hopkins
Secondary Supervisor: Dr Tom J. Vandenbogaerde

A thesis submitted to Auckland University of Technology in fulfilment of the requirements for the degree of Doctor of Philosophy (PhD)

2014

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ATTESTATION OF AUTHORSHIP

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicity defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any degree or diploma of a university or other institution of higher learning.

Chapters 2 to 6 of this thesis represent five separate papers that have either been published or have been submitted to peer-reviewed journals for consideration for publication. My contribution and the contributions of the various co-authors to each of these papers are outlined at the beginning of this thesis (see Co-authored papers section). All co-authors have approved the inclusion of the joint work in this doctoral thesis.

Sian Allen

December 2014

CO-AUTHORED PAPERS

Chapter	Publication Reference	Contribution
Chapter 2	Allen, S. V., & Hopkins, W. G. (submitted). Age of peak competitive performance of elite athletes: A systematic review. *Sports Medicine*.	SA 80% WH 20%
Contribution	SA- Search and review of literature, data extraction and analysis and manuscript writing WH- Guidance on analysis of effects and review of manuscript	
Chapter 3	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2014). Career performance trajectories of Olympic swimmers: Benchmarks for talent development. *European Journal of Sport Science*, *14*, 643-651.	SA 80% WH 10% TV 10%
Contribution	SA- Data collection, statistical modelling and manuscript writing WH- Advice on statistical modelling and review of manuscript TV- Research question, advice on interpretation of findings and review of manuscript	
Chapter 4	Allen, S. V., Vandenbogaerde, T. J., Pyne, D. B., & Hopkins, W. G. (2015). Predicting a nation's Olympic-qualifying swimmers. *International Journal of Sports Physiology and Performance*, *10*, 431-435.	SA 80% WH 10% TV 5% DP 5%
Contribution	SA- Statistical modelling and manuscript writing WH- Advice on statistical modelling and review of manuscript TV- Advice on interpretation of findings and review of manuscript DP- Assistance with data collection, advice on interpretation of findings and review of manuscript	
Chapter 5	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (submitted). Relationships between career training and performance in competitive swimmers. *European Journal of Sport Science.*	SA 80% WH 15% TV 5%
Contribution	SA- Data collection, statistical modelling and manuscript writing WH- Advice on statistical modelling and review of manuscript TV- Research question, assistance with questionnaire design and data collection and review of manuscript	
Chapter 6	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2015). The performance effect of centralising a nation's elite swim programme. *International Journal of Sports Physiology and Performance*, *10*, 198-203.	SA 80% WH 10% TV 10%
Contribution	SA- Data collection, statistical modelling and manuscript writing WH- Advice on statistical modelling and review of manuscript TV- Research question, assistance with data collection, interpretation of findings and review of manuscript	

S. Allen	T. Vandenbogaerde	D. Pyne	W. Hopkins

ACKNOWLEDGEMENTS

"If you have a choice of taking two paths, always take the more daring of the two."

W. J. Slim

Three and half years ago I made the decision to leave my job in the UK and move pretty much as far away from home as physically possible to accept this PhD scholarship. First of all I should probably thank all the people who told me that that was a ridiculous idea. Never let it be said that I don't enjoy a challenge! Seriously though, without the support and guidance of many, many people over the last few years, this PhD would never have been possible.

To my supervisory dream team, Tom and Will, thank you for setting the bar as high as possible in everything you do and always challenging and encouraging me to reach it. Your enthusiasm, dedication, humility and integrity is second to none, and it has been a privilege for me to have been in the presence of your combined genius throughout this PhD. If I have acquired even a hundreth of what you've attempted to teach me over the last three and a bit years then this PhD has truly not been a ridiculous idea. I came to the other side of the world to learn from the best, and you both have been the best supervisors *and* people that I could ever have wished to work with.

To High Performance Sport NZ and Swimming NZ, thank you for creating this PhD scholarship and for providing the funding that made it possible. My thanks also go to Swimming Australia for the collaboration in Chapter 4. In particular, David Pyne, for his ongoing willingness to share the benefit of his extensive experience in applied swimming research.

I'm also greatly indebted to several colleagues and fellow PhD students for their help with data collection for many of the PhD projects. Rebecca, Joe, Kent, and Donna from Swimming NZ, thank you for helping me track down the results data for Chapters 5 and 6, and for your help with tackling the organisational nightmare of collecting data from hundreds of swimmers as part of Chapter 5. Thank you also to Erika, Marissa, and Jodi, who went out of their way to help with this data collection – you guys are stars! To the swimmers and coaches that were involved in this study, your time and effort was massively appreciated, and it was a pleasure to meet and chat with so many of you, so thank you.

Special thanks should also go to Rita Malcata, for not laughing at the daft statistics questions I've thrown her way over the last few years, and for even answering some of them. Rita, your positivity, generosity, and thirst for knowledge has been a great inspiration throughout this PhD – thanks for being a fantastic friend and colleague, you are awesome!

To Pete, thank you for believing in me before I believed in me! Without your guidance I know I wouldn't be anywhere near where I am today. I owe you big time!

To my parents, thank you for always being there for me, no matter what. I hope that this PhD goes some way towards making you as proud of me as I am to be your daughter.

Finally, my amazing husband, Paul… I love you! I know how much you gave up for me to follow this dream, and I can never thank you enough.

ETHICAL APPROVAL

Ethical approval for Chapter 5 was granted by the Auckland University of Technology Ethics Committee (AUTEC). The AUTEC reference for this chapter was:

- 13/329. *Tracking training variables against performance progression in competitive swimmers.* Approved on 21st November 2013.

ABSTRACT

The capacity to objectively track, predict and evaluate changes in competitive performance is a critical component of an effective athlete development programme. This thesis focused on developing objective analytical tools for monitoring and assessing performance progression in swimmers using the mixed modelling procedures in the Statistical Analysis System (SAS) software.

In the first study, a systematic review of estimates of age of peak competitive performance of elite athletes from a variety of sports established the need to generate progression-monitoring tools specific to the sport of swimming. Four original-research studies focused on different aspects of athlete development are then presented: benchmarking, talent identification, career training and performance-enhancing strategies and interventions. First, I developed quadratic trajectories to track the career development of Olympic top-16 swimmers using their annual best performances. These trajectories provided event-specific progression benchmarks that can be used to monitor and assess performance changes of developing swimmers. Secondly, a comparison of the accuracy of four methods for predicting future performance provided some evidence that this trajectories method may be useful for identification and early selection of swimmers tracking towards Olympic-qualification standards. Thirdly, I used a novel application of mixed modelling to quantify the relationships between swim-specific and non-specific career training hours and performance in competitive swimmers. The focus of the final investigation was the development of a method to assess the effects of strategies and interventions on swim performance progression. By quantifying the deviation of top swimmer's performances from their individual trajectories after they joined the centralised elite squad, we showed that Swimming New Zealand's centralisation strategy took several years to produce substantial performance effects. This method also produced annual performance estimates for New Zealand swimming as a whole, and for each New Zealand swimming club, creating a tool that can be used to evaluate performance progression at both the national level and the club level.

In this thesis, I have demonstrated that mixed modelling can be used to provide objective solutions appropriate for monitoring and assessing the performance progression of swimmers. Prospective longitudinal studies are required to improve our understanding of the multiple factors affecting career progression of swimmers, while further research is also needed to adapt the models presented here for other sports.

CHAPTER 1

INTRODUCTION

1.1. Rationale

The sport of swimming is unique in that large amounts of repeated-measures competition performance data are readily accessible online, and the effects of environmental conditions on performance are generally negligible. The primary focus of this PhD was to investigate how statistical modelling of some of these data could help provide solutions to effectively monitor and assess the performance progression of swimmers.

Developing solutions to objectively track and evaluate progression of sport performance is a strategy prioritised by High Performance Sport New Zealand as part of their mission to "create a world leading, sustainable high performance sport system" by 2020 (HPSNZ, 2012). Such solutions provide HPSNZ with a rationale for evidence-based investment decisions, an improved understanding of athlete development pathways, and a means for quantifying the impact of factors affecting sport performance. Given the nation's small population (~4.5 million people) and finite supply of finances for elite sport, solutions that improve talent identification and the effectiveness of available funding are critical for New Zealand's sporting success.

In the first project of the PhD, I was interested in investigating the age-related performance changes of Olympic top-16 swimmers, for the purpose of establishing performance progression benchmarks for New Zealand swimmers. This project was aligned with Swimming New Zealand's key strategic priority of determining elite-level benchmarks to "design a clear athlete pathway… towards Olympic podium results", as outlined in their 2013-2020 High Performance Strategy (SNZ, 2012).

Interest in previous similar research presented by Professor Will Hopkins at the 11th Symposium of Biomechanics and Medicine in Swimming in Oslo in 2010 led to the exciting opportunity for collaboration with Swimming Australia for the second PhD project. Collaborating with one of the most successful swimming nations over the past decade allowed us to access career performance data from substantially greater numbers of high calibre swimmers than would have otherwise been possible. Consequently, I was able to generate career performance trajectories for all Australian swimmers and then use my second PhD study to estimate the uncertainty involved in using this method as a tool for predicting future Olympic-level swimmers. Quantifying the likelihood of developing swimmers achieving future performance criteria was of interest to both Swimming Australia and Swimming New Zealand, in terms of providing objective information to help guide strategic administrative decisions regarding squad selection and funding allocation.

Feedback from several top New Zealand swim coaches and sport-science practitioners in response to a seminar outlining the individual performance trajectories approach to monitoring age-related progression of swimmers that I presented at an internal workshop in 2013 was the inspiration for the third study of this PhD. As a group we discussed some of the reasons that we believe have underpinned the progressions of both successful and unsuccessful swimmers, but

there was much interest in objectively assessing factors critical for the development of top swimmers within the cultural context of New Zealand. The discussions helped design questionnaires that were completed by hundreds of national-level New Zealand swimmers. I analysed the responses alongside each swimmer's performance trajectory to investigate the relationships between career training and competition performance.

The fourth PhD project was concerned with assessing the effects of interventions on performance progression by quantifying deviations from swimmers' expected trajectories. Specifically, Swimming New Zealand administrators and coaches were interested in assessing the performance effect of centralisation of the elite swimming programme in 2002. As part of the approach that I used to investigate this question, I was also able to devise a method to track the annual performance progression of groups of swimmers (e.g., squads or clubs), and of all swimmers within a nation.

In the fifth and final PhD project, I conducted a systematic literature review of estimates of age of peak competitive performance of elite athletes. The differences detected between swimming and other sports provided important rationale for the need to establish solutions to monitor and assess individual performance progression that are specific to the sport of swimming. Therefore, although this study was the last PhD project completed, it is presented before the original-research studies within this thesis.

1.2. Theoretical Framework and Research Objectives

The theoretical framework that informed the research objectives of this thesis was the Long Term Athlete Development (LTAD) model, which was created by Canadian sports scientist Istvan Balyi (1990). The LTAD framework features five developmental stages that define a general pathway of athlete progression from childhood through to international performance success. Swimming-specific versions of the LTAD have since been devised by Australia (Australian Swimming Inc., 1996) and Great Britain (Amateur Swimming Association, 2003). These nations have built on the generic LTAD framework by specifying the weekly frequency and volume of swim training sessions in each phase of development within their models. Both models have received criticism from a number of different fields; academia (Rushall, 2011a), coaching (Greyson, Kelly, Peyrebrune, & Furniss, 2010; Lang & Light, 2010), and applied sports science (Arellano, 2010; Holt, 2010; Treffene, 2010).

In a synthesis of the extant literature, Rushall (2011a) highlighted two main weaknesses of the current swimming-specific LTAD models. First, these models have been constructed from a combination of research, beliefs, dogma, and non-refereed theories, and thus they have a questionable evidence base. Secondly, using such generalised models to define the performance progression pathway of individual athletes who have unique time courses of maturation is contrary to the Principle of Individuality (Rushall & Pyke, 1991), which states that decisions concerning the nature of training should be made on an individualised basis. Therefore, in order to help address some of the limitations of current swimming-specific athlete development models, the aim of my PhD has been to use statistical modelling to develop

objective methods that can be used to monitor and evaluate the age-related longitudinal performance progression of individual swimmers. The research problem and specific research question addressed in this thesis are presented below:

Thesis problem: Current swim-specific models of athlete development lack an objective evidence base and do not adequately account for differences between individuals.

Thesis question: Can *mixed modelling* provide *objective solutions* to appropriately monitor and assess *performance progression* in swimmers?

1.3. Literature Review and Methodological Approach

In order to assess the long term development and performance progression of swimmers, a valid and reliable method for monitoring changes in the ability of such athletes must be developed. Within the sport of swimming most of the available original research on this topic has focused on either mean performance changes of groups of athletes, or monitoring progression of surrogate measures of performance, such as physiological or biomechanical variables. Although competition results are the most easily accessible large-scale repeated-measures data available in swimming, only a few researchers have chosen to use these data to investigate performance changes in individual swimmers. This gap in the literature is likely due to the level of sophisticated statistical analysis required to properly model such repeated-measures data. Here I outline the various analysis methodologies that have been used by different research groups to date. I then discuss their advantages and limitations as they relate to the aims of this PhD: to enhance existing swimming-specific LTAD models by adding an objective evidence base and an individualisation component.

Repeated-measures analysis of variance (ANOVA) is the most commonly used statistical test for analysing differences (or changes) in means of a group of athletes. ANOVA works by calculating the ratio (F statistic) of the observed difference between the participants' mean values and the error variance (the variation due to sampling). The larger this ratio is, the more meaningful the difference in means between the different conditions or time-points is believed to be. However, this principle is based on the sphericity assumption of ANOVA, that the variances of the repeated measures are all equal, or that there are no individual differences in responses to different conditions or between different time-points. Unfortunately, this scenario is unlikely when using elite athletes as subjects, and therefore the sphericity assumption is regularly violated in sports science research (Hopkins, 2003).

One research group from Portugal recently used repeated-measures ANOVA to assess the longitudinal performance stability of groups of elite (Costa et al., 2010) and sub-elite junior swimmers (Costa, Marinho, Bragada, Silva, & Barbosa, 2011) across multiple successive seasons of competition. Substantial mean improvements in performance between each consecutive season were found in both groups of swimmers, but the different rates of progression of individual swimmers could not be tracked or quantified using the ANOVA

procedures employed in these studies. Further to this issue, ANOVA is also unable to deal with missing values in datasets, which typically results in a loss of statistical power as data from subjects with any missing values have to be deleted entirely from the analysis (Hopkins, 2003). ANOVA was therefore deemed an unsuitable methodology for the aims of this thesis.

Another common method of modelling the relationship between the change in a dependent variable, (e.g., performance of an athlete) and the change in an explanatory variable (e.g., age) is to fit a regression equation to observed data and then extrapolate this equation to yield a prediction. Regression models can be linear, whereby their output values are a sum of their input values. They can also be non-linear, such that simple changes in input produce more complex changes in output. For example, linear regression (a first order polynomial) has been employed by an Israeli research group to quantify the contribution of various explanatory factors (distance, stroke, rank, age, final stage preparation days) to the percent performance progression of 301 swimmers from 24 nations between their Olympic selection performance and the 2004 Olympic Games (Issurin, Kaufman, Lustig, & Tenenbaum, 2008). When the relationship between the dependent variables and the explanatory variables does not fit a straight line, more sophisticated curvilinear regression equations (second order and higher polynomials) are often utilised by researchers. Indeed, quadratic regression models provide a good fit to the age-related performance progression apparent in a number of sports, including athletics (Hollings, Hopkins, & Hume, 2014), rowing (Mikulic, 2011), skeleton (Bullock & Hopkins, 2009), swimming (Pike, Hopkins, & Nottle, 2010), and triathlon (Malcata, Hopkins, & Pearson, 2014).

One criticism of such regression models is that since most physical systems and their adaptive processes are inherently complex and non-linear in nature, linear and curvilinear modelling may be able to only approximate adaptive behaviour and thus progression across a small range of the modelled performance output (Edelmann-Nusser, Hohmann, & Henneberg, 2002; Maszczyk et al., 2012). This limitation combined with modern advances in both the availability and the level of sophistication of statistical software packages has likely contributed to the recent trend for more widespread use of non-linear regression modelling within sport performance analysis. For example, a research group from France recently developed a non-linear regression model with two exponential components that tracks the biphasic processes of performance progression and decline in elite performers from track-and-field athletics and freestyle swimming across the human lifespan (Berthelot et al., 2012). Their double exponential model demonstrated extremely high goodness of fit, accounting for 99.7%, and 99.8%, of the variance in the individual performance development with age of 646 track-and-field athletes, and 512 swimmers, respectively. However, such high mean coefficients of determination (R^2 values) may equally be indicative of overfitting. This phenomenon can occur with complex models that contain too many parameters relative to the number of observations. Given the fairly low mean (± standard deviation) number of performances per athlete (6.2 ± 1.4 for track-and-field; 6.6 ± 0.4 for swimming) contributing to the double exponential model in this study, overfitting remains a distinct possibility and a significant drawback of non-linear regression modelling without large datasets. From a performance-progression perspective, another limitation of Berthelot et al.'s (2012) use of one complex equation to model two antagonistic

biological processes (performance progression and decline) is that their rate of progression and age of peak performance findings are inevitably and unavoidably defined to some extent by the rate of decline in performance.

The accuracy of using linear and non-linear regression models to predict freestyle swimming performance at various Olympic Games has been addressed in two studies (Heazlewood, 2006; Stanula et al., 2012) with interesting results. First, Heazlewood (2006) assessed the discrepancies between predictions made of mean performance of freestyle swimming finalists at the 2000 and 2004 Olympics, and actual performance (Lackey & Heazlewood, 1998). In the same study, the author also included a comparison of predictions of mean performance of track-and-field finalists in selected events at the same Olympics, and their actual performance (Heazlewood & Lackey, 1996). In the original prediction studies, eleven different regression models were individually applied in order to identify the model with the best fit for each event. The models ranged from a cubic function (curvilinear, third order polynomial) for some events (men's and women's 400-m freestyle) to a variety of non-linear functions for other events (e.g., inverse function, men's and women's 50-m freestyle; sigmoidal function, men's and women's 200-m freestyle). While there was little difference in the discrepancies between predictions and actual performances for the different types of regression models employed, greater discrepancies did occur in swimming as the race distance increased. Specifically, the models used substantially overestimated the rate of progression in events longer than 200 m.

Secondly, Stanula et al. (2012) used three approaches – time series forecasting using a moving average, and linear and non-linear regression modelling – to predict the performance time range for all eight finalists in every freestyle event at the 2012 Olympics. While similar predictions were obtained from all three models, greater discrepancies between predictions and actual performance times occurred as race distance increased, with each model again predicting substantially faster times in events longer than 200 m. One confounding variable inherent within the historical performance data used to construct the models in both of these studies is the technological advancements made to swimsuits over the last fifteen years. Indeed, Berthelot, Len, Hellard, Tafflet, and Toussaint (2010) identified three years (2000, 2008, 2009) where marked improvements in swimming performances (mean performance gains of 0.3-1.2%) occurred as a direct result of swimsuit innovations. Another confounding variable that may have enhanced the rate of performance progression at certain points during the timeframe analysed in these studies and thus contributed to their overly fast predictions is the improvement in performance typically observed in Olympic years (mean performance gains of ~1%; Pyne, Trewin, & Hopkins, 2004). It is therefore apparent that a further limitation of the standard linear and non-linear regression methods employed in the majority of studies is a lack of functionality to account for and estimate the magnitude of such confounding variables.

A relatively new method that is rapidly gaining popularity as a non-linear tool for modelling and predicting competitive sporting performance is artificial neural-network analysis (Lees, 2002). Artificial neural-networks are self-learning models that use a non-linear weighting system to find patterns in data or to model complex relationships between input (explanatory) and output (dependent) variables. While standard regression models assume the dependent

variable to be equal to the additive effects of the predictor variables, neural networks are not constrained by any assumptions about the relationship between the predictor and dependent variables, and might therefore be expected to more realistically relate the complex non-linear processes of development and training adaptation to performance (Silva et al., 2007).

Neural-network modelling has also been shown to yield more precise predictions of competitive swimming performance compared to standard linear (Edelmann-Nusser et al., 2002) and non-linear (Maszczyk et al., 2012) regression models. Edelmann-Nusser et al. (2002) used input data of 19 competitive 200-m backstroke performances and four weeks of training-load data prior to each competition from one swimmer to predict her performance in this event at the 2000 Olympic Games. The mean error in prediction of the neural-network model across the 19 competitive performances was much lower (12 FINA points) than that of the comparison multiple linear regression model (34 FINA points). Maszczyk et al. (2012) used input data derived from testing 249 competitive swimmers on 20 physiological, anthropometric, technical and swimming specific measures before and after a full season of training. These data were used to build one neural-network model and one non-linear regression model to identify the explanatory variables offering the best prediction of results over 50 m and 800 m from a smaller group of 60 swimmers (n=30 per distance). Once more, the mean error in prediction of the neural-network model was much lower for both 50-m performance (0.7 vs 1.2 s) and 800-m performance (8.4 vs 11.6 s) in comparison to the non-linear regression model.

However, both of the above studies also provide good examples of a major limitation of neural-network modelling. Large volumes of data are typically required initially to 'pre-train' neural models, but in order to increase their predictive precision further, even larger volumes of data are needed. As a guide, the minimum number of datasets required is approximately double the number of connections between neurons in the model. Due to a lack of available data for their Olympic 200-m backstroke participant, Edelmann-Nusser et al. (2002) were forced to use 28 additional datasets from a similar athlete in order to pre-train their neural-network model. This process obviously relies heavily on the assumptions that the documented training loads and adaptive behaviours of both athletes are similar, and therefore it cannot be considered a viable solution. Another issue that has also delayed progress of the application of neural-network modelling to sports performance research has been the complexity associated with executing the method (Lees, 2002).

The methodology of mixed linear modelling addresses many of the limitations of the abovementioned approaches. Mixed linear models include both fixed and random effects. In basic terms, the fixed effects are summarised by parameters that represent the differences or changes in means, and the random effects provide parameters summarising variability within or between subjects or groups. Mixed modelling therefore allows us to adjust for and estimate the magnitude of explanatory and/or confounding variables known to impact performance (e.g., new generation swimsuits) through the specification of fixed effects and the magnitude of other random sources of variability (e.g., individual differences in performance progression with age). This capacity also permits another application of the mixed model: monitoring and quantifying the effects of interventions on performance (Vandenbogaerde & Hopkins, 2010). Furthermore, analysis by mixed modelling uses a likelihood-based method of estimation that adjusts for

missing values in datasets, thus avoiding the loss of data that occurs with ANOVA (Hopkins, 2003).

Another advantage of mixed modelling is that this method allows individual trends to be modelled as polynomials when data show curvilinear patterns (Vandenbogaerde & Hopkins, 2010). Although it is somewhat intuitive that non-linear models more closely approximate the non-linear adaptive behaviour of athletes than polynomial models, quadratic trajectories produced by mixed modelling appear to provide appropriate fits for the age-related performance progression patterns observed in sports such as athletics (Hollings et al., 2014), skeleton (Bullock & Hopkins, 2009), swimming (Pike et al., 2010), and triathlon (Malcata et al., 2014). As discussed above, some of the more complex non-linear regression models have been found to substantially overestimate rates of progression in performance, whereas others may have been susceptible to overfitting. It would therefore seem prudent to adhere to the law of parsimony (Occam's Razor) when deciding which methodology is suitable to address the research questions of this PhD. This philosophical and scientific principle states that assumptions used to explain a process should not be complicated beyond necessity, and that when there are competing theories making similar predictions, the simplest approach should be selected.

In summary, mixed linear modelling appears to have an advantage over alternative methodologies such as ANOVA and standard linear and non-linear regression analyses for the purposes of modelling large amounts of repeated-measures data in order to develop tools and strategies for monitoring and enhancing athletic performance. Neural-network modelling is an interesting and promising methodology, but both the volume of data required to construct models with reasonable predictive power, and the complexities involved in the modelling process, mean it does not constitute a viable option for the majority of the projects of this PhD.

1.4. Thesis Structure

An overview of the thesis structure and brief descriptions of each of the seven chapters are presented in Figure 1. This figure details how each of the chapters of the thesis link to form a cohesive whole. The references for each chapter are collated at the end of the thesis in APA 6th edition format.

The first and present chapter aims to set the scene for the reader by outlining the thesis flow, rationale, theoretical framework, research objectives and methodological approach. The subsequent chapters consist of a systematic review (Chapter 2) and four original investigations (Chapters 3-6). In keeping with the overarching objective of the thesis, each original-research project of the PhD aims to investigate a different aspect of athlete development: benchmarking (Chapter 3), talent identification (Chapter 4), career training (Chapter 5) and performance-enhancing strategies and interventions (Chapter 6).

Three of the original-research studies employed retrospective cohort designs and involved analysing data that were already available online; the exception was Chapter 5, which involved collection of questionnaire data. The rationale behind this selection of study designs for the PhD was twofold. Firstly, we considered it unethical to submit our target population to the rigorous procedures of a prospective intervention study, when the information that was required to

answer the main questions of this PhD was already available to us online. Secondly, prospective intervention studies were impractical, as an intervention lasting at least several years would have been needed to address factors affecting career progression, which was outside the scope of this three-year PhD project.

Presented in Chapter 2 is a systematic review of the age of peak competitive performance of elite athletes, which has been submitted to *Sports Medicine*. Chapter 3 presents age-related performance progression benchmarks for elite-level swimmers and has been published in the *European Journal of Sport Science*. In Chapter 4, I have compared the accuracy of four methods of predicting a nation's Olympic qualifying swimmers. This study was performed in collaboration with Swimming Australia. In Chapter 5, relationships between career training hours and progression of competitive performance in New Zealand swimmers have been investigated. In Chapter 6, I have produced a method for assessing the performance progression of a New Zealand's swim squads and have used the method to evaluate the effects of centralisation of New Zealand's elite swim programme. The manuscripts for chapters 4 and 6 have been published in the *International Journal of Sports Physiology and Performance*, while the manuscript for chapter 5 has been submitted to the *European Journal of Sport Science* for publication. Finally, Chapter 7 draws together the conclusions of each study to answer the overarching research question of the thesis and present suggestions for future research directions.

In the appendices I have first presented samples of the SAS datasets and coding used to run each of the mixed models within the thesis. Next, copies of conference presentations for three of the original-research studies are presented. Appendix B shows the poster of "Career Performance Trajectories of Olympic Swimmers" (Chapter 3), presented at the 17th meeting of the European Congress of Sport Science in Bruges, Belgium, in July 2012. Appendix C contains the PowerPoint slides for "Predicting a Nation's Olympic-Qualifying Swimmers" (Chapter 4) that I presented at the 11th International Symposium of Biomechanics and Medicine in Swimming in Canberra, Australia, in May 2014. Appendix D shows the mini-oral PowerPoint slides for "The Performance Effect of Centralising a Nation's Elite Swim Programme", which won second place in the Young Investigator Award at the 19th meeting of the European Congress of Sport Science in Amsterdam, The Netherlands, in July 2014. In Appendices E and F, copies of the PowerPoint slides for two conference presentations given by colleague and research collaborator Dr Pat Lipinska are displayed. Through my PhD, I assisted with data collection and analysis, interpretation of research findings, and manuscript review for these two studies, which investigated relationships between pacing and performance in distance swimmers. The remaining appendices contain examples of the practical applications of the findings of this thesis. In Appendix G, I have included a sample of the performance report provided to Swimming NZ and the High Performance Sport NZ board in October 2012. This report allows the individual performance trends of members of the New Zealand 2012 Olympic swim team to be compared against the trajectories of the 2012 Olympic medallists, developed as part of Chapter 2. Appendix H contains an example of an Excel-based application designed to allow Swimming NZ to assess the performance progression of any individual swimmer against the performance progression benchmarks of Olympic top-16 swimmers from Beijing and London,

developed in Chapter 2. Finally, in Appendix I, I present an example of an Excel-based application designed to allow Swimming NZ to assess the performance progression of all New Zealand swimming clubs since 2002, and to compare progressions between clubs. The data contained within the application was generated as part of the 6th Chapter of this thesis.

Monitoring and Modelling Swim Performance

Chapter 1 - Introduction

- **Theoretical rationale:** Importance of objectively monitoring individual performance progression for swimmer development
- **Methodological approach:** Mixed linear modelling
- **Thesis question:** Can mixed modelling provide objective solutions to appropriately monitor and assess performance progression in swimmers?

Chapter 2 – Systematic Literature Review

- Age of peak competitive performance of elite athletes: A systematic review *(submitted to Sports Medicine)*

Chapter 3 – Benchmarking

- Career performance trajectories of Olympic swimmers: Benchmarks for talent development *(European Journal of Sport Science, 14, 643-651)*

Chapter 4 – Talent identification

- Predicting a nation's Olympic-qualifying swimmers *(International Journal of Sports Physiology and Performance, 10, 431-435)*

Chapter 5 – Career training

- Relationships between career training and performance in competitive swimmers *(submitted to European Journal of Sport Science)*

Chapter 6 – Interventions

- The performance effect of centralising a nation's elite swim programme *(International Journal of Sports Physiology and Performance, 10, 198-203)*

Chapter 7 – Discussion and Conclusion

- **Theoretical contributions:** Statistical methods and models for assessing the performance progression of swimmers
- **Practical contributions:** Tools and applications for coaches, scientists and national sporting organisations to track and improve swimmer development

Figure 1. Overview of the structure of the thesis.

1.5. Research Publications and Conference Presentations

The research studies from this doctoral thesis (Chapters 2-6) have resulted in conferences presentations and in either journal publications or articles that have been submitted for publication and are currently under peer review (Table 1).

Table 1. Research publications and conference presentations originating from Chapters 2-6 of this PhD thesis.

Chapter	Conference Presentation or Publication
Chapter 2	Allen, S. V., & Hopkins, W. G. (submitted). Age of peak competitive performance of elite athletes: A systematic review. *Sports Medicine*.
Chapter 3	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2014). Career performance trajectories of Olympic swimmers: Benchmarks for talent development. *European Journal of Sport Science*, *14*, 643-651.
	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2012). *Career performance trajectories of Olympic swimmers.* Presented at the 17th meeting of the European College of Sport Science, Bruges, Belgium.
Chapter 4	Allen, S. V., Vandenbogaerde, T. J., Pyne, D. B., & Hopkins, W. G. (2015). Predicting a nation's Olympic-qualifying swimmers. *International Journal of Sports Physiology and Performance*, *10*, 431-435.
	Allen, S. V., Vandenbogaerde, T. J., Pyne, D. B., & Hopkins, W. G. (2014). *Predicting a nation's Olympic-qualifying swimmers.* Presented at the 11th International Symposium of Biomechanics and Medicine in Swimming, Canberra, Australia.
Chapter 5	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (submitted). Relationships between career training and performance in competitive swimmers. *European Journal of Sport Science*.
Chapter 6	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2015). The performance effect of centralising a nation's elite swim programme. *International Journal of Sports Physiology and Performance*, *10*, 198-203.
	Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2014). *The performance effect of centralising a nation's elite swim programme.* Presented at the 19th meeting of the European College of Sport Science, Amsterdam, Netherlands.

CHAPTER 2

AGE OF PEAK COMPETITIVE PERFORMANCE OF ELITE ATHLETES

This chapter comprises the following paper submitted to Sports Medicine:
Allen, S. V., & Hopkins, W. G. (submitted). Age of peak competitive performance of elite athletes: A systematic review. *Sports Medicine.*

Overview

Knowledge of the age at which top athletes achieve peak performance could provide important information for long-term athlete development programmes, for event selection, and for strategic decisions regarding resource allocation. **Purpose:** To systematically review estimates of age of peak performance of elite athletes in various sports and events. **Methods:** We searched SPORTDiscus, PubMed and Google Scholar for studies providing estimates of age of peak performance. Here we report estimates as means only for top athletes. Estimates were assigned to three event-type categories on the basis of the predominant attributes required for success in the given event (explosive power/sprint, endurance, mixed/skill) and then plotted by event duration for analysis of trends. **Results:** For both sexes, linear trends reasonably approximated the relationships between event duration and estimates of age of peak performance for explosive power/sprint events and for endurance events. In explosive power/sprint events, estimates decreased with increasing event duration, ranging from ~27 y (athletics throws, ~1 to 5 s) to ~20 y (swimming, ~21 to 245 s), likely reflecting the need for greater experience to achieve mastery of the complex skills required for successful performance in single-effort explosive events. Conversely, estimates for endurance events increased with increasing event duration, ranging from ~20 y (swimming, ~2 to 15 min) to ~39 y (ultra-distance cycling, ~27-29 h). In longer duration events of a lower absolute intensity, in which factors such as pacing strategies and mental resilience contribute to performance, accumulation of cognitive and/or experiential skills presumably offsets the decline in physical ability that typically occurs beyond mid-20s. There was little difference in estimates of peak age for these event types between men and women. Estimations of the age of peak performance for athletes specialising in specific events, and of event durations that may best suit talent identification athletes can be obtained from the equations of the linear trends. There were insufficient data to investigate trends for mixed/skill events. **Conclusion:** Understanding the relationships between age of peak competitive performance and event duration should be useful for tracking athlete progression and talent identification.

2.1. Introduction

The aging process is a key driver of an athlete's physical and mental development, which in turn plays a critical role in determining their competitive performance (Schulz & Curnow, 1988). Knowledge of age of peak performance in elite sport could provide coaches and scientists with valuable information to guide long-term training plans and to help gauge an athlete's progression towards their performance targets (Rüst, Knechtle, Knechtle, Rosemann, & Lepers, 2012a; Sokolovas, 2006a). Such information could also be beneficial for administrators making athlete-selection decisions for major competitions, and for national sporting organisations tasked with allocating funding and resources based on an athlete's chances of achieving future medal-winning success (Allen, Vandenbogaerde, & Hopkins, 2014; Hollings et al., 2014).

Research into the age-related development of the human species indicates that various biological capacities typically reach their peak at different stages of an individual's life (Schulz, Musa, Staszewski, & Siegle, 1994; Simonton, 1988). For example, exercise-physiology literature suggests that peak physiological function occurs just prior to age 30 (Gabbard, 2004), whereas our ability to accumulate, integrate and apply cognitive skills has been shown to increase until at least age 60 (Salthouse, 2012). It therefore follows that the age of peak competitive performance is likely to vary between athletes from different sports and events, depending on the specific skills and attributes required for success in a particular event. Understanding the differences in the age-performance relationship between different event types could be useful for mature-age talent identification and transfer campaigns, similar to those recently undertaken by UK Sport and the Australian Institute of Sport (Vaeyens, Güllich, Warr, & Philippaerts, 2009). These campaigns aim to systematically "recycle" athletes with transferable talent characteristics developed from participating in popular sports with strong competitive fields, placing them into less popular sports with weaker fields in which athletic performance typically peaks at late enough ages to allow these athletes to develop the sport-specific skills required for success.

Since the first comprehensive study of age of peak performance of top athletes was published in 1988 (Schulz & Curnow, 1988), this topic has become the focus of considerable research interest across a large number of sports. Researchers have employed typically one of three methods: identifying the age at which top athletes achieved their best performance, calculating the age of top-ranked athletes competing at pinnacle events such as the Olympics, or modelling the age of peak performance of top athletes using their age-related career performance data. One aim of such research has been to quantify the changes observed in age of peak performance of elite athletes over time. Studies of several different types of sports, including baseball (Fair, 2008), cycling (Shoak et al., 2013), running (Knechtle, Rüst, Rosemann, & Lepers, 2012), tennis (Kovalchik, 2014), and triathlon (Rüst, Knechtle, Rosemann, & Lepers, 2012b), have consistently observed a marked increase in the age of peak performance of elite athletes between the end of the 20th century and the beginning of the 21st century, presumably owing to factors such as recent advances in technology and greater opportunities for athletes to establish careers through their sporting success. Given this

evidence, there is a clear need to investigate estimates of age of peak competitive performance in elite athletes of the 21st century, in order to establish findings relevant to the modern-day sporting environment.

The present study is the first systematic review on the topic of age of peak competitive performance of elite athletes. Here, we have documented the different methods used by researchers to quantify estimates of age of peak performance. We have also investigated differences in age of peak performance between different types of competitive events and presented estimates of age of peak performance relevant to modern-day athletes.

2.2. Methods

The methods used for this systematic review follow the structure outlined in the guidelines given by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement (Moher, Liberati, Tetzlaff, & Altman, 2009).

Data Search and Study Selection

In October 2014 we undertook a Web-based literature search for estimates of the age of peak performance of elite athletes in different sports. We searched the SPORTDiscus and PubMed databases for the following terms: *(sport or athlete*) and performance and (age or longitudinal) and (peak or progress* or change* or effect)*. A search was also performed in Google Scholar for the key words *age peak performance sport*, and additional studies were selected using the option of searching related articles for relevant citations (this option was limited to 101 citations). One investigator (SVA) then screened all titles obtained through these searches and extracted only studies with appropriate abstracts for full review.

To be included in the literature review, the full-text article had to be written in English, contain a substantial proportion of data from after the year 1999, and report either modelled estimates of the age of peak performance in a sport, or data showing the age at which top athletes achieved their best performance in a sport. Studies reporting the age of top-ranked competitors in a sport or event were also included, provided they contained at least 3 y of data from ≥50 athletes competing at pinnacle events in the sport. We excluded eleven studies in which ages of peak performance were presented for sub-elite athletes, seven studies which reported estimates of age of peak performance over a range of five or more years, seven studies with data predominantly from pre-2000, and six studies with insufficient data. No studies were excluded for reasons of poor quality. Figure 2 summarises our data search and study selection process.

Data Extraction and Analysis

Estimates of age of peak performance for top athletes of each sex in each sport and event are shown as means and standard deviations, with uncertainty expressed as 90% confidence intervals. For three studies in which categorical age and performance was investigated (Brander, Egan, & Yeung, 2014; Fried & Tauer, 2011; Wolfrum, Knechtle, Rüst, Rosemann, &

Lepers, 2013), estimates of the age-range of peak performance are presented, but SDs and confidence intervals were not available. Between-subject SDs are shown for studies in which individual age-related career performance trends were developed (Allen et al., 2014; Brander et al., 2014; Hollings et al., 2014; Malcata et al., 2014) and for one study in which the age of best career performance of top athletes was calculated (Sokolovas, 2006a). In studies where annual data on the age of top-ranked performers at pinnacle events over a number of years were presented (Cejka, Knechtle, Rüst, Rosemann, & Lepers, 2014; Hunter, Stevens, Magennis, Skelton, & Fauth, 2011; Kovalchik, 2014; Rüst et al., 2012b; Rüst, Knechtle, Rosemann, & Lepers, 2013), we chose to calculate means and standard deviations for the age of peak performance using data from the year 2000 onwards, in order to generate estimates relevant to modern-day sport. To negate any confounding effects of secular trends, the presented SDs for these studies are the means of the between-subject SD for each year. Between-subject SDs could not be obtained for a number of studies in which fixed-effects models produced mean estimates of age of peak performance (Anderson, 2014; Berthelot et al., 2012; Brander et al., 2014; Fried & Tauer, 2011; Tilinger, Kovář, & Hlavatá, 2005), but most authors provided standard errors for their models, which we used to compute confidence limits for these estimates. Attempts to contact authors of eight studies in which standard deviations and/or standard errors were not reported (Anderson, 2014; Berthelot et al., 2012; Cejka et al., 2014; Fried & Tauer, 2011; Guillame et al., 2011; Kovalchik, 2014; Tilinger et al., 2005; Tiruneh, 2010), resulted in only one successful outcome (Kovalchik, 2014).
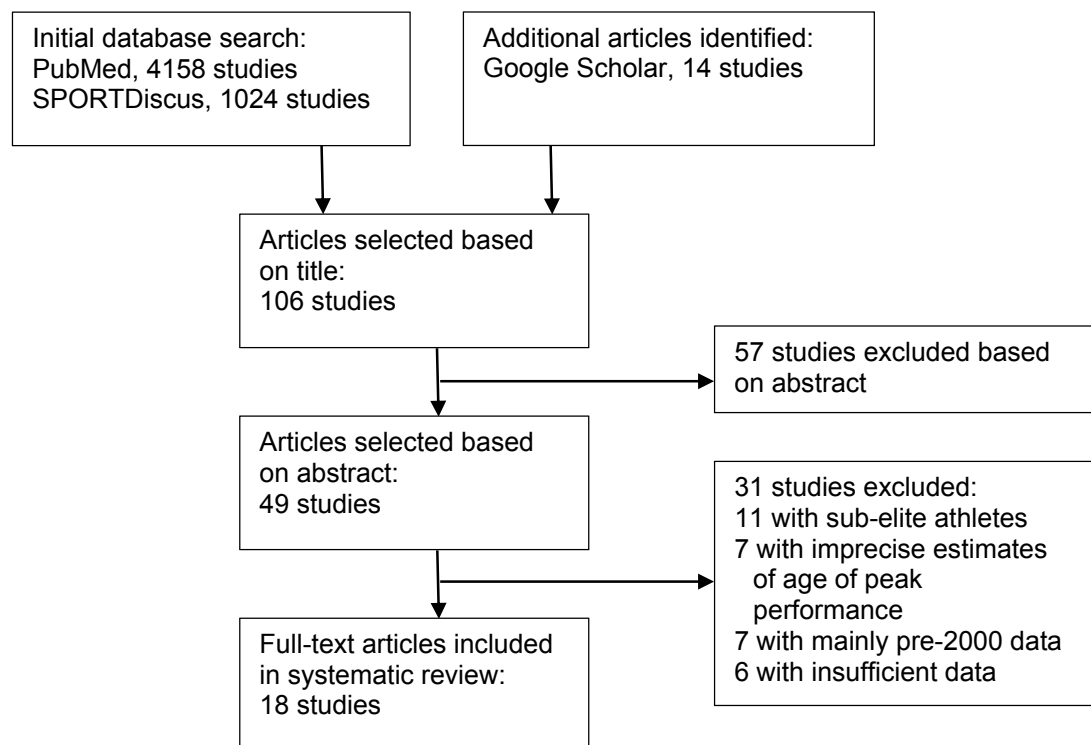
Figure 2. Schematic representation of study search and selection.

To investigate differences in the age of peak performance between different kinds of events, estimates were split into three event-type categories on the basis of the predominant attributes required for success in the given event (explosive power/sprint, endurance, and mixed/skill), and then plotted by event duration. For each event type with estimates across a sufficient range of event durations, we then added best-fit linear regression lines to create graphs that can be used for talent identification and event selection. By working through the data we found that the linear regression lines for both explosive power/sprint events and endurance events were a good fit for the estimates of peak age for middle-distance swimming (200-m to 400-m events), presumably owing to the need for speed and endurance for successful performance in these events. We therefore chose to assign these estimates to both categories. Uncertainty in the accuracy of predictions made with these regression lines was expressed as standard errors of the estimate.

All 18 studies produced estimates of age of peak performance for male athletes, while corresponding estimates for their female counterparts were presented only by 13 of these studies. For studies where data were provided for both sexes, paired t-tests were performed for each event type with a sufficient number of estimates (>5) using a published spreadsheet (Hopkins, 2006a) to investigate the mean differences in age of peak performance between sexes. We used non-clinical magnitude-based inferences to assess these differences (Hopkins, Marshall, Batterham, & Hanin, 2009), whereby the smallest important difference was 0.64 y (0.2 of the combined between-subject SD for age of peak performance for all studies with available data, 3.2 y). Thresholds for moderate, large and very large differences were 1.9 y, 3.8 y, and 6.4 y, respectively (0.6, 1.2, and 2.0 of 3.2 y; Hopkins et al., 2009). Standard errors of the estimate for each of the regression lines were doubled for interpretation of their magnitude using this scale (Smith & Hopkins, 2011). Uncertainty in mean differences was expressed as 90% confidence limits and as likelihoods that the true value of the effect represents a substantial difference between sexes (Batterham & Hopkins, 2006).

2.3. Results

The retrieved estimates of the age of peak performance of top athletes of each sex in each sport and event are summarised in Table 2 and plotted for analysis of trends in Figure 3. In Figure 3, mean estimates of the age of peak performance for each of the three event types are shown by event duration. For both sexes, clear and opposite trends were evident for explosive/sprint events and for endurance events. In explosive/sprint events, estimates showed a similar decrease with increasing event duration for males and females, ranging from a peak age of ~27 y for throwing events in athletics (~1 to 5 s) to ~20 y for swimming events (~21 to 245 s). In endurance events, estimates of peak age increased markedly with increasing event duration in both sexes, ranging from ~20 y for swimming events (~2 to 15 min) to ~39 y for ultra-distance cycling (~27 to 29 h). Patterns for mixed/skill events could not be discerned, owing to the smaller number of estimates retrieved for this event type.

Equations for the best-fit linear regression lines and corresponding standard errors of the estimate for each sex and event-type combination are also shown in Figure 3. The magnitude of these standard errors was large for female endurance events, and moderate for all other sex and event-type combinations. By using simple algebra, we were able to solve the simultaneous equations for explosive/sprint and endurance events for each sex to reveal the points of intersection of the regression lines: event durations of ~4 min (279 s for males, 241 s for females).

For studies where estimates of age of peak performance were presented for both sexes, male explosive/sprint athletes displayed a higher peak-performance age than their female counterparts by a borderline trivial-small mean amount of 0.6 y (90% confidence limits ±0.7 y, possibly substantial). In endurance events, the mean difference in age of peak performance between males and females was trivial in magnitude but unclear (0.1 y, ±1.0 y).

2.4. Discussion

In this systematic review we have reported estimates of age of peak performance of elite athletes for different sports and events from 18 studies. By plotting mean estimates by event duration, we have shown that clear and opposite linear trends closely approximate the relationships between event duration and age of peak performance for explosive power/sprint events and for endurance events. The equations of these linear trends have provided a tool that can be used either to help assess the future prospects of an athlete specialising in a particular event based on their predicted age of peak performance, or to help direct event selection for mature-age talent identification and transfer athletes. Given that the points of intersection of these linear trends occurred at event durations of approximately 4 min for both sexes, athletes typically competing in events shorter than this duration should use the explosive/sprint equations to estimate their age of peak performance, whereas the endurance equations are more appropriate for those specialising in longer events.

Our findings that age of peak performance tended to decrease with increasing event duration for events in which performance is determined mainly by explosive power output and sprint ability may reflect the differing contributions of skill and technique to performance in these events. Athletics throws events (~1-5 s) involve co-ordination of a sequence of complex motor patterns within a rapidly executed single effort in order to efficiently transfer explosive power to the thrown implement (Bartlett, 2007), which inevitably requires many years of training and experience to master (Hollings et al., 2014). In athletics track sprint events (~10-55 s), gross motor patterns are repeated over a number of stride cycles, so performance in these events is likely more dependent on expression of raw power than on acquisition and application of skill (Hollings et al., 2014). Although technique is also a critical determinant of performance in sprint and middle-distance swimming (~21-245 s; Barbosa, Costa, & Marinho, 2013; Figueiredo, Pendergast, Vilas-Boas, & Fernandes, 2013), the younger age of peak performance observed for athletes in these events may relate to differences in the typical age of specialisation in a certain sport between swimmers and athletes from most other sports. For example, among the Olympians of 2004, the mean age of specialisation reported by swimmers was 8 y, compared

Table 2. Estimates of age of peak performance of elite athletes separately by event, event type, sport, and sex. Information regarding event duration, method of estimation of peak age and subjects and data included in the analysis is also shown.

Event type and study	Sport and event	Event duration[a]	Method	Subjects and data	Men[b] Age of peak	Men[b] 90% CL	Women[b] Age of peak	Women[b] 90% CL
Explosive/ Sprint	Athletics	(s)						
Berthelot et al. (2012)	Sprints[c]	10-50	Mean exponential growth and decay curve	Best annual career performances of world-ranked top-10 (1980-2009)	25.8	?	25.7	?
Hollings et al. (2014)	Sprints, hurdles[d]	10-55	Individual quadratic curves via mixed modelling	All competition performances of world-ranked top-12 (field) or top-	25.2 ± 2.3	0.3	25.7 ± 2.4	0.3
	Jumps[e]	5		16 (track) (2000-2009)	25.8 ± 2.1	0.3	25.6 ± 2.7	0.4
	Throws[f]	1-5			28.0 ± 2.5	0.4	26.7 ± 3.3	0.6
Tilinger et al. (2005)	Sprints[g]	10-20	Mean quadratic curve via regression	16 world-prominent sprinters	24.5	?	-	-
	Jumps[h]	5		55 world-prominent jumpers	24	?	-	-
	Throws[i]	1		31 world-prominent throwers	26.5	?	-	-
	Swimming							
Allen et al. (2014)	50 to 100-m all Olympic events	21-65	Individual quadratic curves via mixed modelling	Best annual career performances of Olympic top-16 (2008, 2012)	25.0 ± 1.9	0.3	23.3 ± 2.8	0.6
Berthelot et al. (2012)	50 to 100-m free	21-54	Mean exponential growth and decay curve	Best annual career performances of world-ranked top-10 (1980-2009)	22.4	?	22.8	?
Sokolovas (2006a)	50 to 100-m all Olympic events	21-65	Age at best career performance	Top-10 best swimmers in history	23.1 ± 2.6	0.6	21.3 ± 4.1	1.0
Wolfrum et al. (2013)	50 to 100-m breast free	27-65 21-54	Age-group of top-ranked performers at pinnacle events	Top-8 World Championships finishers between 2003 and 2011	26-27 28-29		22-23 24-27	
Endurance	Athletics	(h)						
Hollings et al. (2014)	Middle-distance[j]	0.03-0.5	Individual quadratic curves via mixed modelling	All competition performances of world-ranked top-12 (2000-2009)	24.9 ± 2.4	0.3	26.7 ± 3.0	0.5
Berthelot et al. (2012)	Middle-distance[k]	0.03-0.5	Mean exponential growth and decay curve	Best annual career performances of world-ranked top-10 (1980-2009)	25.0	?	25.3	?
Berthelot et al. (2012)	Marathon	2.1-2.3	Mean exponential growth and decay curve	Best annual career performances of world-ranked top-10 (1980-2009)	31 .6	?	27.1	?
Hunter et		2.1-2.3	Age of top-ranked performers	Top-5 World Marathon Majors	28.8 ± 3.7	0.4	29.8 ± 3.8	0.4

29

		(h)						
al. (2011)			at pinnacle events	finishers (2000-2009)				
Cejka et al. (2014)	100-km ultra-marathon	6.5-7.5	Age of top-ranked performers at pinnacle events	Annual top-10 fastest athletes from all top races (1960-2012)	34.5 ± ?	0.2	34.9 ± ?	0.2
Rüst et al. (2013)	100-mile ultra-marathon	12-14	Age of top-ranked performers at pinnacle events	Top-10 finishers from all top races (2000-2011)	37.3 ± 6.3	0.3	38.6 ± 5.6	0.2
	Cycling							
Anderson (2014)	Cyclo-cross	1	Mean quadratic curve estimated from race rankings	103 cyclo-cross riders across 8 World Cup races (2012-2013)	30.2	?	-	-
Shoak et al. (2013)	Ultra-distance	27-29	Age of top-ranked performers at pinnacle events	Furnace Creek 508 and Swiss Cycling Marathon winners (2000-2011)	38	1.8	39	2.5
	Swimming							
Allen et al. (2014)	200 to 1500-m all Olympic events	0.03-0.25	Individual quadratic curves via mixed modelling	Best annual career performances of Olympic top-16 (2008, 2012)	23.6 ± 1.9	0.3	22.1 ± 2.0	0.3
Berthelot et al. (2012)	200 to 1500-m free	0.03-0.25	Mean exponential growth and decay curve	Best annual career performances of world-ranked top-10 (1980-2009)	20.4	?	20.0	?
Sokolovas (2006a)	200 to 1500-m all Olympic events	0.03-0.25	Age at best career performance	Top-10 best swimmers in history	21.7 ± 2.5	0.5	19.8 ± 3.1	0.6
Wolfrum et al. (2013)	200-m breast free	0.04 0.03	Age-group of top-ranked performers at pinnacle events	Top-8 World Championships finishers between 2003 and 2011	20-21 22-23		22-23 22-23	? ?
	Triathlon							
Malcata et al. (2014)	Olympic-distance	1.8-2.1	Individual quadratic curves via mixed modelling	All competition performances of top-30 triathletes (2000-2012)	27.6 ± 2.1	0.6	27.1 ± 3.6	1.1
Rüst et al. (2012b)	Ironman	8-9	Age of top-ranked performers at pinnacle events	Top-10 at World Championships every year (2000-2012)	32 ± 3	0.4	34 ± 4	0.5
Mixed		(h)						
Brander et al. (2014)	Ice hockey	1	1. Age-group of top-ranked performers	Scoring index for Top-10 NHL forwards (1997-2012)	27-29		-	-
			2. Age-group (1-y categories) with best mean performance	Scoring index for all NHL forwards (1997-2012)	28		-	-
			3. Mean cubic curve via regression		27.6	0.4	-	-
			4. Individual quadratic curves		27.7 ± 3.3	0.2	-	-
			1. Age-group of top-ranked	Plus-minus index for Top-10 NHL	23-33		-	-

Study	Sport	Duration (h)[a]	Method	Sample	Men[b]	CL	Women[b]	CL
			performers	defencemen (1997-2012)				
			2. Age-group (1-y categories) with best mean performance	Plus-minus index for all NHL defencemen (1997-2012)	27		-	-
			3. Mean quadratic curve via regression		27.8	3.0	-	-
			4. Individual quadratic curves		28.2 ± 3.9	0.4	-	-
Guillaume et al. (2011)	Tennis	2-3.5	Individual exponential growth and decay curves	Top-10 world-ranked players (1985-2009)	23.3 ± ?	?	21.5 ± ?	?
Kovalchik (2014)			Age of top-ranked performers	Top-30 world-ranked players (2000-2012)	25.8 ± 3.1	1.0	-	-
Skill		(h)						
Fried & Tauer (2011)	Golf	5	1. Rolling mean (1-y categories)	Earnings index of PGA tour golfers (2004-2006)	36	?	-	-
			2. Mean quadratic curve via regression		35	?	-	-
Tiruneh (2010)		5	Age of top-ranked performers at pinnacle events	PGA tour winners (2003-2007), LPGA tour winners (2002-2006)	35.1 ± 6.2	0.7	29.9 ± ?	?

CL confidence limits

[a]Approximate range of event durations are shown for top performers in each event.

[b]Data are mean ± SD, apart from for methods estimating an age-group (range) of peak mean performance. Between-subject SDs are shown for methods with individual age-performance trends and for methods investigating age at best performance. For methods investigating age of top-ranked performers at pinnacle events over a number of years, a mean of the between-subject SD for each year is presented. SDs are missing where between-subject SDs could not be obtained owing to the nature of the method utilised. The ? symbol denotes that information required to calculate between-subject SDs or 90% CL was not provided. The – symbol denotes that estimates were not generated for women.

[c]100-m and 400-m runs

[d]100-m, 200-m and 400-m runs; 100-m (women), 110-m (men) and 400-m hurdles

[e]High jump, long jump, pole vault, triple jump

[f]Discus throw, hammer throw, javelin throw, shot put

[g]100-m and 200-m runs

[h]Long jump, pole vault

[i]Discus throw, shot put

[j]800-m, 1500-m, 3000-m steeple, 5000-m and 10000-m runs

[k]800-m, 1500-m, 5000-m (men), 10000-m runs
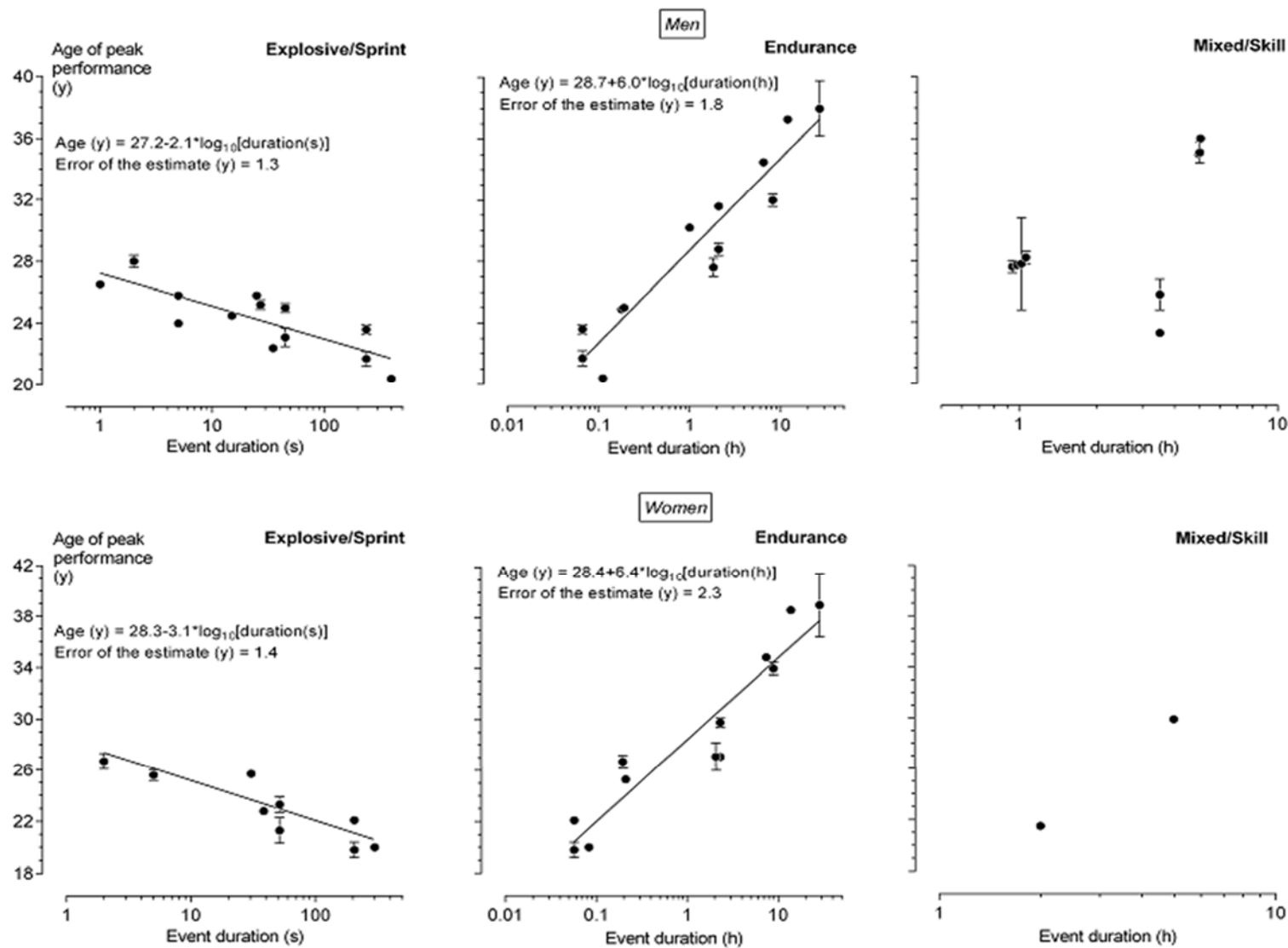
Figure 3. Age of peak competitive sporting performance (mean ± 90% confidence limits) of elite male and female athletes, shown by event duration (logarithmic scale). Where a grouped estimate is presented for multiple events of different durations, the duration shown is a mean for those events. Data are presented separately for three different event types; explosive/sprint events, endurance events, and mixed/skill events.

with 14 y for athletics competitors (Vaeyens et al., 2009). While the kinesthetic learning and reinforcement needed to develop and maintain the efficient aquatic motion necessary for successful swim performance is thought to require greater time investment than that for successful performance in most land-based sports (Balyi, 2010), it is likely that early specialisation at least partially contributes to the early peaking phenomenon observed in swimmers.

The trend of increasing age of peak performance with increasing event duration for events in which performance is primarily contingent upon endurance has been documented previously within studies of age of peak performance across multiple events (Lepers, Sultana, Bernard, Hausswirth, & Brisswalter, 2010; Schulz & Curnow, 1988). One explanation for this trend may be that physical attributes important for success in ultra-endurance events, such as aerobic capacity and movement economy, generally increase progressively with increasing training histories and thus age (Zaryski & Smith, 2005). However, research into the age-related development of the human species shows that most physical capacities tend to peak around the age of 30 (Gabbard, 2004), implying that factors other than physiology must contribute to the older estimates observed for events such as marathon running, ironman triathlon, ultra-endurance cycling and cyclo-cross (e.g., pacing and nutritional strategies, anticipating and dealing with environmental conditions, and mental resilience). In some events it may therefore be possible for older athletes to continue progressing by accumulating improvements in cognitive and/or experiential capacities that offset the inevitable plateau in physical ability. This explanation aligns well with evidence that increased age is often associated with improved job performance. Despite well-established declines in indicators of fluid intelligence (e.g., problem-solving, speed of information processing) from age ~27 onwards, corresponding impairments in job performance beyond this age are rarely observed, owing to the human capacity to continue accumulating crystallised intelligence (e.g., knowledge, experience) until the age of at least 60 (Salthouse, 2012).

Overall, it seems possible to reach peak performance at much older ages in endurance events than in explosive/sprint events. This difference may be explained by the fact that the shorter duration and higher absolute intensity of explosive/sprint events mean it is much harder for athletes in these events to offset declines in their physical ability with any gains in knowledge, experience, skill and/or cognitive ability. Indeed, one proposed explanation for the lack of observable declines in job performance of older adults is that human physical and cognitive capacities are often assessed at their maximal level of functioning, but very seldom used at that level (Salthouse, 2012).

While our literature search did not yield a sufficient number of estimates for trends to be quantitatively investigated for sports in the mixed/skill category (ice hockey, tennis, golf), observation of the available estimates reveals that peak performance in these events can be achieved at a wide range of ages, presumably depending on the contribution of physical, technical and tactical capacities to performance in each event. For example, the low physical demands of golf combined with the high importance of skill and mental fortitude for performance would seem to fit with the relatively high age of peak performance (~35 y). Perhaps surprisingly, given the apparent importance of accumulating physical fitness, skill and tactical knowledge for

success in racquet sports, ages of peak performance for tennis players were reasonably young (~24 y). However, data from one study did show a progressive yearly increase in the annual average age of top-30 ranked tennis players, with estimates of peak age rising from ~25 y in 2006 to ~27 y in 2012 (Kovalchik, 2014). While these data led the author to speculate that this shift in the age of the world's top tennis players was reflective of evolution in the factors critical for performance success in the sport (e.g., greater endurance), these factors may have always been critical for successful tennis performance, but with recent advances in science, technology and funding/resource provision for athlete development, more players have begun to develop them. Similar to that in swimmers, early specialisation has typically been common in tennis players (Balyi, 2010), potentially leading to artificially early ages of peak performance. With the improved long-term athlete development plans of modern-day national sporting organisations, the observed ages of peak performance of athletes in these sports may start to more closely reflect the ages at which the physical, mental, technical and strategic capacities required for successful performance typically peak within humans. If so, we would also expect to observe corresponding improvements in the standard of performance of these sports in the coming years as the capacity of their top athletes evolves.

Of the studies that investigated changes in age of peak performance of top athletes over a number of years, five contained evidence of trends showing annual increases in age of peak performance since the year 2000 (Cejka et al., 2014; Guillaume et al., 2011; Kovalchik, 2014; Rüst et al., 2012b; Shoak et al., 2013). Five studies also included a substantial proportion of data from athletes prior to the year 2000 (Berthelot et al., 2012; Cejka et al., 2014; Guillaume et al., 2011; Sokolovas, 2006a; Tilinger et al., 2005), which we were unable to exclude from our results, owing to either the analysis method of the study, or the manner in which authors presented their estimates. Given this evidence, it is likely that differences in datasets were at least partly responsible for the between-study differences in estimates of peak age for similar events.

Another factor that probably contributed to the variation observed between peak age estimates for similar events was differences in the methods used to quantify age of peak performance. Indeed, one study quantified age of peak performance of ice hockey players using four different methods, producing estimates that varied by ~1 to 2 y (Brander et al., 2014). For studies in which the age of top-ranked performers in an event was investigated, peak age estimates may be slightly elevated, owing to the fact that older athletes are likely to be higher ranked than their younger counterparts. Additionally, studies that employed either this method or the method of identifying the age at which top athletes achieved their best performance may have misestimated the timing of an athlete's true performance peak, if it happened not to coincide with a major competition. While studies that used statistical modelling to quantify age of peak performance were not subject to these limitations, estimates produced by fixed-effects modelling of mean age-performance relationships do not appropriately account for the individual differences in these relationships that inevitably exist. Studies that modelled unique age and performance trends for each individual athlete may therefore have produced the most robust age of peak performance estimates; however, these estimates may also have been affected by differences in the availability of each athlete's career performance data, given that a minimum

number of observations (typically 3 to 5) are required to produce a peak age estimate for an individual.

On the whole, between-study differences (standard errors of the estimate) in estimates of peak age for similar events were moderate to large but our regression equations for each sex and event-type combination should still be useful to predict the age of peak performance in a given event. If more authors had provided standard deviations and standard errors or confidence limits for their peak-age estimates, it would have been possible to weight and meta-analyse the study estimates, which would probably have improved the precision of our prediction equations. Additionally, with a greater number of peak-age estimates for female athletes, we would have been able to meta-analyse the differences between sexes. As it was, males were possibly older at their peak performance than females in explosive/sprint events, which can presumably be explained by the earlier onset of puberty in females (Baxter-Jones & Sherar, 2006). A similar pattern may also exist for endurance events, but more studies are required.

Given the ongoing evolution of age of peak performance in many sports, as noted above, future research should continue to track these trends in order to provide peak-age estimates valid for current athletes. There is also a need for further research into the age of peak performance in more mixed/skill-based sports, as the majority of published articles were for sports with a predominant explosive power/sprint or endurance component. This imbalance likely reflects the difficulty of operationalising performance in sports without objective measurement of an individual's performance (time, distance or score), such as most team sports and judgement-based sports, including combat sports, diving, and gymnastics.

2.5. Conclusion

The age of peak competitive performance of elite athletes ranges widely between different events, likely owing to differences in the attributes required for success between events and differences in the points at which these attributes typically reach their peak capacity within an athlete's career. In explosive power/sprint events and endurance events, linear trends reasonably describe the relationships between age of peak performance and event duration. By estimating the equations of these trends, we have created a tool that should be useful for predicting the age of peak performance of athletes specialising in specific events, and for helping identify events that may best suit mature-age talent identification and transfer athletes.

CHAPTER 3

CAREER PERFORMANCE TRAJECTORIES OF OLYMPIC SWIMMERS

This chapter comprises the following paper published in the European Journal of Sport Science: Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2014). Career performance trajectories of Olympic swimmers: Benchmarks for talent development. *European Journal of Sport Science*, *14*, 643-651.

Overview

The age-related progression of elite athletes to their career-best performances can provide benchmarks for talent development. **Purpose:** The purpose of this study was to model career performance trajectories of Olympic swimmers to develop these benchmarks. **Methods:** We searched the Web for annual best times of swimmers that were top 16 in pool events at the 2008 or 2012 Olympics, from each swimmer's earliest available competitive performance through to 2012. There were 6959 times in the 13 events for each sex, for 683 swimmers, with 10 ± 3 performances per swimmer (mean ± SD). Progression to peak performance was tracked with individual quadratic trajectories derived using a mixed linear model that included adjustments for better performance in Olympic years and for the use of full-body polyurethane swimsuits in 2009. Analysis of residuals revealed appropriate fit of quadratic trends to the data. **Results:** The trajectories provided estimates of age of peak performance and the duration of the age window of trivial improvement and decline around the peak. Men achieved peak performance later than women (24.2 ± 2.1 vs 22.5 ± 2.4 y), while peak performance occurred at later ages for the shorter distances for both sexes (~1.5-2.0 y between sprint and distance event groups). Men and women had a similar duration in the peak performance window (2.6 ± 1.5 y) and similar progressions to peak performance over four years (2.4 ± 1.2 %) and eight years (9.5 ± 4.8 %). **Conclusion:** These data provide performance targets for swimmers aiming to achieve elite-level performance.

3.1. Introduction

A clearly defined pathway of progression to elite-level sporting performance is a key component of a comprehensive talent development programme. By benchmarking the age-related performance progression of their athletes against that of Olympic athletes, national sporting organisations could systematically identify those who are tracking towards future success and allocate funding and resources accordingly. The career progression profiles of top athletes could also be used to assist coaches with planning towards the long-term goal of winning an Olympic medal by allowing them to establish realistic short-term performance targets for younger athletes.

While estimates of the progression required for an elite swimmer to maintain and/or increase their chances of medalling at an Olympics have already been established (Pyne et al., 2004), information about performance changes of top swimmers during their early competition years is needed to extend the pathway to elite performance. Performance changes at any stage of a swimmer's career are likely due to complex interactions between a myriad of genetic and environmental variables (Barbosa et al., 2013). However, during their development years, athletes are also likely to vary substantially in factors contributing to performance such as aerobic and anaerobic capacities, muscle mass and power, motor control and skill acquisition, and psychological development, owing to the non-linear processes of growth and maturation (Malina, 1994). Indeed, previous research investigating the progression of young swimmers has established relationships between the development of various physical, physiological and biomechanical parameters and changes in swim performance (Lätt et al., 2009a; Lätt et al., 2009b), although estimates of such variation in the early competition years of top swimmers are currently lacking.

Given the multitude of factors that are involved in determining the performance of young swimmers, developing an appropriate method for tracking the career progression of top swimmers' performances is a challenging process that clearly warrants research attention. A method of using quadratic trajectories to model the performance progression of individual athletes' official competition times was first introduced for the winter Olympic sport of skeleton (Bullock & Hopkins, 2009). This method has since been adapted and applied to swimming (Pike et al., 2010), track-and-field athletics (Hollings et al., 2014) and triathlon (Malcata et al., 2014). The swimming study and other previous longitudinal studies of annual changes in performance of individual swimmers have been limited to sub-elite swimmers (Costa et al., 2011), or performances in freestyle events (Costa et. al., 2010; Berthelot et al., 2012). In the present study, we have produced quadratic trajectories for career performances of top swimmers in all Olympic pool events. The aim of the study was to produce estimates of age-related progression that can serve as benchmarks for talent development and age-related competition investment.

3.2. Methods

The swimmers we selected for this study were the top 16 in all pool events at the 2008 or 2012 Olympic Games. We searched recognised data sources (Swimnews, swimnews.com;

Swimrankings, swimrankings.net; Infostrada, infostradasports.com; National Swimming Federations' official databases) for each swimmer's annual best times between 2012 and their earliest available competitive performance, and their date of birth. This search resulted in 6959 times for 683 swimmers in the 13 stroke and distance combinations for each sex (23-29 swimmers per event). Number of performances per swimmer was similar for all events (9-12 ± ~3; range in event means ± SD). Between each swimmer's earliest and latest competitive performances, 317 times for 172 swimmers were missing, presumably owing to factors such as swimmers taking breaks from the sport, focusing more on different events or experiencing illness or injury in particular years.

Performance times were log-transformed for analysis of percent changes using the mixed linear model procedure (Proc Mixed) in the Statistical Analysis System (Version 9.2, SAS Institute, Cary, NC). The model included fixed effects to estimate a mean quadratic trend for chronological age, to estimate and account for a single mean improvement in performance for Olympic year swims, and to estimate and account for a single mean improvement for 2009 (the year where results were most affected by the full-body polyurethane swimsuits; from 2010 onwards these suits were banned). Random effects were included for the unique effect of age on each swimmer's performance times modelled as individual quadratic trajectories. The residual random effect in the model represented differences between observed and modelled performance times; a different residual variance was specified for three age-ranges (<17, 17-19, >19 years). A few performances (0 to 4 per event) with a standardised residual of >4.5 were classified as outliers (Hopkins et al., 2009) and were deleted from the data set for the final analysis. No clear pattern was evident as to when the outliers occurred.

To create benchmarks for talent development, we calculated the percent performance time difference between the predicted performance time of each swimmer at each integer age from 12 to 30 y and the gold medal time at the 2012 Olympics for each event. The individual athletes' time differences were averaged with a meta-analytic mixed model (using Proc Mixed in SAS) in which the inverse of the square of the standard error of the estimate was a weighting factor. By working through the data we found that middle-distance swimmers generally reached peak performance one year earlier than sprinters, and one year later than distance swimmers. To account for these differences, we adjusted the estimates of sprint (50-100 m) and distance swimmers (400-1500 m) to the profile of middle-distance swimmers (200 m) by subtracting one year from each integer age for sprinters and adding one year to each integer age for distance swimmers before including them in the meta-analysis. The model provided estimates of the adjusted mean (fixed effect) and the between-swimmer standard deviation (random effect) of the percent performance time difference. A reference range for each integer age was calculated by assuming a t distribution given by the modelled mean and a standard deviation equal to the square root of the sum of the squares of the between-swimmer standard deviation, the standard error of the estimate of the mean, and the residual variance (from the analysis of the quadratic trends). We then plotted the adjusted mean percent performance time difference (± 90% reference range) against age for each event to create graphs that can be used to track the performance of any swimmer against elite-level benchmarks.

The modelled trajectories were used to estimate age of peak performance and the duration of the age window of trivial improvement and decline around the peak for each swimmer (peak performance window), using methods described previously (Hollings et al., 2014). In brief, the duration of the window was $2(\sqrt{\Delta/a})$, where Δ = the smallest worthwhile change in performance, and a = the quadratic coefficient of each swimmer's trajectory. The smallest worthwhile change in performance used to define the duration of the peak performance window was calculated as 0.3 of the within-swimmer variability in performance between international competitions (Hopkins et al., 2009). This variation has been established as 0.7% for ≤400-m events, and 1.0% for >400-m events (Pyne et al., 2004), resulting in smallest worthwhile effects of 0.21% and 0.30% respectively. Progression of performance in the years leading to the peak was derived from each athlete's individual quadratic trajectory. Swimmers who hadn't reached their peak by the 2012 Olympics were excluded from these analyses, owing to the uncertainty involved in forecasting when their peak will occur.

We examined the residuals from the mixed model to assess the suitability of using quadratic trends to model elite swim performance. We rescaled each swimmer's age of peak performance to zero and plotted the mean value of the residuals against age for each event. Quadratics were considered to be an appropriate fit to our data, as we observed no systematic deviation of the residuals above or below the smallest worthwhile effects for each event.

The magnitude of differences in age of peak performance, the duration of the peak performance window, and progression of performance in the years leading to the peak were calculated as standardised differences and assessed using a scale with thresholds of 0.2, 0.6, 1.2, and 2.0 for small, moderate, large and very large respectively (Hopkins et al., 2009). Inferences about differences between events, event-groups, sexes, and between medallists and non-medallists by sex were based on uncertainty in magnitude using these values and were realised using a spreadsheet (Hopkins, 2006a). Uncertainty in effects was expressed as 90% confidence limits.

3.3. Results

Mean age-related performance time difference (±90% reference range) from the 2012 Olympic gold medal time for each event is shown by sex in Figure 4. Each plot includes the best annual times and modelled career performance trajectory of one Olympic medallist swimmer. These trajectories were chosen to exemplify the suitability of quadratic trends for modelling the best annual performance times of individual swimmers, individual differences in the quadratic curves contributing to the shape of the mean progression band, and individual differences in the performance pathways of top swimmers.

Estimates of the age of peak performance, duration of the peak-performance window, and progression to peak performance are presented for each individual event in Table 3, and for each sex, distance-group and stroke in Table 4. All substantial differences were clear for any comparison of sex, distance-group or stroke means, but some trivial differences were unclear.

Table 3. Age (y) of peak performance, number of years in the peak performance window and progressions to peak performance for each event.

Event	Men					Women				
	n	Age of peak performance	Window of peak performance	Four-year progression to peak (%)	Eight-year progression to peak (%)	n	Age of peak performance	Window of peak performance	Four-year progression to peak (%)	Eight-year progression to peak (%)
100-m Backstroke	18	24.5 ± 1.4	2.1 ± 0.6	2.3 ± 0.7	9.4 ± 2.7	17	22.6 ± 2.7	2.6 ± 1.8	2.7 ± 1.8	10.7 ± 7.4
200-m Backstroke	15	25.2 ± 1.8	3.2 ± 1.0	1.6 ± 0.8	6.5 ± 3.1	15	21.9 ± 2.3	2.4 ± 1.5	2.7 ± 1.4	10.6 ± 5.7
100-m Breaststroke	21	25.2 ± 1.8	2.7 ± 1.6	2.3 ± 1.2	9.3 ± 4.8	13	22.2 ± 1.7	2.9 ± 2.1	2.1 ± 0.9	8.5 ± 3.7
200-m Breaststroke	19	24.1 ± 1.9	2.2 ± 1.3	2.7 ± 1.3	10.7 ± 5.4	12	23.7 ± 2.4	3.5 ± 1.0	1.4 ± 0.4	5.7 ± 1.5
100-m Butterfly	25	24.0 ± 1.9	2.4 ± 1.8	2.9 ± 1.6	11.5 ± 6.4	17	23.1 ± 2.5	2.2 ± 1.0	2.6 ± 1.2	10.5 ± 5.0
200-m Butterfly	17	24.3 ± 1.6	3.3 ± 2.6	2.2 ± 1.3	8.8 ± 5.4	16	22.0 ± 2.3	2.4 ± 1.7	2.9 ± 1.6	11.5 ± 6.5
50-m Freestyle	20	25.9 ± 1.9	3.1 ± 1.8	1.9 ± 0.9	7.6 ± 3.5	6	26.1 ± 4.0	4.8 ± 2.9	1.3 ± 0.9	5.4 ± 3.4
100-m Freestyle	20	25.3 ± 2.0	2.6 ± 1.3	2.1 ± 0.8	8.3 ± 3.1	15	24.2 ± 2.6	2.9 ± 1.2	1.9 ± 0.8	7.5 ± 3.1
200-m Freestyle	18	23.6 ± 2.4	2.1 ± 1.0	2.4 ± 1.0	9.7 ± 4.0	17	22.3 ± 1.4	2.5 ± 1.6	2.4 ± 0.9	9.5 ± 3.7
400-m Freestyle	21	22.9 ± 2.0	2.3 ± 1.3	2.7 ± 1.4	10.7 ± 5.7	20	22.3 ± 1.9	2.1 ± 1.1	2.5 ± 1.1	9.8 ± 4.4
800-m Freestyle	-	-	-	-	-	12	21.9 ± 1.5	2.8 ± 1.3	2.3 ± 0.9	9.3 ± 3.4
1500-m Freestyle	17	22.9 ± 2.2	2.9 ± 1.5	2.4 ± 1.1	9.5 ± 4.3	-	-	-	-	-
200-m IM	14	24.8 ± 1.4	3.0 ± 1.1	1.7 ± 0.4	6.7 ± 1.7	18	21.7 ± 1.9	2.1 ± 1.2	2.8 ± 1.3	11.2 ± 5.2
400-m IM	19	22.7 ± 1.5	2.2 ± 1.1	2.7 ± 1.5	10.9 ± 5.9	16	21.4 ± 2.0	2.3 ± 1.3	2.5 ± 1.0	10.0 ± 4.1

Note: Data are mean ± SD. IM = Individual Medley.

Uncertainties (±90% confidence limits) for pairwise comparisons are ~±1.3 y, ~±1.0 y, ~±0.7 %, and ~±2.6 % for age of peak performance, window of peak performance, four-year progression to peak, and eight-year progression to peak, respectively.

Differences of > ~0.8 y, > ~0.7 y, > ~0.4 %, and > ~1.7 % are clear at the 90% level for pairwise comparisons for each respective variable (e.g., clear difference in age of peak performance for men 100-m backstroke vs men 400-m freestyle). Increase these thresholds by a factor of 1.6 for clarity at the 99% level

Table 4. Age of peak performance, duration of the peak-performance window, and progressions to peak performance by sex, distance-group, and stroke.

	n	Age (y) of peak performance	Window of peak performance (y)	Four-year progression to peak (%)	Eight-year progression to peak (%)	Uncertainty in group means (proportion of s)[a]
Male swimmers	244	24.2 ± 2.1	2.6 ± 1.5	2.3 ± 1.2	9.4 ± 4.8	0.10
Sprint	104	25.0 ± 1.9	2.6 ± 1.5	2.3 ± 1.1	9.3 ± 4.6	0.16
Middle-distance	83	24.4 ± 1.9	2.8 ± 1.6	2.2 ± 1.1	8.7 ± 4.5	0.17
Distance	57	22.8 ± 1.9	2.5 ± 1.3	2.4 ± 1.3	10.4 ± 5.3	0.22
Backstroke	33	24.8 ± 1.5	2.6 ± 1.0	2.0 ± 0.8	8.1 ± 3.2	0.29
Breaststroke	40	24.6 ± 1.9	2.5 ± 1.4	2.5 ± 1.3	10.0 ± 5.1	0.27
Butterfly	42	24.1 ± 1.8	2.8 ± 2.2	2.6 ± 1.5	10.4 ± 6.1	0.26
Freestyle	96	24.2 ± 2.4	2.6 ± 1.4	2.3 ± 1.1	9.2 ± 4.3	0.17
IM	33	23.6 ± 1.8	2.5 ± 1.1	2.3 ± 1.3	9.1 ± 5.0	0.29
Female swimmers	194	22.5 ± 2.4	2.6 ± 1.6	2.4 ± 1.2	9.6 ± 4.9	0.12
Sprint	68	23.3 ± 2.8	2.8 ± 1.8	2.3 ± 1.3	9.1 ± 5.2	0.21
Middle-distance	78	22.3 ± 2.1	2.5 ± 1.5	2.5 ± 1.3	9.9 ± 5.2	0.19
Distance	48	21.9 ± 1.9	2.4 ± 1.2	2.4 ± 1.0	9.8 ± 4.0	0.25
Backstroke	32	22.3 ± 2.5	2.5 ± 1.6	2.7 ± 1.6	10.7 ± 6.5	0.30
Breaststroke	25	22.9 ± 2.2	3.2 ± 1.7	1.8 ± 0.8	7.2 ± 3.1	0.34
Butterfly	33	22.6 ± 2.4	2.3 ± 1.4	2.8 ± 1.4	11.0 ± 5.7	0.29
Freestyle	70	23.0 ± 2.5	2.7 ± 1.6	2.2 ± 1.0	8.8 ± 3.9	0.20
IM	34	21.6 ± 2.0	2.2 ± 1.2	2.7 ± 1.2	10.6 ± 4.7	0.29

Note: Data are mean ± SD. Sprint events are 50-100 m; middle-distance events are 200 m; distance events are 400-1500 m. IM = Individual Medley.
[a]Uncertainty (±90% confidence limits; CL) for each group mean is given by the product of each mean's s and this factor.
Uncertainties (±90% CL) for pairwise comparisons of distance-group means are ~0.6 y, ~0.4 y, ~0.3 %, and ~ 1.4 % for each respective variable.
Differences of >~0.1 y, >~0.1 y, >~0.1 %, and >~0.4 % are clear at the 90% level in comparing distance-group means for each respective variable.
Uncertainties (±90% CL) for pairwise comparisons of stroke means are ~0.8 y, ~0.6 y, 0.5 %, and ~ 1.8 % for each respective variable.
Differences of >~0.3 y, >~0.3 y, >~0.2 %, and ~0.9 % are clear at the 90% level in comparing stroke means for each respective variable.
Increase the difference-thresholds by a factor of 1.6 for clarity at the 99% level.
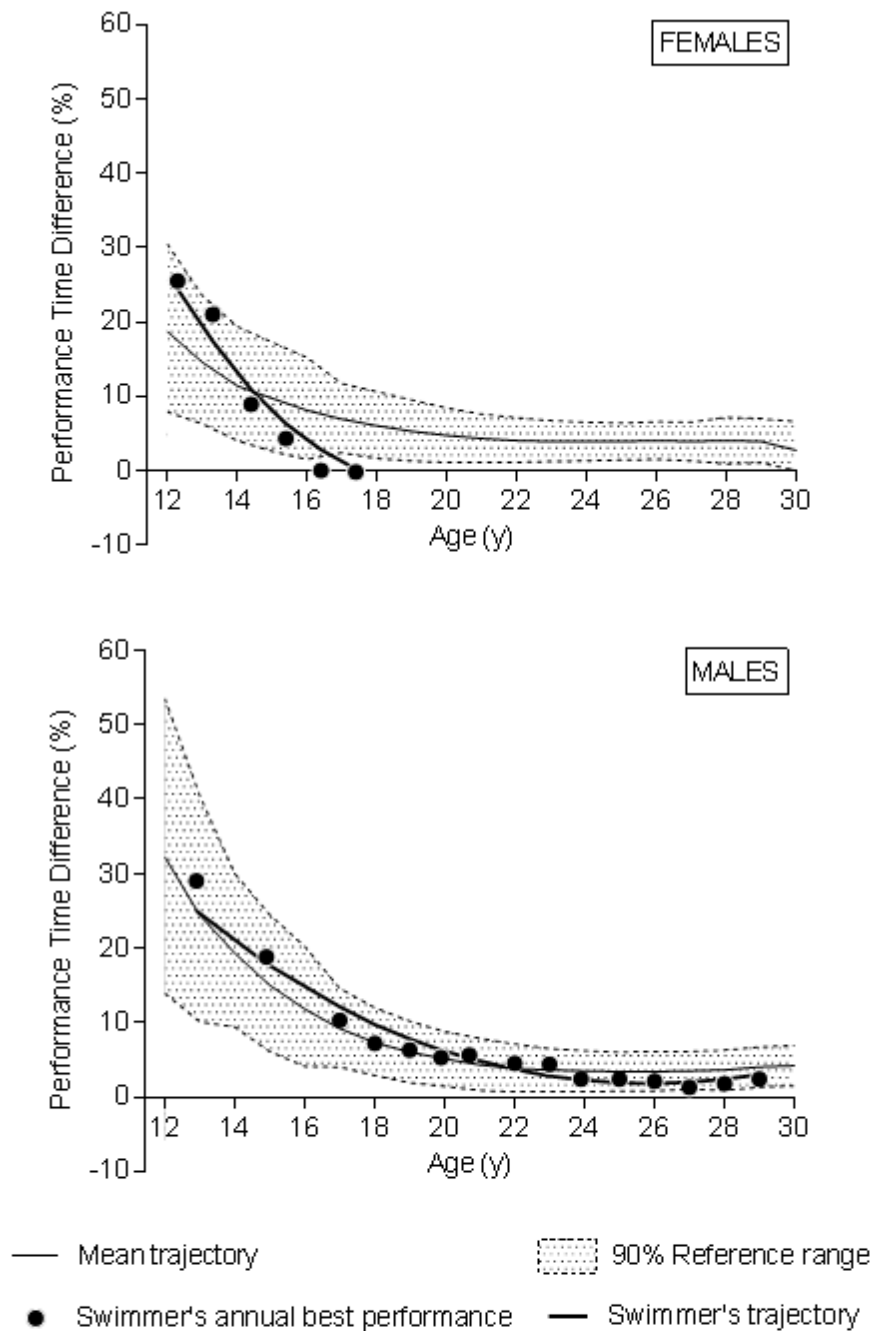
Figure 4. Mean performance time difference (%) and 90% reference range between age-related predicted performance time and 2012 Olympic gold medal time for female and male middle-distance (200 m) swimmers. Examples of annual best performance times and career trajectories (adjusted for event, see Methods) are shown for one Olympic medal-winning swimmer of each sex: the female swimmer is Katie Ledecky, gold medallist at the 2012 Olympics; the male swimmer is Ryan Lochte, eleven-time Olympic medallist across three Olympic Games (2004, 2008, 2012).

Male Olympic top-16 swimmers were around two years older than their female counterparts (a moderate difference) when they achieved their peak performance. Both sexes reached their performance peak at later ages for the shorter distances, with moderate differences of ~2 y between the sprint (≤100-m) and distance (≥400-m) groups for the men, and ~1.5 y for the women. The duration of the peak-performance window was similar for men and women, and for most distance-groups (~2.5 y), although female sprint swimmers had a wider window of peak performance than female distance swimmers (a small difference). Men and women displayed similar rates of progression over four and eight years leading to peak performance (~2.5% and ~9.5%), but male distance swimmers showed greater progression than male sprint and middle-distance swimmers, with small differences for both distance-group comparisons. Individual medley (IM) swimmers reached peak performance at earlier ages than swimmers in all single-stroke events for both sexes (small to moderate differences). Female breaststrokers experienced a shorter duration in the peak-performance window, and smaller rates of progression to peak performance than swimmers of all other strokes, with small to moderate differences for each between-stroke comparison. All other differences between strokes were trivial to small with no discernible trends.

Medallists showed slightly (trivial) higher age of peak performance compared with non-medallists for men (difference in means of 0.2 y, 90% confidence interval -0.3 to 0.8 y) and women (0.4, -0.3 to 1.0 y). Compared with female non-medallists, female medallists displayed greater progression over four years (0.5, 0.2 to 0.8 %) and eight years (1.9, 0.6 to 3.2 %) leading to peak performance, and a narrower window of peak performance (-0.5, -0.2 to -0.8 y); all of these differences were clear and small in magnitude.

Age of peak performance as predicted by the trajectories and age of actual best performance (data not shown) were similar for all between sex, stroke and distance-group pairwise comparisons. Residual variance between observed and modelled swim times averaged over all events for both sexes was 3.0%, 1.3%, and 1.0% for the <17 y, 17-19 y and >19 y age-groups respectively.

Olympic years and the polyurethane swimsuit year (2009) accounted for additional performance enhancements in all events of 1.0 ± 0.3 % and 1.0 ± 0.5 % respectively (mean ± between-event SD). Most of the differences were clear for each event. The Olympic effect was similar for men and women, whereas the swimsuits provided greater performance enhancements for the men than the women (difference in means of 0.32%, 90% confidence interval 0.28 to 0.36 %).

3.4. Discussion

In the present study we have modelled the career performances of Olympic top-16 swimmers using individual quadratic trajectories to produce benchmarks that should be valuable for talent development. By plotting the age-related performance progression of elite-level swimmers towards the 2012 Olympic gold medal winning time (Figure 4), we have created a tool that can be used to clearly and easily evaluate the progress of any swimmer between the ages of 12 and 30 years. The estimates of age of peak performance for different distance-

groups can be used to add another level of specificity to this tool. As swimmers specialising in sprint events typically peak approximately one year later than the adjusted mean for each sex (Table 4), sprint-event swimmers should subtract one year from their age when plotting each of their performances. Following the same logic, distance-event swimmers should add one year. To evaluate progress towards pinnacle events in future years, secular trends in performance times of the best swimmers need to be taken into account. When plotting performances against age, swim times can be adjusted to future years by adding the product of the percent annual change in top swimmers' performances since 2012 and the number of years after 2012 to their percent performance time difference at each age.

Analysis of the residuals from the mixed model revealed appropriate fit of quadratic curvature for tracking the individual age-related progression of top swimmers' performances. Paradoxically, the plots for mean age-related performance in Figure 4 show progression to a plateau, rather than a quadratic trend. The two individual trajectories help elucidate the origin of this plateau; when individual trajectories with such substantial between-swimmer variation in quadratic curvature and points of truncation are combined, the result is a mean performance progression band with a lengthy plateau beyond the adolescent years of substantial progression. The variation in the quadratic trajectories between swimmers probably results from factors such as individual differences in physical maturation, training adaptation, skill acquisition, and racing experience (Lätt et al., 2009a; Lätt et al., 2009b; Mikulic, 2011; Simonton, 1988). If any of these factors were to result in a plateau in performance for a substantial proportion of individual swimmers, then on average the residuals beyond the modelled age of peak performance would be negative, which we did not observe. In fact, performance declines were evident for swimmers who continued competing beyond their peak (data not shown), further supporting our use of quadratic modelling.

Previous models of changes in individuals' swimming performances (Berthelot et al., 2012, Costa et al., 2010) have not focused on including adjustments for factors such as level of competition and the introduction of major technological innovations. Our use of mixed modelling allows specification of fixed effects to account for and estimate the impact of Olympic years and of the polyurethane swimsuit year on the individual performance trajectories of top swimmers. The similarity of our estimates (both ~1% enhancements) to those of previous researchers provides additional evidence to support the suitability of our modelling. In a study of the progression and variability of competitive performance of Olympic swimmers, Pyne et al. (2004) found that mean performance improved by ~1% over the year leading up to the Olympics. Across 2008 and 2009, polyurethane swimsuits were estimated to provide top swimmers with mean performance gains of 0.3-1.2% on top of their expected progression (Berthelot et al., 2010). Our estimate falls within this range, although we chose to include a fixed effect in our model only for 2009, the year in which polyurethane swimsuits became universally prevalent at top swimming competitions. It is likely that swimsuits also contributed to extra performance enhancements off their trends that many swimmers showed in 2008, in addition to the Olympic year effect.

The mixed model has also allowed us to account for and quantify changes in variability of the performance of top swimmers from year-to-year by specification of different residual random

effects across three age ranges. Previous researchers in this area have estimated between-competition variability in within-swimmer performance only in two distinct career phases, not over the course of individual swimmers' entire careers. Pyne et al. (2004) estimated that between-competition performance for Olympic swimmers typically varied by 0.8%, which aligns well with our model's estimated residual of 1% for the >19 age-group. Costa et al. (2011) presented the means and standard deviations for the year-to-year performance changes of Portuguese male freestyle swimmers between the ages of 12 and 18. Dividing these standard deviations by $\sqrt{2}$ (Hopkins, 2000) gives a typical error of ~1.7%, which is somewhat less than the 3% residual variance that we estimated for the <17 age-group. The considerable difference between these estimates can be explained presumably by the greater random deviation from quadratic trends in annual best performances that occurs at earlier ages. This deviation likely results from the greater variability in physical and psychological maturation, skill acquisition, racing experience and competition preparation that is inevitably present in younger swimmers. Investigating different residual variances within the 12-16 age-bracket would have allowed more detailed assessment of the variability in developing swimmers, but the size of our dataset prevented us from specifying different residuals for more than three age-groups. Younger swimmers (12-13 y) have been shown to display greater variability than those closer to 16 y (Costa et al., 2011), and readers should be mindful of this caveat when interpreting the 90% reference range of the mean progression band shown in Figure 4 across these age-ranges.

The trajectories predicted mean age of peak performance in top swimmers of ~24 y for men and ~22 y for women. Whilst these predictions aligned well with the age at which top swimmers achieved their best performance, both are greater than previous published estimates. Schulz and Curnow (1988) found that Olympic freestyle gold medallists between 1948 and 1980 achieved their winning performances at ~20 y for men and ~18 y for women. Estimates may have been greater in the present study because of recent increases in funding and resources that have allowed top swimmers to forge a career in the sport and thereby continue training and competing to ages closer to their true performance peak than previously possible. Indeed, Berthelot et al. (2012) found peak performance in all freestyle swimmers ranked in the annual world top 10 between 1980 and 2009 occurred around 21 y, consistent with an upward secular trend in age of peak performance.

Our findings that top male swimmers achieved peak performance ~2 y later than their female counterparts and that peak performance occurred at later ages for the shorter distances for both sexes are consistent with previous research (Berthelot et al., 2012; Schulz & Curnow, 1988). Given that progressions to peak performance were similar for both sexes (Table 4), the difference in age of peak performance between sexes appears to be explained almost entirely by the ~2-year earlier onset of puberty in females compared with males (Baxter-Jones & Sherar, 2006). Reasons for the differences in age of peak performance between distance-groups and between IM swimmers and single-stroke swimmers are less apparent, but may relate to the greater external training loads typically undertaken by swimmers specialising in longer distances or in all four strokes. As distance and IM swimmers get older they may become unwilling to, or physiologically unable to, sustain the training loads required to achieve top performances in their events. Alternatively, these swimmers may sustain the training loads but

the training stress takes its toll in the form of injury (Gaunt & Maffulli, 2012) or staleness (Morgan, Brown, Raglin, O'Connor, & Ellickson, 1987). Either scenario could result in a premature peak in performance and/or premature drop-out. For example, when explaining her decision to retire from competitive swimming at age 23, multiple Olympic distance freestyle medallist Rebecca Adlington stated in an article published in The Daily Telegraph (2013), "I've noticed over the years that I can't do the same level of work as I used to be able to do and I need a lot more rest and recovery."

Another factor that could contribute to later peaking in the shorter distances is a tendency for distance swimmers to switch to shorter events as they get older in order to remain competitive. Research from other sports (e.g., in athletics) has found conflicting evidence about differences in ages of peak performance between shorter and longer distance events (Hollings et al., 2014; Schulz & Curnow, 1988). A comprehensive review of research into differences in ages of peak performance between and within sports is needed in order to better understand the complex relationships between athlete development, training and sport performance.

We found that top swimmers hold their performance peak for ~2.5 y (±1.5 y), irrespective of event. This duration seems quite short considering that several top swimmers have achieved success across multiple Olympic Games (e.g., Michael Phelps, Ryan Lochte). The explanation for this apparent paradox may be that supremely talented swimmers are able to win medals whilst not at peak-performance, owing to their substantially greater performance levels in comparison to their competitors. For example, Katie Ledecky won the gold medal in the 800-m freestyle at the 2012 Olympics, but subsequently substantially improved her performance time in 2013, indicating she has not yet reached her performance-peak (Figure 4).

Our study is the first to quantify the longitudinal age-related progression to peak performance for top swimmers. Costa et al. (2010) found that male top-150 world-ranked freestyle swimmers improved by approximately 3-4% over five seasons, but these improvements were effectively averages over a wide age-range. Whilst they are similar to the ~2.5% four-year progression to age of peak performance found in the present study, our age-related and stroke-specific estimates should be more useful for talent development. Swimmers and coaches can also use these estimates for short-term performance goal-setting.

The slower rates of progression to peak performance, and wider windows of peak performance of female breaststrokers compared to female swimmers of other strokes might be explained by between-stroke differences in technical demands. Our findings concur with anecdotal observations that breaststroke is the hardest stroke for developing swimmers to learn owing to complexities in mastering the timing and co-ordination required to effectively execute the stroke.

As also stated in the results, the four and eight-year progressions for female medallists are a little greater than those of their non-medallist counterparts. Explanations for these differences in progression between female, but not male swimmers, are unclear but may be related to differences in maturation between the sexes. For example, neuromuscular spurts within one year of peak height velocity have been detected in adolescent boys, but not in girls (Hewett, Myer, & Ford, 2002), implying that males may have a greater capacity for performance progression through technical improvements during maturation (Rushall, 2011b). However, as

46

recent research found no substantial differences in several physical, physiological and biomechanical variables known to affect performance between young male and female swimmers (Morais et al., 2013), reasons for the differences in performance progression between genders requires further research. Any enhanced capacity for skill acquisition and technique development is probably best utilised by male distance swimmers, as shorter distance swimmers may require full maturity to generate enough power to allow them to perfect their technique at swimming speeds close to race-pace. Such complex interactions between technical and maturational factors may account for the greater rates of progression to peak performance of male distance swimmers compared with male sprint and middle-distance swimmers, and also contribute to the later ages of peak performance in shorter distance swimmers.

The uncertainty in our estimates of progression increased with increasing years prior to peak performance. Beyond eight years prior to the peak age (~16 y for men, ~14 y for women), there may be too much uncertainty for our estimates to be considered sensitive benchmarks for talent development. Costa et al. (2011) also found evidence to suggest that the performance of sub-elite male freestyle swimmers does not become sufficiently stable to yield meaningful predictions of adult performance until age 16. More research on this aspect of talent development is needed.

3.5. Conclusion

We have developed a method for producing quadratic trajectories to track the career development of Olympic swimmers using their annual best performances. This method has provided event-specific performance-progression benchmarks and estimates of age of peak performance that should be useful for coaches, scientists and national sporting organisations interested in tracking the development of their swimmers. Practical applications of our method for talent development could be extended by modelling age-related trajectories for swimmers of any standard using their competition and/or time-trial performances.

CHAPTER 4

PREDICTING A NATION'S OLYMPIC-QUALIFYING SWIMMERS

This chapter comprises the following paper published in the International Journal of Sports Physiology and Performance:

Allen, S. V., Vandenbogaerde, T. J., Pyne, D. B., & Hopkins, W. G. (2015). Predicting a nation's Olympic-qualifying swimmers. *International Journal of Sports Physiology and Performance*, *10*, 431-435.

Overview

Talent identification and development typically involve allocation of resources towards athletes selected on the basis of early career performance. **Purpose:** To compare four methods for early career selection of Australia's 2012 Olympic-qualifying swimmers. **Methods:** Performance times from 5738 Australian swimmers in individual Olympic events at 101 competitions between 2000 and 2012 were analysed as percentages of World Record times using four methods that retrospectively simulated early selection of swimmers into a talent-development squad. For all methods, squad-selection thresholds were set to include 90% of Olympic qualifiers. One method used each swimmer's given-year performance for selection, while the others predicted each swimmer's 2012 performance. The predictive methods were regression and neural-network modelling using given-year performance and age, and quadratic trajectories derived using mixed modelling of each swimmer's annual best career performances up to the given year. All methods were applied to swimmers in 2007 and repeated for each subsequent year through 2011. **Results:** The regression model produced squad sizes of 562, 552, 188, 140, and 93 for the years 2007 through 2011. Corresponding proportions of the squads consisting of Olympic qualifiers were 11%, 11%, 32%, 43%, and 66%. Neural-network modelling produced similar outcomes, but the other methods were less effective. Swimming Australia's actual squads ranged from 91 to 67 swimmers but included only 50-74% of Olympic qualifiers. **Conclusion:** Large talent-development squads are required to include most eventual Olympic qualifiers. Criteria additional to age and performance are needed to improve early selection of swimmers to talent-development squads.

4.1. Introduction

The primary aim of talent identification programmes is to systematically identify athletes with high potential for success in senior elite sport. The increasing competition between nations for medals at major international events such as the Olympic Games and World Championships in recent years (de Bosscher, de Knop, van Bottenburg, & Shibli, 2006) has driven many national sporting organisations to attempt to focus their available resources more effectively by identifying talented athletes well in advance of these events (Vaeyens, Lenoir, Williams, & Philippaerts, 2008).

The typical approach to talent identification of most national sporting organisations has been early recruitment of athletes into talent-development programmes based primarily on their age-related competition performance (Güllich & Emrich, 2012). This approach relies upon the assumption that early sporting success is a pre-requisite for senior elite success (Güllich & Emrich, 2006). However, given the generally low conversion rates of elite junior athletes into elite senior athletes in swimming (Barreiros, Côté, & Fonseca, 2014) and similar sports (cycling, Schumacher, Mroz, Mueller, Schmid, & Ruecker, 2006; running, Hollings & Hume, 2010), this assumption appears contentious. Furthermore, research into the progressions of athletes within a national sporting system has found that the higher their age of selection to any national squad, the higher the squad level that an athlete ultimately reached (Güllich & Emrich, 2012). Several researchers have consequently questioned the utility of talent identification on the basis of performance at early ages (Gulbin, Weissensteiner, Oldenziel, & Gagné, 2013; Régnier, Salmela, & Russell, 1993; Vaeyens et al., 2008) but this approach has rarely been evaluated quantitatively.

In the present study we compared four methods for early selection of Australia's 2012 Olympic-qualifying swimmers using age-related competition performance data. First, we established the accuracy of selecting swimmers to a talent-development squad based solely on their competitive performance in a given year. Secondly, we used regression analysis to assess the validity of the assumption that successful junior athletes progress consistently through to senior elite success. Thirdly, we extrapolated each swimmer's quadratic age-related career performance trajectory (Allen et al., 2014) to evaluate the predictive relationship between past and future performance. Finally, we used the non-linear method of neural-network modelling to attempt to relate the complex development of swimmers to performance. Previous comparisons of the accuracy of statistical methods for predicting swim performance have shown neural-network modelling to produce more precise predictions than standard linear (Edelmann-Nusser et al., 2002) and non-linear (Maszczyk et al., 2012) regression models, and the linear method of discriminant function analysis (Hohmann & Seidel, 2010), although no such research has been conducted in the context of nationwide talent identification.

4.2. Methods

Official long-course performance times from all Australian swimmers in individual Olympic events from 101 age-group and open domestic and international competitions between 2000

and 2012 were provided by Swimming Australia. Each swimmer's best annual times in a given event were converted into percentages of given-year World Record times for analysis. Overall, there were 84,868 times from 5,738 swimmers, 70 of whom recorded at least one performance time faster than an individual FINA A Olympic-qualifying standard in 2012. Throughout this research we have referred to these 70 swimmers as "Olympic-qualifying swimmers", although only 45 swimmers were ultimately selected to represent Australia at the 2012 Olympics.

Four methods were used to retrospectively simulate early selection of Australia's 2012 Olympic-qualifying swimmers to a talent-development squad. All methods were applied to swimmers in 2007 and then repeated for each subsequent year through 2011. One method ranked swimmers in order of their given-year performances, while the other three methods used each swimmer's performance and age data to predict their 2012 performance.

The first predictive method was regression of given-year performance (linear) and age (linear and quadratic), which were specified as fixed effects using the mixed linear model procedure (Proc Mixed) in the Statistical Analysis System (Version 9.2, SAS Institute, Cary, NC). The second predictive method also used Proc Mixed in SAS 9.2 to model each swimmer's best annual career performances in a given event, together with the best annual career performances of Olympic top-16 swimmers in the given event (Allen et al., 2014), to produce quadratic performance trajectories for each Australian swimmer with at least three years of performance data. These trajectories were then extrapolated forwards to 2012 to generate predicted times for each swimmer, as demonstrated by the example shown in Figure 5. The fixed and random effects specified within this model were the same as those included in the individual-trajectories mixed model outlined previously by Allen et al. (2014).

The final predictive method was a multilayer feed-forward neural-network model with the structure 3-3-1, with three input variables (given-year performance, age and event), three neurons in the hidden layer, and one output variable (predicted 2012 performance time). We conducted this modelling in SAS Enterprise Miner (Version 12.3, SAS Institute, Cary, NC), using 95% of our given-year dataset for model training, the remaining 5% for validation, and the default iterative Levenberg-Marquardt algorithm to optimise model learning.

For a given predictive method in a given year each swimmer's top predicted performance from all events was retained for the squad selection process. For all methods, thresholds for squad selection were set to ensure 90% of Olympic qualifiers with data for a given year would be included, on the basis that the threshold for the smallest substantial proportion is 10% (Hopkins et al., 2009). Final squad sizes therefore also included all non-qualifying swimmers with actual (first method) or predicted times faster than the set thresholds.

We determined the effectiveness of our methods by evaluating the proportions of the talent-development squads consisting of Olympic qualifiers. These proportions served as a proxy measure for the sizes of the squads, allowing us to assess differences between methods regardless of the number of swimmers with available performance data for each method. Proportion ratios representing year-to-year differences within methods and within-year differences between methods were evaluated using a scale with thresholds of 1.11, 1.43, 2.0, 3.3, and 10 for small to extremely large increases, respectively, and their corresponding inverses for decreases (Hopkins et al., 2009). Qualitative mechanistic inferences about the true

value of a difference were based on uncertainty in the magnitude of the ratio (expressed as 90% confidence limits): if the confidence interval overlapped values for a substantial increase and decrease, the ratio was deemed unclear; otherwise, the ratio was deemed clear and reported as the magnitude of the observed value (Batterham & Hopkins, 2006).
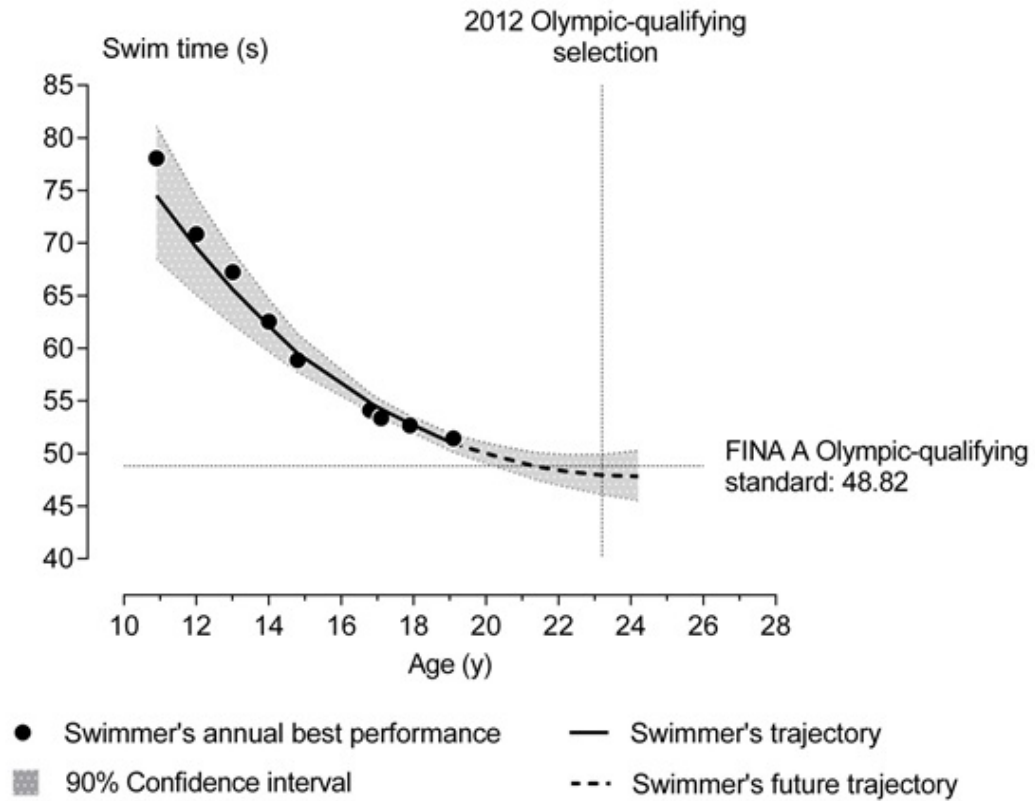
Figure 5. Best annual performance times, career performance trajectory and future trajectory (both plus 90% confidence interval) for an Australian male 100-m freestyle swimmer predicted in 2008 to go on to achieve the FINA A Olympic-qualifying standard in 2012**.**

4.3. Results

Numbers of swimmers selected into the talent-development squads and the corresponding proportions of the squads consisting of Olympic-qualifying swimmers for each of the four selection methods are shown in Table 5. These proportions increased substantially with each year after 2008, with clear small to large year-to-year increases (1.3-2.9; range of proportion ratios) observed for all methods and year-to-year comparisons. Confidence limits for all of these pairwise comparisons were ~×/÷1.2.

Neural-network modelling and regression of swim time and age produced the highest proportions of Olympic qualifiers in the squads over the selection period. The neural-net method generally performed marginally better than the regression method by trivial to small but mostly unclear amounts (0.8-1.2). Both methods typically outperformed the selection of swimmers on the basis of their given-year swim time by clear small to moderate amounts (1.2-1.5). In 2007

Table 5. Talent-development squad sizes required to ensure inclusion of 90% of 2012 Olympic qualifiers for each of four methods in each year (2007-2011). Proportions (%) of the squads consisting of eventual Olympic qualifiers are also shown.

Squad selection method	2007		2008		2009		2010		2011	
	Squad size	Olympic qualifiers	Squad size	Olympic qualifiers	Squad size	Olympic qualifiers	Squad size	Olympic qualifiers	Squad size	Olympic qualifiers
Swim time as % of World Record	685	9%	511	12%	272	22%	128	48%	112	55%
Regression of swim time and age	562	11%	552	11%	188	32%	140	43%	93	66%
Quadratic performance trajectories[a]	413	12%	329	17%	262	22%	201	30%	168	38%
Neural-network modelling	475	13%	498	12%	226	27%	129	47%	92	66%

The number of swimmers with available performance data in each year was 2690 ± 240 (mean ± SD). The number of 2012 Olympic qualifiers with available performance data in each year was 67 ± 1.

[a]At least three years of performance data in a given event were required to create individual quadratic trajectories. The number of swimmers with available performance data for this method in each year was 1690 ± 150. The number of 2012 Olympic qualifiers with available performance data for this method in each year was 64 ± 6.

Table 6. Swimming Australia's actual squad sizes, proportions (%) of the squads consisting of 2012 Olympic qualifiers, and proportions (%) of eventual Olympic qualifiers who were included in the squads in each year (2007-2011).

	2007	2008	2009	2010	2011
Squad size	88	91	90	69	67
Proportion of squad consisting of Olympic qualifiers	40%	47%	57%	65%	78%
Proportion of Olympic qualifiers included in the squad	50%	61%	73%	64%	74%

and 2008, the trajectories method performed better than most other methods by clear small to moderate amounts (1.1-1.5), but from 2009 onwards it was outperformed by all other methods by clear small to moderate amounts (1.2-1.8). Confidence limits for all of these pairwise comparisons were ~×/÷1.3.

Table 6 shows the actual number of swimmers who received Olympic-preparation funding and resources from Swimming Australia in the five-year period prior to the 2012 Olympics, the proportions of these squads consisting of Olympic qualifiers, and the proportions of the 70 Olympic qualifiers who were selected to the squads in each year. Proportions of eventual qualifiers correctly selected by Swimming Australia were less than the 90% estimated in our analysis by clear moderate amounts in 2007 and 2008 (1.5-1.8, ~×/÷1.1; range of proportion ratios, ×/÷90% confidence limits) and by clear small amounts in 2009 through to 2011 (1.2-1.4, ~×/÷1.1). Proportions of the Swimming Australia squads consisting of Olympic qualifiers were greater than those estimated in our analysis by clear large to very large amounts in 2007 and 2008 (2.8-4.5, ~×/÷1.2), moderate to large amounts in 2009 (1.8-2.6 ~×/÷1.2), and small to moderate amounts in 2010 and 2011 (1.2-1.5, ~×/÷1.1).

4.4. Discussion

In the present study we have compared the predictive accuracy of four methods for early selection of Australia's 2012 Olympic-qualifying swimmers using a retrospective simulation approach. By analysing the age-related competition performance data of all Australian swimmers in the five years prior to 2012, we have been able to quantitatively evaluate the efficacy of conducting a theoretical national talent-identification programme on the basis of early performance.

The neural-network modelling and regression of swim time and age methods generally produced the highest proportions of Olympic qualifiers in the talent-development squads. The superior predictive accuracy of both methods compared with the selection of swimmers based solely on their given-year performance was unsurprising, owing to the well-established effects of age on swim performance (Allen et al., 2014; Berthelot et al., 2012; Costa et al., 2011).

However, the similar predictive accuracy of the regression method to the neural-network analysis was somewhat unexpected, given that previous research has found neural-network modelling to produce more precise predictions of swim performance than standard linear (Edelmann-Nusser et al., 2002) and non-linear (Maszczyk et al., 2012) regression models. While standard regression models assume the dependent variable to be equal to the additive effects of the predictor variables, neural networks are not constrained by any assumptions about the relationship between the predictor and dependent variables, and might therefore be expected to more realistically relate the complex non-linear processes of maturation and training adaptation to performance in developing swimmers (Silva et al., 2007). One explanation for neural-network modelling failing to outperform regression in the analysis could be that our regression model appropriately represented the underlying relationship between early and future performance. Therefore, the neural net might have been unable to produce more accurate performance predictions without the inclusion of input variables additional to the three (age, performance and event) specified in our analysis. Indeed, a neural-network analysis predicting the senior talent grouping of over 700 junior German swimmers from 21 physical and technical variables achieved substantially more success than a linear discriminant-function model (Hohmann & Seidel, 2010).

An insufficient amount of input information might also explain why all of our performance and age-based methods produced substantial proportions (≥10%; Hopkins et al., 2009) of squad members who were incorrectly identified as Olympic qualifiers in any given year. Consistent with this assertion, previous research has shown that performances of developing swimmers do not become sufficiently stable to yield meaningful predictions of adult performance until around age 16 (Costa et al., 2011). Another study also found that the majority of swimmers selected to national squads as juniors did not progress consistently through their developmental years to become senior national squad members (Güllich & Emrich, 2006). Consequences of such erroneous early classification include inefficient use of the finite supply of Olympic-preparation funding and resources available to most national sporting organisations. Therefore, to improve the predictive accuracy of early selection of swimmers into talent-development squads and enhance the efficiency of funding and resource allocation, it would seem prudent to consider variables additional to age and performance as part of the talent-identification process.

The challenge to national swimming federations will undoubtedly be how best to systematically capture and track the myriad variables important for swim performance (Barbosa et al., 2013) from enough swimmers to provide useful information for talent identification alongside the more readily available age and performance data. The general consensus between recent research into the relative contributions of many such variables to performance (Figueiredo et al., 2013) and coaching knowledge and experience (Sweetenham, 2001) seems to be that biomechanical and technical factors form the primary determinants of successful development of swimming performance. Therefore, a useful starting point for the process of widespread monitoring of variables other than age and performance may be assessment of stroke mechanics and efficiency parameters plus anthropometrical measurement at regular talent-development squad camps using well-established and practically viable testing procedures (Savage & Pyne, 2013).

Our trajectories method involved analysing more information than the other methods; each swimmer's age-related career performance history was modelled together with the best annual career performances of Olympic top-16 swimmers in a particular event. The lowest predictive accuracy demonstrated by this method after 2008 was presumably due to the over-optimistic assumption that all Australian swimmers would fit the age-related performance progression profiles of Olympic top-16 swimmers, which likely resulted in over-prediction of many swimmers' 2012 performance times. However, the trajectories method did manage to outperform most of our other methods in 2007 and 2008, indicating that it may still offer a useful tool for national talent-identification programmes. For example, one advantage of the trajectories method may be its potential as an initial screening tool to recruit all swimmers tracking towards achieving Olympic-qualification standards into a talent-development squad, if some of these swimmers were missed by our other methods. For this strategy to allow screening of as many swimmers as the other methods, modelling of larger amounts of performance data (i.e., more regional competitions) than those included in our analysis would be required. A limitation of the present study was that in a given year we were unable to consider many swimmers for selection to the talent-development squads using the trajectories method, owing to the fact that at least three years of performance data in a given event were necessary to model individual trajectories.

Compared to Swimming Australia's squads, our analysis methods produced talent-development squads consisting of substantially smaller proportions of Olympic qualifiers, along with larger corresponding squad sizes. However, the proportions of eventual qualifiers who were not selected by Swimming Australia for funding and resource allocation were also substantially greater than the smallest important proportion (10%; Hopkins et al., 2009) used as the threshold for selection in our analysis. Indeed, the Independent Review of Swimming (Australian Sports Commission, 2013, p. 48) conducted by the Australian Sports Commission after the 2012 Olympics stated that, by focusing primarily on age-related performances in their talent-identification strategy, Swimming Australia had been relying on "talent rising to the top in an almost ad-hoc fashion". By targeting resources towards larger groups of swimmers several years out from an Olympics, Swimming Australia and other national swimming federations might further improve the performance–and thus the medal prospects–of those swimmers who would eventually achieve Olympic-qualification times without the benefit of early access to resources. While this strategy appears logical, contradictory evidence from the German elite sport system showed that athletes recruited to talent-development squads at young ages exited the system earliest, and that use of athlete support services was not substantially related to greater attainment of senior success (Güllich & Emrich, 2012). The applicability of these findings to other national sporting systems, and to sports such as swimming in which athletes typically specialise at early ages (Vaeyens et al., 2009), is uncertain and clearly warrants the attention of future research.

4.5. Practical Applications and Conclusions

We have presented a quantitative analysis of the efficacy of conducting a national talent-identification programme on the basis of current swim performance and age. Our analysis has demonstrated that Australian talent-development squads selected on this basis would need to contain hundreds of swimmers several years out from an Olympics to ensure 90% of eventual qualifiers were included in the squads. Identifying swimmers with performances tracking towards Olympic-qualification standards on an annual basis using our individual trajectories screening tool, and then inviting swimmers to regular camps to capture and monitor identified variables additional to age and performance, should improve the predictive accuracy of early selection of swimmers into talent-development squads. Targeting Olympic-preparation funding and resources towards larger groups of swimmers might further improve the prospects of those who achieve Olympic-qualification times without the benefit of early selection to talent-development squads. Such a strategy would give appropriate early recognition of talent, while also producing more swimmers capable of meeting Olympic-qualification times.

CHAPTER 5

RELATIONSHIPS BETWEEN CAREER TRAINING AND PERFORMANCE IN COMPETITIVE SWIMMERS

This chapter comprises the following paper submitted to European Journal of Sport Science: Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (submitted). Relationships between career training and performance in competitive swimmers. *European Journal of Sport Science*.

Overview

Understanding the career training that leads to successful performance is important for athlete development. **Purpose:** To quantify the relationships between career training durations and performance in competitive swimmers. **Methods:** Retrospective questionnaires obtained the weekly hours of pool, dryland and other-sports training completed by 324 national-level swimmers (age-range 13.3-28.7 y) at each chronological age of their careers. Each swimmer's best two annual long-course competition performances in each event between 2002 and mid-2014 were downloaded from takeyourmarks.com (~43,600 performances), and career (cumulative) training hours leading up to each performance were calculated. Performance differences between tertiles of career swim-specific training (pool+dryland hours), and the modifying effects associated with tertiles of career non-specific training (other-sports hours) were estimated for sex and distance groups (sprint, ≤100-m; middle-distance, 200-m; distance, ≥400-m) for five age-groups using mixed linear models that adjusted for individual quadratic effects of age. **Results:** More swim-specific training was related to better performance in the younger age-groups (sprint and middle-distance, <13 y; distance, <15 y). In the oldest age-group (≥19 y), the upper tertile of swim-specific training (>~10,500 h) was associated with clear performance advantages for females, which increased with event distance from small for sprinters (0.7%, ±0.5%; mean, ±90% confidence limits) to very large for distance swimmers (2.3%, ±0.6%), while no one tertile was clearly superior for males. Other-sports training hours showed little association with performance, except for the oldest female ≤200-m swimmers, for whom the middle tertile (~2000 h) was typically best. **Conclusion:** Cumulative training hours are important for talent development at an early age in swimmers, but at the most senior level only females may continue to benefit from a history of more swim-specific training.

5.1. Introduction

The career training of athletes plays a key role in determining their competitive performance (Tucker & Collins, 2013). Knowledge of the relationships between specific and non-specific career training durations and performance could provide coaches, scientists and national sporting organisations with valuable information to guide training programmes and improve long-term athlete development.

Research into the acquisition of expert performance has produced two contrasting theories of the contribution of training history to elite sporting success. Ericsson, Krampe and Tesch-Römer's (1993) deliberate-practice model states that ~10,000 hours of domain-specific training is both necessary and sufficient to produce expert performance. Conversely, Côté, Baker and Abernethy's (2007) developmental model of sport participation proposes that early diversification of training followed by late specialisation is the optimal path to athletic expertise. At present the strengths and weaknesses of both theories remain a subject of much debate in the sport-science literature, owing to inconsistent research findings within and between sports (Güllich & Emrich, 2014).

Within the sport of swimming, the typical approach to athlete development has been early specialisation, with high durations of training often being performed at early ages (Lang & Light, 2010). This approach has received criticism for overtraining swimmers (Rushall, 2011a) and for detracting from technique development (Arellano, 2010), leading to impaired long-term performance. Previous studies of training history and swim performance have generally observed weak relationships between swim-specific training hours and <200-m performance (Hodges, Kerr, Starkes, Weir, & Nananidou, 2004; Johnson, Tenenbaum, & Edmonds, 2006), although large positive correlations have been found for longer-distance events (Hodges et al., 2004). However, quantitative assessments of the relationships between training duration and performance were made only by Hodges et al. (2004), who investigated linear relationships using regression analysis. The more probable scenario is a non-linear relationship with an optimum duration, given the fine balance of training time and recovery time required for successful performance (Halson & Jeukendrup, 2004). Therefore, a different method is needed to quantify the relationships between different durations of career swim-specific training and competitive performance in a non-linear manner.

In the present study we used mixed modelling to estimate the differences in swim performance between lower, middle and upper tertile groups of career swim-specific training hours. For the best tertile at each age, we also quantified the modifying effects associated with tertiles of career other-sports training hours, in an attempt to investigate the pathway to high-level swim performance. Although previous research has found some evidence of greater career engagement in other-sports training in elite versus sub-elite swimmers (Johnson et al., 2006), no studies have yet quantified the relationships between performance and career durations of other-sports training for swimmers with different swim-specific training backgrounds.

5.2. Methods

Swimming New Zealand provided contact details for all 76 New Zealand clubs with swimmers who competed at either the national age-group or national open championships in 2013. Retrospective training background questionnaires were administered to 535 national-level swimmers (245 female, 290 male) from 72 of these clubs. Completed questionnaires were returned by 153 females (age 17.0 ± 2.5 y; mean ± SD) and 171 males (age 17.5 ± 2.6 y) from 65 clubs, which equated to a 61% response rate. All swimmers provided informed consent as required by the AUT University Ethics Committee, which approved the study.

We developed the questionnaire with the aid of several national-level swim coaches and the High Performance Sport New Zealand athlete-development team. The questionnaire was trialled on several club-level and retired national-level swimmers a month before the start of the study. The first section of the questionnaire ascertained each swimmer's full name and birthdate, allowing us to match their responses with their competitive performance data. The second section obtained information about the swimmer's training history in sports other than swimming. For each sport swimmers were asked to report their age when they began participating, their years of participation, and their average weekly participation hours. In the third section swimmers provided their pool-training history, reporting their average weekly training hours at each chronological age of their careers. The final section of the questionnaire required swimmers to document their average weekly hours spent engaging in dryland activities designed to enhance their swimming performance at each age. Throughout the final two sections swimmers were asked for additional details about their pool and dryland training to stimulate more accurate recollection of training time; these questions obtained information on session frequency, types of training engaged in, and details of their coach, swim club, and squad. Analyses of these data are not presented here.

All official long-course competition performance times between 2002 and mid-2014 were downloaded for all swimmers from the official database of competitive swimming results in New Zealand, takeyourmarks.com. Each swimmer's questionnaire responses were matched to their best two annual performances in each event with at least three years of data. Overall, there were 20,437 female performances and 23,155 male performances, with a similar number of performances per swimmer per event for both sexes (13.2 ± 4.8). We then calculated the career hours of swim-specific training (pool plus dryland hours) and other-sports training associated with each performance by summing swimmer-reported annual hours for each career year up to the performance date and multiplying by 48, the approximate number of coach-reported training weeks per year for New Zealand swimmers (Stewart & Hopkins, 2000a).

To allow for non-linearity in the relationships between career training durations and swim performance, we decided to investigate differences in performance between groups of low, medium and high training durations at different ages. Performances were first split into five age-groups (Table 7) and then split into lower, middle and upper tertiles of career swim-specific training hours for each age-group. All performance times were log-transformed for analysis of percent effects using the mixed linear model procedure (Proc Mixed) in the Statistical Analysis System (Version 9.2, SAS Institute, Cary, NC). The first model included a fixed effect to

estimate the mean performance effect associated with each tertile of career swim-specific training for each age-group (age-group*swim-train tertile), and a fixed effect to account for the mean difference between each swimmer's annual best and second-best performance for each age-group (age-group*swim rank). Fixed and random effects for age accounted for the mean and individual quadratic effects of age on each swimmer's performance times, respectively. A within-swimmer random nominal effect for year adjusted for consistent deviation from each swimmer's quadratic trend in a particular year (due to injury, illness, etc.), such that the residual random effect in the model represented within-swimmer race-to-race variability in performance. A different residual variance was specified for each age-group to account for the greater stability of swim performance with increasing age (Costa et al., 2011). We applied the model separately to each of the 17 stroke and distance event combinations for each sex, but female performances in the 1500-m freestyle and male performances in the 800-m freestyle were subsequently excluded from the analysis, owing to insufficient data for model convergence (<150 performances per event). Given previous verification of the appropriateness of quadratic trends for modelling swim performance (Allen et al., 2014), we considered this model to be a suitable option for quantifying the relationships between career training and performance of competitive swimmers.

To investigate the modifying effects associated with career non-specific training for swimmers with different swim-specific training backgrounds, performances in each of the three swim-specific training tertiles for each age-group were split again into tertiles of career other-sports training. We then added a fixed effect for the interaction between tertile of career other-sports training, tertile of career swim-specific training and age-group to our original model and repeated the analysis for each of the 32 sex and event combinations. This fixed effect provided estimates of the mean modifying effect of career non-specific training associated with the performance of swimmers with low, medium and high career durations of career swim-specific training.

Percent differences in swim performance time between tertiles of career training and their associated uncertainties (90% confidence limits) for each event were combined into three event-distance groups (≤100 m, sprint events; 200 m, middle-distance events; ≥400 m, distance events) for each sex using a spreadsheet (Hopkins, 2006a). The resulting performance differences were evaluated using non-clinical magnitude-based inferences (Hopkins et al., 2009). Thresholds for assessing these differences were set separately for each age-group within each event-distance group for each sex, with the smallest important differences being 0.3 of the within-swimmer standard deviation in race-to-race performance (Hopkins et al., 2009), as specified by the residual random effect from the mixed model. Thresholds for moderate, large, very large and extremely large effects were 0.9, 1.6, 2.5, and 4.0 times the within-swimmer variability for each age-group and sex and event-distance groups, respectively (Hopkins et al., 2009). Uncertainty in estimates of all effects is expressed as 90% confidence limits and as likelihoods that the true value of the effect represents a substantial performance difference between tertiles (Batterham & Hopkins, 2006). To account for inflation of error owing to the large number of relationships investigated in this study, we have focused only on the effects that are clear with 99% confidence intervals in our results.

Table 7. Age (y) of each age group, number of performances in each age group for each sex and event-distance combination, and total number of swimmers contributing performances to each sex and event-distance combination.

Age group	Age	Females			Males		
		Sprint	Middle-distance	Distance	Sprint	Middle-distance	Distance
<13 y	11.3 ± 1.1	5827	2102	440	5583	2122	555
13-14 y	14.0 ± 0.6	3350	1620	725	3725	1879	830
15-16 y	15.9 ± 0.6	2247	1161	557	2839	1499	749
17-18 y	17.8 ± 0.6	883	444	223	1290	729	364
≥19 y	20.8 ± 1.8	492	229	137	548	293	150
Total number of swimmers		149	148	108	168	164	126

Age data are mean ± SD.

Differences in career training durations between event-distance groups, between sexes, and between age-groups were assessed via standardisation using thresholds of 0.2, 0.6, 1.2, and 2.0 for small, moderate, large and very large, respectively (Hopkins et al., 2009). Given that only moderate effects would be clear at the 99% confidence level with a sample size of ~85 in each of two compared groups (Hopkins, 2006b), we have highlighted only moderate or larger differences in our results.

Durations of career training are presented as mean ± SD for each age-group within each sex and event-distance combination. (The upper and lower tertile boundaries occur at ~0.5 SD above and below the mean.) Differences in swim performance time between tertiles of career training are shown for the middle tertile minus the lower tertile and the middle tertile minus the upper tertile. The modifying effects associated with career other-sports training are presented only for the tertile of career swim-specific training with the greatest performance benefits. Where the most beneficial tertile of career swim-specific training is not clear, effects are presented for the swim-specific training tertile with the greatest performance benefits associated with career other-sports training.

5.3. Results

The number of career hours of swim-specific and other-sports training leading up to performances for each age-group within each sex and event-distance group are displayed in Figure 6. Each sex and event-distance combination showed large to very large increases in swim-specific training hours between consecutive age-groups. Within the youngest age-group, female distance swimmers had performed moderately more swim-specific training than female sprinters, and by the oldest age-group, male sprint and middle-distance swimmers had accumulated moderately more other-sports training hours than their female counterparts. All other differences in career training durations between event-distance groups, between sexes, and between age-groups were trivial to small in magnitude.

The mean performance differences between tertiles of career swim-specific training for each age-group within each sex and event-distance combination are presented in Figure 7. In the youngest age-group (<13 y), more swim-specific training was related to better performance (likelihoods, possibly to most likely), with clear small performance benefits (0.7% to 1.7%, ~±0.3%; range in means, ±90% confidence limits) evident for the upper tertile of most sex and event-distance groups. These benefits continued into the second age-group (13-14 y) for distance swimmers, with the upper tertile of swim-specific training being associated with clear small performance advantages (0.4% to 0.6%, ~±0.3%; possibly to likely) for both sexes. However, for most sex and event-distance combinations, there was little performance benefit associated with the upper tertile of swim-specific training between the ages of 13 and 18. Indeed, male middle-distance and distance swimmers in the top tertile of swim-specific training experienced clear small performance impairments (-0.4% to -0.9%, ~±0.2%; likely to most likely) between the ages of 15 and 18.

In the oldest age-groups (sprint and middle-distance, ≥19 y; distance, ≥17 y and ≥19 y), the upper tertile of swim-specific training (>~10,500 h) was associated with clear performance advantages (likely to most likely) for females. These advantages increased in magnitude with increasing event distance, ranging from small for sprinters (0.7%, ±0.5%; mean, ±90% confidence limits), through to large for middle-distance swimmers (1.5%, ±0.7%), and very large for distance swimmers (2.3%, ±0.6%). The upper tertile of swim-specific training (>~9250 h) was also related to clear small performance benefits (0.7%, ±0.4%; likely) in the oldest age-group of male distance swimmers, but for the oldest male middle-distance swimmers the lowest tertile of swim-specific training (<~6500 h) was associated with best performance by clear large amounts (1.5%, ±0.6%; most likely). While no one tertile was clearly superior for male sprint swimmers in the oldest age-group, the middle tertile of swim-specific training (~6000-9000 h) was associated with clear small performance advantages (0.5%, ± 0.4%; likely) over the lower tertile (<~6000 h).
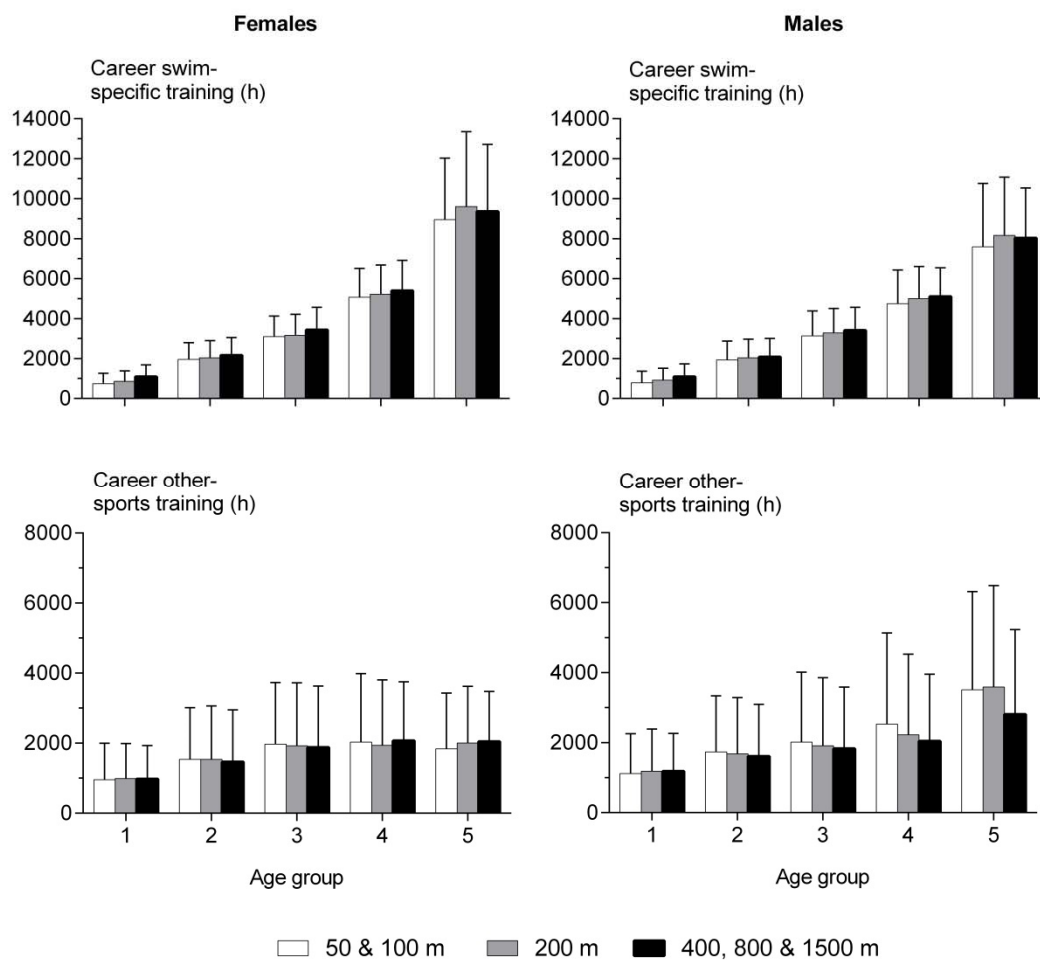
Figure 6. Career hours of swim-specific training (pool plus dryland hours) and other-sports training leading up to female and male swim performances in each age-group for the three event-distance groups. Data are means; error bars are SD.
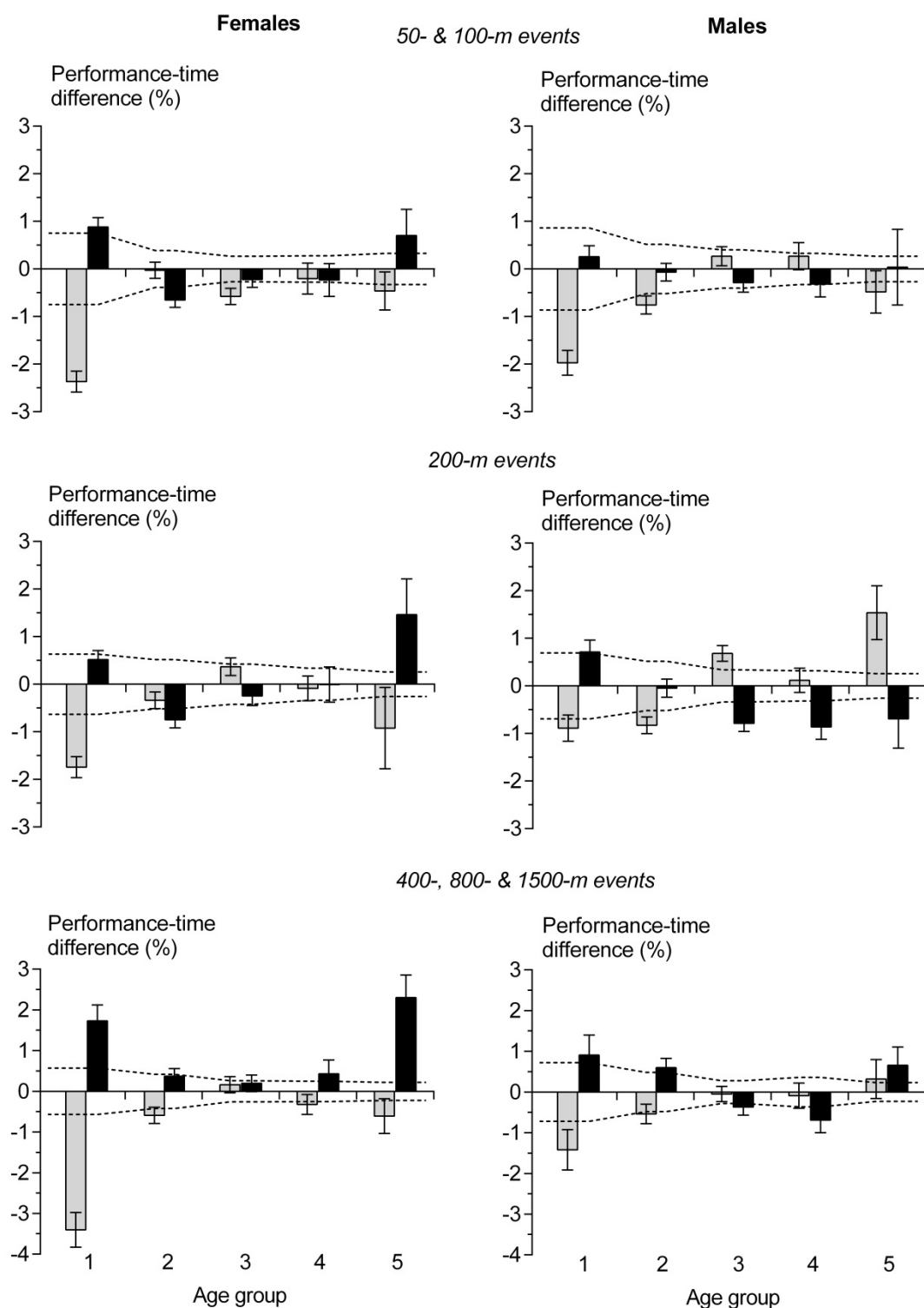
Figure 7. Differences in swim performance time (mean, ±90% confidence limits) between tertiles of career specific training (pool plus dryland hours) for each age-group. Differences are shown for the middle tertile minus the lower tertile (grey bars) and the middle tertile minus the upper tertile (black bars). Thresholds for the smallest important differences in swim time are represented by the dashed lines.
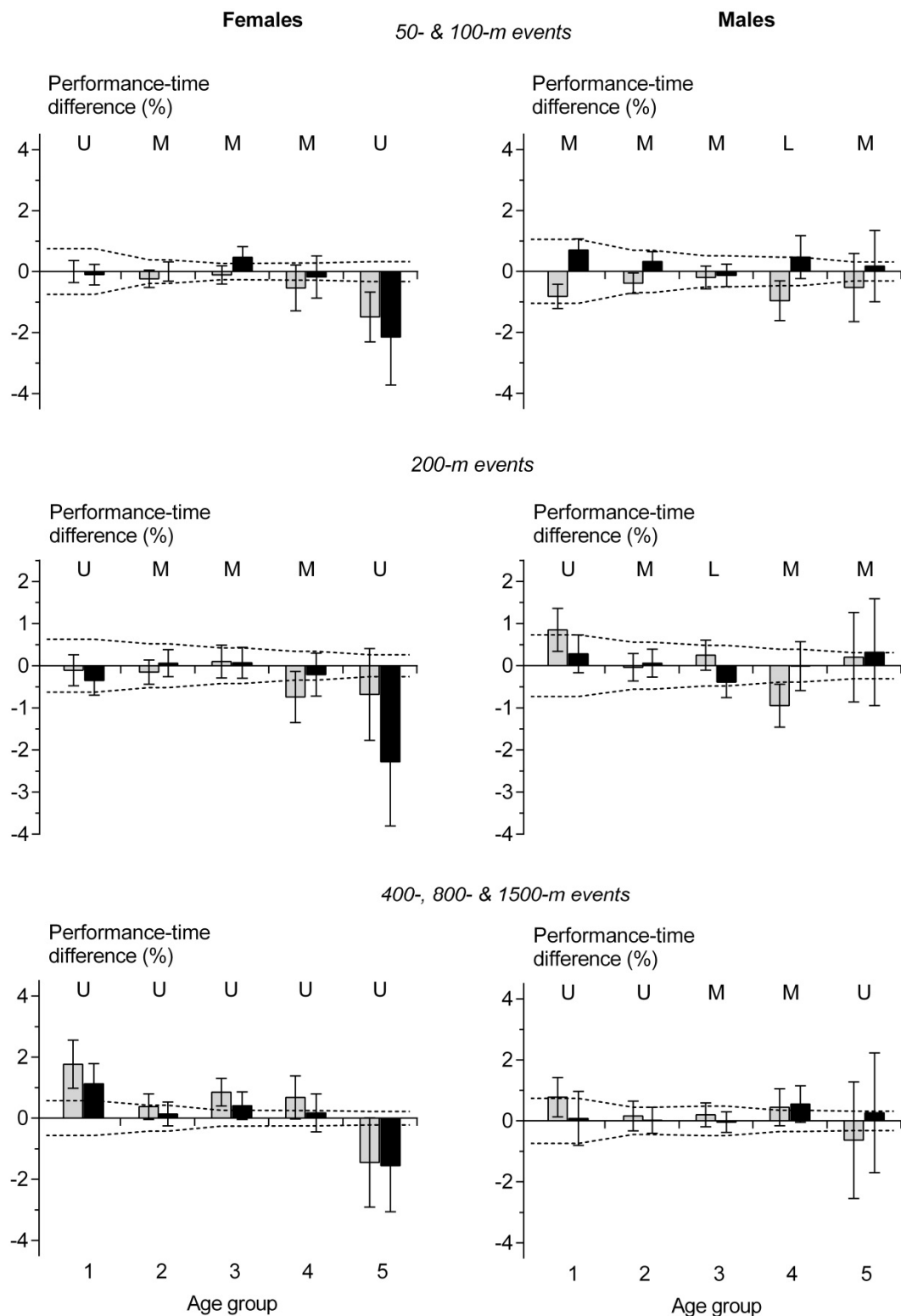
Figure 8. Differences in swim performance time (mean, ±90% confidence limits) between tertiles of career non-specific training (other-sports hours) for the best tertiles of career swim training (L, lower; M, middle; U, upper), for each age-group. Differences are shown for the middle tertile minus the lower tertile (grey bars) and the middle tertile minus the upper tertile (black bars). Thresholds for the smallest important differences in swim time are represented by the dashed lines.

Figure 8 shows the mean performance differences between tertiles of career other-sports training, for the tertiles of career swim-specific training with the greatest performance benefits for each age-group within each sex and event-distance group. For the youngest age-group (<13 y) of male middle-distance swimmers and distance swimmers of both sexes, the lower tertile of other-sports training (<~500 h) was associated with possibly to likely performance benefits, which were clear and small to moderate in magnitude (0.8% to 1.8%, ~±0.6%). Thereafter, most differences between tertiles of other-sports training were either trivial in magnitude or unclear at the 99% confidence level, with the exception of female performances in the oldest age-group. For these swimmers in all event-distance groups, the greatest performance effects tended to be associated with the middle tertile of other-sports training (~2750 h), which typically displayed clear large to very large benefits over the upper tertile of other-sports training (2.2% to 2.3%, ~±1.5%; likely).

The within-swimmer standard deviation of race-to-race performance typically decreased progressively with increasing age for all sex and event-distance groups. Male sprint swimmers generally displayed the greatest race-to-race variability for each age-group (2.9%, 1.7%, 1.3%, 1.1%, and 0.9%, youngest to oldest age-groups), while female distance swimmers showed the least variability (2.0%, 1.1%, 0.8%, 0.6%, 0.8%, youngest to oldest age-groups). Multiplied by 0.3, the standard deviations for these and the other event-distance groups appear in Figures 7 and 8 as thresholds for the smallest important performance effects for each age-group (Hopkins et al., 2009).

5.4. Discussion

In the present study we have quantified the relationships between career durations of training and swim performance using a novel application of mixed linear modelling. By estimating the performance differences between lower, middle and upper tertile groups of career swim-specific training hours, we have shown that the relationships between cumulative training durations and swim performance appear to be non-linear. In fact, our analysis revealed that accumulating more career swim-specific training by senior level may be of benefit only to female swimmers (Figure 7).

For the oldest age-group of female swimmers in our study (≥ 19 y), the career durations of swim-specific training associated with the best performance effects were above the 10,000 hours proposed by Ericsson et al.'s (1993) deliberate-practice model to be necessary and sufficient for development of expert athletic performance. While this finding contrasts with much evidence showing that top athletes from other sports often accumulate far less than 10,000 hours of domain-specific training (Bullock & Hopkins, 2009; Helsen, Starkes, & Hodges, 1998; Oldenziel & Gagne, 2004), comparable research with high-level swimmers has found large to very large positive correlations between career swim-specific training hours and performance (Hodges et al., 2004). Explanations for this discrepancy between swimming and most other sports may relate to differences in the medium of locomotion. The kinesthetic learning and reinforcement needed to develop and maintain the efficient aquatic motion necessary for

successful swim performance is thought to require greater time investment than that for successful performance in most land-based sports. Consequently, swimming has typically been considered an early specialisation sport, or a sport in which engaging in high practice volumes from early ages is beneficial for long-term performance (Balyi, 2010). Given that greater career domain-specific training hours have been shown to differentiate world-class performers from their national-level counterparts in another early specialisation sport, rhythmic gymnastics (Law, Côté, & Ericsson, 2008), it may be that long-term performance in certain sports can benefit from early specialisation, as proposed within deliberate-practice theory.

In contrast, our findings that senior-level male swimmers of most event distances seem to perform best with lower or moderate amounts of cumulative swim-specific training are inconsistent with the 10,000-hour rule of deliberate-practice theory. Previous similar research has also shown that swimmers at both the elite and sub-elite level manage to accumulate ~10,000 hours of career swim-specific training (Johnson et al., 2006). On the basis of this evidence, 10,000 hours of career domain-specific training appears to be neither necessary nor sufficient for the acquisition of optimal performance. Therefore, even within an early specialisation sport like swimming, key elements of Ericsson et al.'s (1993) model look to be too restrictive to provide a comprehensive explanation for the complex development of high-level sporting performance.

Reasons for greater career training hours generally being associated with better performance in senior-level female but not male swimmers may relate to differences in recovery between genders. Current evidence shows that oestrogen may play a role in reducing the inflammatory response to exercise-induced muscle damage (Kendall & Eston, 2002), lending support to the anecdotal belief of many swim coaches that females are able to recover faster than males because they have less muscle damage to repair (Maglischo, 2003). If females were to recover more quickly than males, then over the course of their careers they could theoretically accumulate more high-intensity training, stimulating more race-specific physiological and neurological adaptation, resulting in greater long-term improvements in performance. By the same logic, inadequate recovery owing to high career training hours may reduce the training quality of male swimmers, consequently impairing their long-term performance, particularly in shorter-distance events (Rushall, 2013). Additionally, female athletes are thought to be more susceptible to adding more size than strength through maturation, thus increasing their resistive drag profile without a concurrent increase in their ability to overcome this drag by applying more propulsive force, resulting in restricted post-pubertal performance progression (Maglischo, 2003). By maintaining high training durations at early ages, females may be able to better regulate their energy balance through their development, consequently minimising the detrimental increases in body mass typically triggered by puberty and facilitating better performance at senior-level (Vorontsov, 2005).

Our study found evidence of female distance swimmers accumulating more career swim-specific training hours at early ages compared with female sprinters. Improved regulation of energy balance owing to the effects associated with these greater training durations may again help to explain why senior-level females in the present study experienced increasing performance benefits with increasing event distance. Another likely explanation is that more

career swim-specific training typically helps develop the aerobic efficiency that is more critical for performance in distance swimming than in shorter-distance events (Maglischo, 2003). The same rationale may also account for the performance advantages observed in the present study for senior male distance swimmers with greater training histories.

Better performance in developing swimmers is typically considered to result primarily from the effects of early maturation and greater career training durations (Sokolovas, 2006b). By including age as a quadratic random effect in our mixed modelling we have effectively adjusted for the unique effects of growth on each individual swimmer, such that our results reflect only the performance effects associated with training. In general, more career training appeared to help swimmers under the age of 13, but given that we found little performance benefit associated with greater training history in the adolescent years thereafter, improvements in performance over this period can presumably be ascribed mainly to the ongoing effects of individual variation in maturation and talent.

Our study is the first to quantify within-swimmer race-to-race variability in performance at all career stages for national-level swimmers in all sex, stroke and distance event combinations. Variations within swimmers in each of the four youngest age-groups were of a similar magnitude to those derived from estimates of year-to-year performance stability of developing male freestyle swimmers produced by Costa et al. (2011), while the race-to-race variability of our senior swimmers was also consistent with previous estimates (Pyne et al., 2004). The smaller variability that we observed between performances of female distance swimmers compared with those of male sprint swimmers possibly relates again to the greater recovery capacity of females, allowing them to produce more consistent performances even within heavy training phases. Additionally, swimmers are presumably less likely to enter longer-distance races without adequate preparation, potentially resulting in greater reliability of performances in these events.

Cöté et al.'s (2007) theory that early diversification followed by late specialisation provides the optimal pathway to sporting expertise was the basis for investigating the modifying effects on performance associated with other-sports training durations in the present study. According to this theory, other-sports participation during development benefits long-term performance by reducing the risk of motivational weariness from single-sport training, and by stimulating development of a broad range of transferable physiological and neurological capacities. Our finding that senior female swimmers experienced clear performance advantages associated with the middle tertile of career other-sports training was concordant with this theory. However, in general there were few other clear associations between career other-sports training durations and swim performance, which is consistent with previous similar research (Hodges et al., 2004). One explanation for these findings might relate to the fact that there is typically limited transferability of motor skills and energetic capacities from land-based training into swimming (Rushall, 2013), but moderate amounts of career other-sports training may have benefitted the long-term performance of our oldest females by reducing their risk of staleness.

There were several limitations to the present study. First, the use of retrospective methods may have resulted in inaccurate recall of career training amongst our swimmers, despite our attempts to trigger improved recollection using additional questioning. Secondly, our results

reflect only associations between performance and career training durations, not cause and effect relationships. It may be that the better-performing senior female swimmers possessed more innate talent and therefore engaged in greater amounts of career training as a consequence of being selected to top squads on the basis of their talent. From our data we were unable to investigate the influence of genetics on performance, but given evidence from genomic studies that substantial inter-individual variation exists in response to standardised training programmes (Bouchard et al., 2011), it seems likely that better performance results from interactions between both training and talent (Tucker & Collins, 2013). The time and computational power required to run further analyses in the present study prevented us from investigating any additional random effects that would account for individual responses, which undoubtedly exist. Future research quantifying individual responses to both acute and cumulative training loads would provide valuable programming recommendations to help coaches and national sporting organisations individualise their swimmer-development pathways. Finally, our data were unable to account for differences in training intensity or frequency, and the quality of training due to factors such as coaching experience, and access to facilities and resources. Considering the well-documented importance of technique in determining elite swimming performance (Arrelano, 2010), future research on the long-term performance effects of career training durations should also be prospective to properly quantify training quality.

5.5. Conclusion

Using the career performances and training histories of national-level swimmers and a novel application of mixed linear modelling for analysis, we have demonstrated that the relationships between cumulative training hours and swim performance are non-linear in nature and differ between sexes. At early ages, cumulative training hours appear to be important for swim performance, but at the most senior level beneficial associations between career training and performance were apparent only for females, specifically those with histories of high swim-specific training hours and moderate other-sports training hours. With respect to theories of the acquisition of expert sporting performance, our results provide some support for elements of both deliberate-practice theory and early-diversification theory, but on the whole, neither theory appears to offer a framework fully applicable to the sport of swimming. Elite swim performance more likely results from optimising each swimmer's adaptation to training; future research in this area should therefore aim to prospectively quantify individual responses to both acute and cumulative training loads in order to generate practical recommendations for individualising swimmer development.

CHAPTER 6

THE PERFORMANCE EFFECT OF CENTRALISING A NATION'S ELITE SWIM PROGRAMME

This chapter comprises the following paper published in the International Journal of Sports Physiology and Performance:

Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W. G. (2015). The performance effect of centralising a nation's elite swim programme. *International Journal of Sports Physiology and Performance*, *10*, 198-203.

Overview

Many national sporting organisations recruit talented athletes to well-resourced centralised training squads to improve their performance. **Purpose:** To develop a method to monitor performance progression of swimming squads, and to use this method to assess the progression of New Zealand's centralised elite swimming squad. **Methods***:* Best annual long-course competition times of all New Zealand swimmers with at least three years of performances in an event between 2002 and 2013 were downloaded from takeyourmarks.com (~281,000 times from ~8500 swimmers). A mixed linear model accounting for event, age, club, year, and elite-squad membership produced estimates of mean annual performance for 175 swim clubs and mean estimates of the deviation of swimmers' performances from their individual quadratic trajectories after they joined the elite squad. Effects were evaluated using magnitude-based inferences with a smallest important improvement in swim time of -0.24%. **Results:** Before 2009, effects of elite-squad membership were mostly unclear and trivial to small in magnitude. Thereafter, both sexes showed clear additional performance enhancements, increasing from large in 2009 (males -1.4%, ±0.8%; females -1.5%, ±0.8%; mean, ±90% confidence limits) through to extremely large in 2013 (males -6.8%, ±1.7%; females -9.8%, ±2.9%). Some clubs also showed clear performance trends during the 11-year period. **Conclusions:** Our method of quantifying deviations from individual trends in competition performance with a mixed model showed that Swimming New Zealand's centralisation strategy took several years to produce substantial performance effects. The method may also be useful for evaluating performance-enhancement strategies introduced at national or club level in other sports.

6.1. Introduction

Tracking the performance progression of a nation's elite sporting squads is important for evaluating the impact of national strategies introduced to improve athletes' medal-winning prospects. Such strategic interventions have become common over recent years, owing to increasing competition between nations for medals at major international events such as the Olympic Games and World Championships (de Bosscher, Bingham, Shibli, van Bottenburg, & de Knop, 2008).

While ~50% of a nation's international sporting success is accounted for by largely immutable macro-level factors, such as population size, economic welfare and geographical resources (Storm & Nielsen, 2010), it can also be substantially influenced by more controllable meso-level factors, such as strategic policies aimed at improving the systems around elite athletes (de Bosscher et al., 2008). Six critical policy factors determine the quality of these elite sport systems: funding, talent identification and development, clarity and simplicity of administration, international competition opportunities, facilities, and sport-science and sports-medicine service provision (Houlihan & Green, 2008). Of these factors, funding appears to be the strongest predictor of international sporting success (de Bosscher et al., 2008; UK Sport, 2006).

Given the finite supply of finances for elite sport in many nations, several national sporting organisations have attempted to maximise the effectiveness of their available funding by "centralising" their elite sporting programme. The centralisation process usually involves a nation's top athletes leaving home training programmes to join better resourced elite squads. Although this process has been widely credited for much of the recent Olympic medal-winning success of teams such as British Cycling (based at the National Cycling Centre in Manchester, UK), British Sailing (Weymouth, UK) and Rowing New Zealand (Lake Karapiro, New Zealand), the success of centralisation strategies in elite sport has rarely been evaluated objectively.

Within the swimming community, current opinion on the efficacy of centralisation policies for elite swim performance appears divided. Some proponents within British Swimming believe swimmers can fully progress only by leaving home clubs for well-resourced programmes that can provide more for them in the long-term (Greyson et al., 2010), while critics argue that elite programmes are too results-focused and may not produce a sustainable and lasting performance impact (Lang & Light, 2010). Observational evidence from Swimming Australia also appears equivocal (Rushall, 2011a), given both the long-term success of swimmers who remained with their original coaches and programs (e.g., Grant Hackett) and swimmers who have joined dedicated elite training centres (e.g., Alicia Coutts, Australian Institute of Sport).

In the present study we have developed a method for analysing the performance progression of a nation's swim squads. We have then used this method to assess the progression of New Zealand's centralised elite swimming squad since its inception in 2002. This research is the first quantitative evaluation of the performance impact of a centralised swim training programme.

6.2. Methods

All official long-course performance times from all 1030 competitions for New Zealand swimmers between 2002 and 2013 were downloaded from takeyourmarks.com. Club affiliations associated with each performance were obtained from the same website. Best annual times of all swimmers with at least three performances in an event were retained for analysis (49.2% of the nation's swimmers). Overall, there were 153,199 times from 4809 female swimmers, and 127,626 times from 3690 male swimmers, with a similar number of performances per swimmer per event for females (4.5 ± 1.6; mean ± SD) and males (4.6 ± 1.8). Swimmers of both sexes also had a similar number of club affiliations (1.3 ± 0.5) over their careers.

Start and end dates of membership for the 20 female and 24 male swimmers who were part of the centralised elite squad (highest FINA points score 859 ± 57) between 2002 and 2013 were provided by Swimming New Zealand. For all performances a dummy variable was then coded as either 0 or 1 to represent membership or non-membership of the elite squad, respectively. Duration of elite-squad membership was similar for females (4.3 ± 2.1 y) and males (4.2 ± 2.2 y), with 595 female performances and 619 male performances being coded 1.

Performance times were log-transformed for analysis of percent changes using the high-performance mixed linear model procedure (Proc Hpmixed) in the Statistical Analysis System (Version 9.4, SAS Institute, Cary, NC). Separate analyses were performed for males and females. The model included fixed effects accounting for the mean effects of event (34 levels of stroke and distance), age (numeric linear and quadratic), year (12 levels), and the interaction between elite-squad membership (dummy variable) and year. Random effects for swimmer and age within-swimmer (numeric linear and quadratic) were included to derive individual trends for each swimmer, and random effects for club affiliation (175 levels of New Zealand swimming clubs) and the interaction between club affiliation and year were included to produce estimates of mean annual performance for each of the clubs. In this model the elite-squad interaction with year provided estimates of the mean deviation of swimmers' performances from their individual quadratic trajectories after they left their home club and joined the elite squad. The fixed effect for year provided estimates of annual mean performance of all New Zealand swimmers. Given that the mean of a random effect in a mixed model is equal to zero, the sum of the value of the random effect for a given club and the value of its interaction with a given year provided an estimate of the mean percent performance difference of that club's swimmers from the mean performance of all New Zealand swimmers in that year.

The suitability of using quadratic trends to model swim performance has been established previously (Allen et al., 2014; Malcata et al., 2014), so this model was deemed a plausible option to quantify performance changes arising from the effect of an intervention, such as swimmers becoming members of an elite squad. Means and standard deviations of residuals for each age decile were examined to evaluate the goodness of fit of the model for each sex. To investigate the performance effects of different durations of elite-squad membership, we added a fixed effect for the interaction between year and years of elite-squad membership (numeric linear) to our original model and repeated the analysis for both sexes. This fixed effect provided

estimates of the initial performance effect of elite squad membership and the ongoing simple additive effect per year of elite-squad membership thereafter.

Elite-squad and club effects were evaluated using non-conservative clinical magnitude-based inferences, while year effects were evaluated mechanistically (Hopkins et al., 2009). For elite-squad effects, the smallest important improvement in swim time was -0.24% (0.3 of the race-to-race variability in performance of top swimmers of 0.8%; Pyne et al., 2004). Thresholds for moderate, large, very large and extremely large effects were -0.72%, -1.3%, -2.0%, and -3.2%, respectively (0.9, 1.6, 2.5, and 4.0 of 0.8%; Hopkins et al., 2009). Thresholds for club and year effects were -0.42%, -1.3%, -2.2%, -3.5%, and -5.6%, (small to extremely large, respectively), which were derived in a similar manner using race-to-race variability in performance of sub-elite swimmers of 1.4% (Stewart & Hopkins, 2000b). Between-club standard deviations in performance derived from the mixed model were doubled for interpretation of their magnitude using this scale (Smith & Hopkins, 2011). Uncertainty in estimates of effects was expressed as 90% confidence limits (provided by Proc Hpmixed) and as likelihoods that the true value of the effect represents substantial change (improvements or impairments in performance; Batterham & Hopkins, 2006). Hpmixed in SAS 9.4 did not provide confidence limits for the random-effect variances.

6.3. Results

Mean performance effects due to membership of the centralised elite squad between 2002 and 2013 are presented for each sex in Figure 9. Females showed additional performance benefits from 2009 onwards (likelihoods, very likely to most likely), increasing from large in 2009 (-1.5%, ±0.8%; mean, ±90% confidence limits) to very large in 2010 (-2.7%, ±0.9%), to extremely large in the years 2011 (-4.3%, ±1.1%), 2012 (-5.1%, ±1.2%), and 2013 (-9.8%, ±2.9%). The observed effects of elite-squad membership for females were mostly trivial to moderate in magnitude before 2009 and the true effects were unclear, with the exception of 2002 (-1.5%, ±1.5%; a likely beneficial moderate effect). Male elite-squad members experienced large extra performance benefits in 2003 (-1.5%, ±1.3%; very likely beneficial), but likely harmful moderate performance impairments in 2005 (0.7%, ±1.1%), 2006 (1.2%, ±1.1%), and 2007 (0.7%, ±1.0%). All other effects prior to 2009 for males were unclear and small to moderate in magnitude. With the exception of 2010 (an unclear trivial effect), males then also showed clear very likely to most likely additional performance benefits, increasing from large in 2009 (-1.4%, ±0.8%), to very large in 2011 (-2.5%, ±1.0%), through to extremely large in 2012 (-4.4%, ±1.2%) and 2013 (-6.8%, ±1.7%).

In the analysis in which the elite-squad effect was partitioned into separate membership and years-of-membership effects, both effects were mostly trivial to small and unclear before 2009 for females. Thereafter, membership effects were clearly beneficial and ranged from moderate (-0.7%, ±1.2%) to extremely large (-3.6%, ±2.5%), while each year of membership contributed a generally clear and small additional performance enhancement (~-0.6%, ~±0.6%).
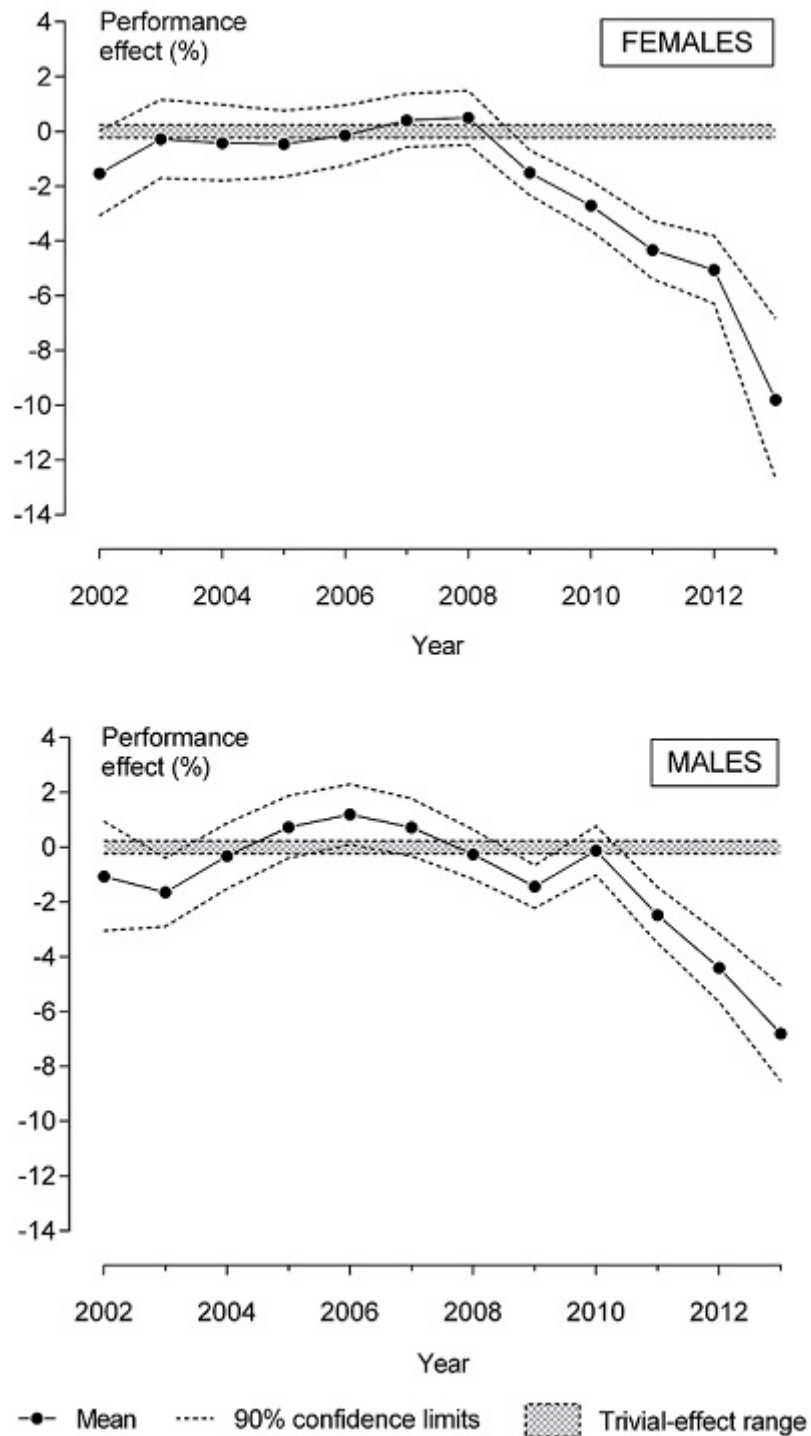
Figure 9. Mean annual deviation (%, ±90% confidence limits) of top New Zealand female and male swimmers' performance times from their individual quadratic trajectories due to membership of the centralised elite squad. Thresholds for the smallest important improvement (-0.24%) and impairment (0.24%) in swim time define the trivial-effect range (shaded area).
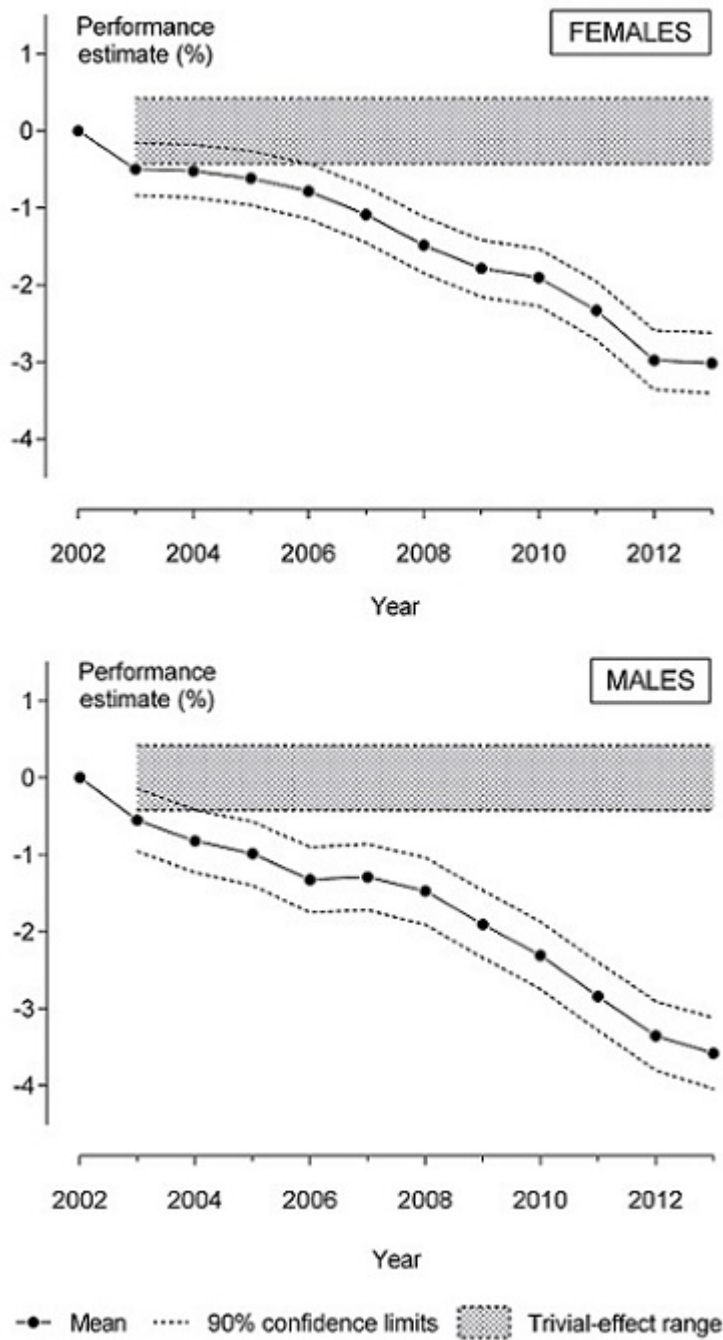
Figure 10. Mean annual performance (%, ±90% confidence limits) of all New Zealand swimmers' shown as changes since 2002. Thresholds for the smallest important improvement (-0.42%) and impairment (0.42%) in swim time define the trivial-effect range (shaded area).
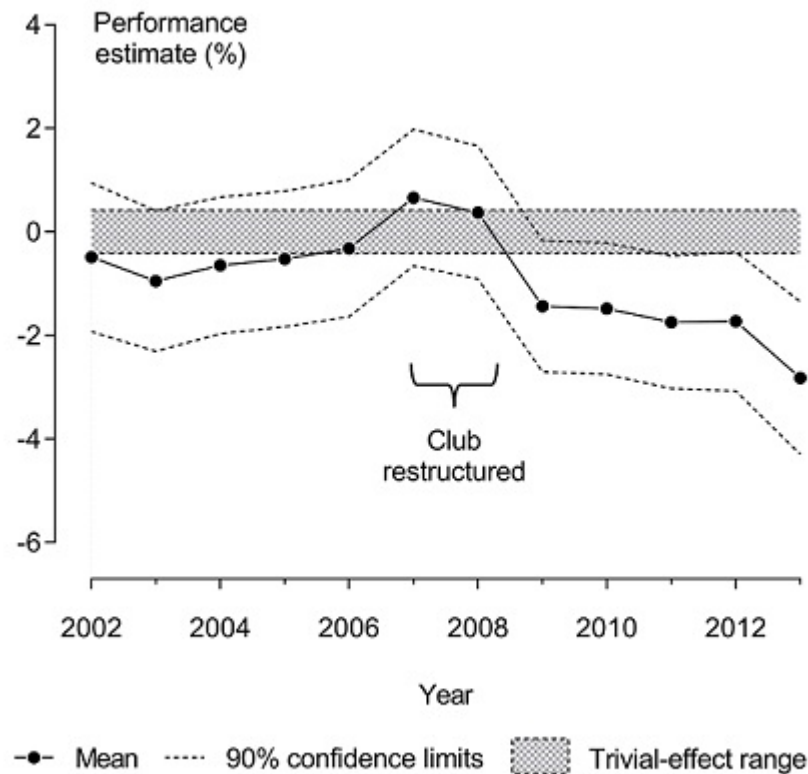
Figure 11. Mean annual deviation (%, ±90% confidence limits) of one New Zealand club's female swimmers' performance times from the mean annual performance times of all New Zealand female swimmers. From mid-2007 to end-2008, a new head coach initiated a performance-enhancing intervention: a major restructuring of the club's squad system and management team. Thresholds for the smallest important improvement (-0.42%) and impairment (0.42%) in swim time define the trivial-effect range (shaded area).

For males, membership effects were mostly also clearly beneficial from 2009 onwards and ranged from large (-1.5%, ±1.0%) to extremely large (-5.5%, ±3.6%), but years-of-membership effects were generally trivial and unclear, with the exception of a clear potentially harmful small per-year effect in 2012 (0.3%, ±0.4%). There was a clear moderate per-year effect for the females compared with the males (-0.9%, ±0.7%; likely beneficial).

Calendar-year trends in mean performance of all New Zealand swimmers are presented in Figure 10. Both sexes showed gradual annual improvements in performance, with clear large changes for females (-3.0%, ±0.4%; most likely substantial) and clear very large changes for males (-3.6%, ±1.0%; most likely substantial) between 2002 and 2013.

Over the 11-year period, 157 clubs had at least three years of performance estimates for both sexes. The random effects for club and for the interaction of club and year were combined to give a standard deviation representing typical differences between clubs in the mean ability of their swimmers in any given year (the average standard deviation over the 11-year period). The values were ±4.0% for female swimmers and ±4.3% for male swimmers, both extremely large. Confidence limits for these values could not be computed.

The individual estimates comprising the club random effects were used to produce plots of progression of mean performance of the swimmers in each club. Figure 11 shows a plot for the female swimmers of one club chosen to illustrate a sustained substantial change in performance. Prior to 2009, differences between the club's female swimmers and the average New Zealand female swimmer were trivial to small in magnitude but unclear. In mid-2007, the club appointed a new head coach with many years of coaching experience both overseas and within New Zealand. The new coach immediately initiated major restructuring of the club's squad system and management team, which was completed at the end of 2008. From 2009 onwards, the club's female swimmers then performed better than the average New Zealand female swimmer by clear likely to most likely substantial amounts, increasing from moderate in 2009 (-1.4%, ±1.3%) to large in 2013 (-2.8%, ±1.5%). The club's male swimmers also experienced extra performance benefits beyond 2008, with their performance estimates increasing from moderate in 2007 and 2008 (-1.8%, ±1.5%; likely beneficial), to large in 2009 (-2.3%, ±1.4%; very likely beneficial) through to 2013 (-3.2%, ±1.6%; most likely beneficial).

Overall residual variance between observed and modelled performance times was 2.9% for female swimmers and 3.1% for male swimmers. Analysis of residuals by age deciles produced borderline trivial-small negative mean residuals (-0.25% to -0.27%) for elite female swimmers above the age of 18. We observed no other systematic deviation of the mean residuals across each age decile above or below the smallest worthwhile effects for elite or sub-elite swimmers. The standard deviations of the residuals were largest for the youngest age deciles and showed a progressive reduction through the age-range, with values for the oldest age deciles being ~50% of those of the youngest deciles.

6.4. Discussion

In the present study we have developed a model to assess the performance progression of a nation's swim squads based on the individual performance trajectories of all of the nation's competitive swimmers. By quantifying the deviation of top swimmers' performances from their trajectories after they joined the centralised elite squad, we have shown that Swimming New Zealand's centralisation strategy took several years to produce substantial performance effects (Figure 9). Our method also produced performance estimates for each New Zealand swimming club between 2002 and 2013, creating trends that can be used to objectively evaluate factors that could affect performance at club level (e.g., Figure 11).

Over the 11-year period, the standard of all New Zealand performances improved gradually year-on-year by a magnitude similar to that of all of the top-150 world ranked performances between 1990 and 2010 (mean ~0.3% improvement per year, equivalent to ~3.3% over 11 years; O'Connor & Vozenilek, 2011). Our model therefore allows direct evaluation of the overall annual progression of a nation's sporting performance, which should be useful for national sporting organisations and for guiding national funding decisions.

Our analysis produced mostly clear beneficial performance effects for elite-squad members between 2009 and 2013 for both sexes. The nature of the mixed model is such that these

effects were adjusted for all other effects in the model; that is, our analysis produced estimates of the elite-squad effects as if all swimmers were the same age, from the same club, swimming the same event, in the same year. Established performance effects of full-body polyurethane swimsuits in 2008 and 2009 (Berthelot et al., 2010) were also adjusted for, as swimmers across all ages and clubs wore them over these two years. Accordingly, the increasing performance benefits for top swimmers from 2009 onwards can be attributed to elite-squad membership, rather than to the potential confounding effects of age, calendar-year, swimsuits, or changes in the proportions of swimmers in different events. Although our study does not directly address the aspects of elite-squad membership responsible for the enhancement in performance in the last few years, by reviewing the history of the squad we have been able to identify some of the likely factors responsible, many of which appear closely aligned with the six critical sport policy factors for successful elite sport systems (Houlihan & Green, 2008). First, government funding of national sporting organisations in New Zealand has been increasing annually since 2002, with swimming having been identified as a priority sport since 2006 (Collins, 2008). Secondly, the inception of the centralised elite-squad coincided with the opening of a dedicated training facility (including a 50-m pool, gym, recovery area and a physiotherapy/rehabilitation centre) in Auckland, which has since been upgraded on an ongoing basis. This training facility also houses sport-science and sports-medicine practitioners, who began to provide continuous support to the elite squad from late-2006. Critically, from this time there was also a succession of appointments of four established coaches with previous international success. At the 2013 World Championships, a female elite-squad member achieved three medals (the first medals for New Zealand at a World Championships since 1994). Although we observed substantial performance effects arising from elite-squad membership for females in 2013, these medals must have resulted from this swimmer improving at a greater rate than other top swimmers in those events. In order for a nation to systematically equate performance improvements of their swimmers to improved medal-winning prospects, improvement rates of rival swimmers (Allen et al., 2014) also need to be accounted for.

The mostly unclear elite-squad effects for the first seven years of the centralisation intervention may be explained by all of the above factors requiring several years to begin operating effectively enough to result in improved athletic performance. Within this period, the beneficial performance effects of elite-squad membership for females in 2002 and males in 2003 can presumably be ascribed to some sort of Hawthorne effect (Landsberger, 1958), whereby swimmers' performances initially improved in response to the novelty of a new training environment, before returning to expected levels in subsequent years. One explanation for the likely harmful performance effects of centralisation that we observed for male swimmers between 2005 and 2007 is that relocation of swimmers from home squads to train under different coaches with new and often more intense training programmes may not have been appropriate or may have required too much adjustment for some individuals. Indeed, around this period, several male elite-squad members chose to either retire from swimming or to leave the centralised programme to join other squads. If this negative effect on some individuals is still continuing, it is now masked by the beneficial effects on performance of the majority of squad members. To mitigate the possibility of this negative effect, Swimming New Zealand has also

introduced trial periods for new squad members before they permanently relocate: a seemingly sensible policy for management of any centralised elite-squad.

Reasons for the likely extra performance benefits per year of elite-squad membership for females but not males might relate to gender differences in attitudes towards training. Research into cultural personality traits found that New Zealand females tend to be more conscientious than their male counterparts (Schmitt, Realo, Voracek, & Allik, 2008). If mirrored in the elite-squad members, this trend could have permitted females to gain greater long-term performance benefits through continually applying themselves to their training. Alternatively, female elite-squad members may have continued to be pushed to improve by training alongside faster male swimmers, while their male counterparts may have struggled to improve without an equivalent daily challenge.

The elite-squad effects were quantified as deviations from swimmers' individual trajectories; as such these effects were not affected by a swimmer's ability and were therefore not due to recruitment of the best swimmers to the elite squad. Club effects were estimated differently and therefore have an uncertain contribution from recruitment and from the clubs' approaches to training and preparation of their swimmers. The contribution of recruitment would be negligible with sufficient transfer of swimmers between clubs, because the mixed model could then estimate swimmer ability independent of club effects. Some swimmers did switch clubs at least once throughout their careers, but simulations would be needed to establish how much transfer is required to eliminate the effect of recruitment from the club effects. If most of the changes in a club's performance were due to the club's approach to training and preparation of their swimmers–which seems likely given the example shown in Figure 11–then our analysis provides two valuable insights into the club performance. First, the analysis produces annual trends that can be used to objectively evaluate the effects of factors that could influence a club's performance. Secondly, the extremely large differences between clubs along with the identities of the clubs can provide evidence for national sporting organisations to guide decisions about allocation of resources at the club or individual-swimmer level.

Analysis of residuals from the mixed model revealed appropriate fit of quadratic trends to the performances of a nation's competitive swimmers. There was some evidence of systematic non-fitting of the model for elite female swimmers above the age of 18, but the borderline trivial-small magnitude of the mean residuals for these swimmers was negligible in comparison with the magnitude of the elite-squad performance effects that we observed. Furthermore, the confidence intervals for these effects are also likely to be wider than necessary. With more computing power we could have specified different error (residual) variances for the elite squad and other age groups; the error variance for the elite squad would undoubtedly have been smaller than that of any other group, resulting in narrower confidence intervals for the elite-squad effects than those provided by the present analysis limited to only one error variance.

Of the other methods that have been developed to assess the performance progression of sporting squads, neither would have been suitable for quantifying longitudinal performance changes of squads of athletes within a nation arising from the effects of an intervention. Malcata, Hopkins and Richardson (2012) modelled the performance progression of an academy's soccer teams over five seasons using game scores as a single team performance

measure. We could have applied this model by computing mean annual performance times (expressed as percent of world record) of each squad before further analysis, but in the process we would have lost the identity of the athletes and would therefore have been unable to assess performance changes due to athletes joining the elite squad. Vandenbogaerde, Hopkins and Pyne (2012) presented a competition-based design to assess the effects of an intervention on a squad of elite athletes. The analysis required a reasonable number of athletes from different squads to be racing against each other on a regular basis which, if applied to the present data, would exclude most performances. The power of our method is due mainly to the inclusion of the best annual competition performances of all swimmers within a nation over an extended period. Although we have developed this method for a sport in which the effects of environmental conditions on performance are assumed to be negligible, the model could presumably be applied to certain other sports by adding clustering variables to adjust for and estimate the effects of environmental conditions on performance times (Malcata et al., 2014).

6.5. Practical Applications and Conclusions

We have presented a new method for analysing the performance progression of a nation's swim squads. This method has provided annual estimates of the performance of all of a nation's swim clubs, the performance effect of centralising a nation's elite swim programme, and the change in performance of all of a nation's swimmers. These estimates should be useful for coaches, scientists, national sporting organisations and funding bodies interested in objectively evaluating the success of interventions introduced to improve performance at club or national level. The method could be developed further within swimming to assess a squad's strengths and weaknesses by investigating performance differences between strokes, distance groups, or age groups. Other sports in which athletes have individual performance scores and are grouped into squads, clubs or regions may also benefit from the application of this method.

CHAPTER 7

DISCUSSION AND CONCLUSION

The overall aim of this thesis was to use mixed modelling to develop objective analytical tools that can be used to monitor and assess the performance progression of swimmers. First, a systematic review of estimates of age of peak competitive performance of elite athletes from a variety of sports (Chapter 2) was presented to outline the need for progression-monitoring tools specific to the sport of swimming. Next, I presented four original-research projects, in which mixed modelling was used to investigate four different aspects of performance progression and athlete development: benchmarking (Chapter 3), talent identification (Chapter 4), career training history (Chapter 5), and performance-enhancing strategies and interventions (Chapter 6). This chapter binds the thesis as a cohesive whole by summarising the findings of the five PhD projects and highlighting their theoretical contributions and practical applications. Limitations and future research directions are also presented. An overview of the main outcomes of the thesis is shown in Figure 12.

7.1. Contributions to Theory

The theoretical framework that informed the research objectives of this thesis was the Long Term Athlete Development (LTAD) model (Balyi, 1990). Originally developed for all sports, the LTAD framework features five developmental stages that define a general pathway of athlete progression from childhood through to international performance success. This generic framework has since been adapted and applied to a number of different sports, including swimming (Australian Swimming Inc., 1996; Amateur Swimming Association, 2003), although not without criticism from academics, coaches and applied sports scientists embedded within the sport. Following interviews with eleven coaches on the topic of implementation of the LTAD within English swimming, Lang & Light (2010) identified two main problems with applying the LTAD approach to swimming: training prescriptions adapted from the generic LTAD model interfering with swim technique development, and coaches misinterpreting the LTAD principles. In a subsequent commentary on this swim-specific LTAD model, Rushall (2011a, p. 3) provided a stronger view, claiming "the proposal that *'one model [the LTAD model] fits all'* sports, is preposterous". Outlining his rationale for this claim, he stated "to think that chess, track and field, ballroom dancing, synchronised swimming, competitive rock-climbing, ice-hockey, and sport-parachuting have much in common that spans the lives of potential participants boggles the mind". While much anecdotal evidence exists to substantiate the broad spectrum of typical career spans of different sports, Chapter 2 of this PhD is the first systematic review to present objective evidence showing that the age of peak competitive performance of elite athletes ranges widely between sports (from ~20 y to ~39 y). With the first PhD project, I have therefore provided a theoretical rationale to support the development of sport-specific models of long-term athlete development. In addition, in order to address the research objectives of this thesis, I

Monitoring and Modelling Swim Performance

Chapter 1 - Introduction

- **Theoretical rationale:** Importance of objectively monitoring individual performance progression for swimmer development
- **Methodological approach:** Mixed linear modelling
- **Thesis question:** Can statistical modelling provide solutions to appropriately monitor and assess performance progression of swimmers?

Chapter 2 – Systematic Literature Review

- Linear trends in age of peak performance of elite athletes by event duration
- **Equation tool** for talent identification, to estimate peak age & guide event selection

Chapter 3 – Benchmarking

- Career performance **trajectories tool**, benchmarks from Olympic top-16 swimmers
- Mean age of peak performance and peak performance window duration

Chapter 4 – Talent identification

- Four methods for **predicting** Australia's 2012 Olympic-qualifying swimmers
- Track variables other than age and performance to improve selection accuracy

Chapter 5 – Career training

- **Non-linear relationships** between career training and swim performance
- Elite performance likely results from optimising individual adaptation to training

Chapter 6 – Interventions

- The performance effect of centralising New Zealand's elite swim programme
- Tool for monitoring performance progression of **nations** and **clubs**

Chapter 7 – Discussion and Conclusion

- **Theoretical contributions:** Evidence-based rationale to justify need for new swim-specific long-term athlete development model. Objective data to inform content and structure of future models.
- **Practical contributions:** Individual performance-trajectories method provides a tool for coaches, scientists, administrators and national sporting organisations to:
    - assess progression of developing swimmers against elite benchmarks;
    - predict future performance;
    - evaluate relationships between training and performance;
    - assess performance effects of interventions.

Figure 12. Overview of the main outcomes of the thesis.

established a clear need to develop new analytical methods for monitoring and assessing athletic performance that were specific to the typical progression pathways within the sport of swimming.

In my second PhD study (Chapter 3), I used mixed modelling to develop individual career performance trajectories of Olympic top-16 swimmers. Analysis of these trajectories using a meta-analytical model produced age-related performance-progression benchmarks that should provide a useful evidence base to underpin new swim-specific frameworks of long-term athlete development. The mean age of peak performance and mean duration in the peak performance window for elite swimmers were also quantified in each of the 26 Olympic pool events. The estimates of mean peak-performance age for 2008 and 2012 Olympic top-16 swimmers were ~2 y greater than estimates of peak performance of all freestyle swimmers ranked in the annual world top 10 between 1980 and 2009 (Berthelot et al., 2012). These data are consistent with an apparent upward secular trend in the age of peak swim performance, likely owing to recent increases in funding and resources that have allowed top swimmers to forge a career in the sport and thereby continue training and competing to older ages than previously possible. Considering evidence from Chapter 2, these older ages may be closer to the ages at which the physical, mental, technical and strategic capacities required for successful performance typically peak within humans. Therefore, as knowledge of long-term athlete development improves, it seems likely that we will observe continued improvements in the standard of swim performances in the coming years as the capacity of top swimmers evolves towards their true potential. Indeed, in 2014 there have been over 20 new world records in short-course and long-course individual and relay swimming events, indicating that we are not yet close to reaching the limits of human swimming performance. Further research should continue to track secular trends in the age-performance relationship to allow benchmarks within swim-specific models of athlete development to be appropriately adjusted for future years.

In Chapter 4, I extended the individual trajectories approach to develop career performance trends for all Australian swimmers with sufficient data. By including a random effect for age, the mixed model was able to effectively account for the unique effects of age on each individual's performance progression, aligning well with the Principle of Individuality (Rushall & Pyke, 1991). Next, I compared the predictive accuracy of this approach for identifying future Olympic-qualifying swimmers with that of three other methods, all of which also used age and performance as predictor variables. In any given year, all four methods produced substantial proportions (≥10%) of swimmers who were incorrectly identified as Olympic qualifiers. These findings have therefore provided a theoretical rationale for considering variables additional to age and performance as part of the talent identification process within new swim-specific models of long-term athlete development. While recent research into the relative contributions of many such variables to performance shows that biomechanical and technical factors form the primary determinants of successful development of swimming performance (Figueiredo et al., 2013), prospective longitudinal research designs are required to properly quantify the contribution of these factors to career performance progression.

In view of the three-year timeframe of this PhD, it was possible only to retrospectively investigate the contribution of variables other than age and prior performance to performance

progression. In particular, I used self-reported training histories of several hundred New Zealand competitive swimmers to investigate relationships between specific and non-specific career training hours and performance in the fourth study of the PhD (Chapter 5). Utilising a novel application of mixed modelling, this study was the first to empirically demonstrate that the relationships between career training hours and swim performance appear to be non-linear, and to differ widely between individuals. When developing new swim-specific models of long-term athlete development, researchers should therefore be mindful of the fact that elite swim performance is more likely to result from optimising each swimmer's adaptation to training than from adhering to prescriptive training-load models. Future research in this area should aim to prospectively quantify individual responses to both acute and cumulative training loads in order to generate practical recommendations for individualising swimmer development.

The fourth PhD study also provided evidence contributing to the ongoing theoretical debate regarding the optimal training pathway to athletic expertise. To date, research into the acquisition of expert performance has produced two contrasting theories about the contribution of training history to elite sporting success. Ericsson et al.'s (1993) deliberate-practice model states that ~10,000 hours of domain-specific training is both necessary and sufficient to produce expert performance, while Côté et al.'s (2007) developmental model of sport participation proposes that early diversification of training followed by late specialisation is best. Our findings that senior-level male swimmers of most event distances seemed to perform best with ≤~9,000 h of career swim-specific training were inconsistent with the posited 10,000-hour rule of deliberate-practice theory. Additionally, we observed few clear associations between career training in other sports and swim performance, lending little support to the early-diversification theory. Therefore, neither theory appears to offer a framework adequately describing the optimal training background required for developing expert performance in swimming, supporting the conclusion in Chapter 2 for the need for a new long-term athlete development model specific to the sport of swimming.

The final PhD project (Chapter 6) contained a novel extension of the individual performance-progression modelling used in the previous projects. Here, I developed a method to assess the performance effect of interventions by quantifying deviations from swimmers' expected performance trends after implementation of the intervention. This study also provided annual performance estimates for New Zealand swimming as a whole, and for each New Zealand swimming club, creating a method that can be used to evaluate performance progression at both the national level and the club level. Therefore, this method should provide a useful tool to assess the performance effects of strategies implemented within swim-specific long-term athlete development models on a number of different levels: individual, club, and national. Within Chapter 6, I used the method to objectively quantify the annual performance effect of the centralisation strategy introduced by Swimming NZ in 2002. The findings that centralisation delivered substantial performance benefits provide evidence supporting the inclusion of this strategy within swim-specific long-term athlete development models. However, performance effects were apparent only several years after implementation, suggesting that fine-tuning is required before centralised programmes begin to operate effectively.

While the scope of this PhD thesis was not broad enough to permit construction of a new swim-specific model for long-term athlete development, the findings of the five projects provide considerable rationale for the need for further research in this area. Each PhD study has produced objective data to help inform the content of future models, and guide future research directions.

7.2. Practical Applications

Many of the projects of this PhD were created in collaboration with coaches, scientists, administrators and managers working primarily in an applied setting within high-performance swimming. In focusing on developing solutions to objectively track and evaluate performance progression, this PhD was also designed to align with High Performance Sport New Zealand's mission to "create a world-leading, sustainable high performance sport system" by 2020 (HPSNZ, 2012). Such solutions provide HPSNZ with a rationale for evidence-based investment decisions, an improved understanding of athlete development pathways, and a means for quantifying the impact of factors affecting sport performance. Given the nation's small population (~4.5 million people) and finite supply of finances for elite sport, solutions that improve talent identification and the effectiveness of available funding are critical for New Zealand's sporting success. Within the PhD, Chapters 3, 5 and 6 have produced practical outcomes for HPSNZ and Swimming NZ, while our collaboration with colleagues in Australia in Chapter 4 provided practical applications for Swimming Australia.

In Chapter 2, my systematic review of estimates of age of peak performance of elite athletes produced an unexpected practical outcome with utility for all sports and athletes: a tool using predicted peak age for assessing the future prospects of an athlete specialising in a particular event, and for guiding event selection for talent identification and transfer athletes. In this project, we first split the mean peak-age estimates from each study into three event-type categories on the basis of the predominant attributes required for success in the given event (explosive power/sprint, endurance and mixed/skill), and then plotted the estimates by event duration. In explosive power/sprint and endurance events for both sexes, linear trends closely approximated the relationships between event duration and peak-performance age. The equations of these linear trends represent a tool that should be useful for coaches, scientists and national sporting organisations interested in tracking athlete progression and improving talent identification. Further research investigating age of peak performance for both sexes across a wider range of sports and events would likely improve the precision and utility of these prediction equations.

The career performance trajectories of Olympic top-16 swimmers produced in Chapter 3 provide an analytical tool that can be used to assess the age-related performance progression of a swimmer. For example, these data were included in a report compiled for Swimming NZ and the HPSNZ board, which aimed to provide an objective assessment of the performance of New Zealand's swim team at the 2012 Olympic Games (Appendix G). By comparing the performance trajectories of New Zealand swimmers with those of Olympic medallists, this report

provided evidence to help guide HPSNZ's resource allocation and funding decisions for the subsequent Olympic campaign.

The plots of age-related performance progression of elite-level swimmers towards the 2012 Olympic gold medal winning time in Chapter 3 represent a tool allowing clear visual evaluation of the progress of any swimmer between the ages of 12 and 30 years. I used the data from this study to develop an Excel-based application, designed to allow Swimming NZ to assess the performance progression of any individual swimmer against the performance progression benchmarks of Olympic top-16 swimmers from Beijing and London (Appendix H). This project has therefore helped Swimming NZ deliver on their key strategic priority of determining elite-level benchmarks to "design a clear athlete pathway… towards Olympic podium results", as outlined in their 2013-2020 High Performance Strategy (SNZ, 2012).

In Chapter 4, I extended the performance-trajectories approach to produce a performance-prediction tool for Swimming Australia. By extrapolating the trajectories of individual swimmers forward, it was possible to generate performance predictions and associated uncertainties for all Australian swimmers with sufficient data. Identifying swimmers with performances tracking towards Olympic-qualification standards on an annual basis should provide a valuable screening tool to help Swimming Australia improve the accuracy of early selection of swimmers into talent-development squads. Future research should aim to improve the predictive accuracy of this tool by including variables additional to age and performance in the model.

The mixed model used for the analysis in Chapter 5 was itself an analytical tool that evaluated the relationships between career training hours and performance of New Zealand competitive swimmers. The findings that beneficial associations between career training and performance were apparent only for females should have practical utility for guiding the future development of New Zealand swimmers. Additionally, this study provided Swimming NZ with an overview of the specific and non-specific career training hours undertaken by current national-level swimmers at different chronological stages of their development. This information should help Swimming NZ to identify gaps in their current athlete-development programme, although further prospective research is required to better understanding how to improve each swimmer's performance progression by optimising their individual response to training.

Chapter 6 resulted in a number of practical applications. First, our method of quantifying deviations from swimmer's expected trends provided HPSNZ and Swimming NZ with a tool for quantifying the effect of strategies or interventions introduced at a national, regional, club, or individual level to enhance performance. Specifically, our findings that centralisation delivered substantial performance effects to New Zealand swimmers provides evidence supporting the maintenance of this strategy within future Swimming NZ high-performance plans. Secondly, our model was able to quantify the annual performance progression of all New Zealand swimmers. By comparing these data with the magnitude of progression of top swimmers (O'Connor & Vozenilek, 2011), Swimming NZ has therefore been able to assess the extent to which its programme has been improving over the last decade in relation to elite-level benchmarks. Thirdly, by including club as a random effect within our mixed model, we have also developed a tool that allows Swimming NZ to monitor and assess the performance progression of each of the 157 clubs within New Zealand. I used the data from this study to develop an Excel-based

application, designed to allow Swimming NZ to assess the performance progression of any New Zealand swimming club since 2002, and to compare progressions between clubs (Appendix I). As demonstrated with an example in Chapter 6, this tool also provides Swimming NZ with a means to objectively evaluate factors that could affect performance at club level, such as club restructuring or recruitment of new coaching staff.

In summary, the projects of this PhD have resulted in many practical applications. I have developed tools that can be used to assess progression of developing swimmers against elite benchmarks, predict future performance, evaluate relationships between training and performance, and assess the performance effects of interventions. Many of these tools have been adopted by coaches, scientists, administrators and managers from organisations such as HPSNZ, Swimming NZ and Swimming Australia to help direct funding and resource allocation decisions, guide long-term training plans, and improve talent-identification processes.

7.3. Limitations and Future Research Directions

The projects of this PhD have been subject to several limitations, owing to factors such as time and resource constraints. Some of these limitations have helped guide the suggestions for future research directions that I have detailed below.

In Chapter 2, the differences in estimates of peak age between studies for similar events were moderate to large in magnitude, limiting the accuracy of the regression equations to predict the age of peak performance in a given event. If more authors had provided standard deviations and standard errors or confidence limits for their peak-age estimates, it would have been possible to weight and meta-analyse the study estimates, which would probably have improved the precision of our prediction equations. Future research should aim to generate more peak-age estimates for female athletes, which would also allow differences between sexes for different types of events to be meta-analysed. Given the ongoing evolution of age of peak performance in many sports, as noted in Chapter 2, researchers should continue to track these trends in order to provide peak-age estimates valid for current athletes. There is also a need for further research into the age of peak performance in more mixed/skill-based sports, as the majority of published articles included in the review were for sports with a predominant explosive power/sprint or endurance component.

Although we were able to quantify the rates of progression to peak performance shown by Olympic top-16 swimmers using a mixed modelling method in Chapter 3, the uncertainty in the estimates of progression increased with increasing years prior to peak performance. Beyond eight years prior to the peak age (~16 y for men, ~14 y for women), there may be too much uncertainty for the estimates to be considered useful benchmarks for talent development. Given that Costa et al. (2011) also found evidence to suggest that swim performance does not become sufficiently stable to yield meaningful predictions of adult performance until age 16, future research should aim to investigate the effect of including variables other than age and performance in the modelling process on the magnitude of these uncertainties. Support for this future research direction is also provided by the findings from Chapter 4, that talent-

identification methods based only on age and performance resulted in substantial proportions (≥10%) of swimmers being incorrectly identified as Olympic qualifiers.

Chapter 5 was the only study of this PhD that required data to be retrospectively collected from athletes; sufficient data were available online for all other studies. Consequently, this study had a number of unique limitations, including potential problems with swimmer recall of training information, and an uncertain cause-and-effect relationship between training and performance. The data were also unable to account for the contributions of training intensity, training frequency, access to facilities and resources, quality of training due to factors such as coaching experience, and the influence of genetics on training adaptation. We recommend that future research in this area is prospective and comprehensive in nature in order to properly assess the contribution of training to career performance progression.

A limitation of primarily using pre-existing online data within the projects of the PhD is that understanding the context of the data is inevitably problematic. For example, in Chapter 6, I found that Swimming New Zealand's centralisation strategy took several years to deliver substantial performance benefits, but the performance data were unable to reveal any insights into the reasons underpinning these effects. Using the anecdotal observations of swimmers, coaches, scientists and administrators involved within the Swimming NZ programme since the inception of the centralised elite training squad, I was able to provide several speculative explanations for these findings. With prospective and multi-disciplinary research designs for future investigations of this type, it should be possible to elucidate some of the reasons underpinning the performance progressions observed.

In view of the three-year timeframe of this PhD, it was not possible to employ the prospective research designs required to properly assess more of the myriad factors affecting the career performance progression of swimmers. We encourage future researchers in this area to address this limitation. We also recommend that future researchers explore the application of the models and methods presented in this thesis for monitoring and assessing the progression of athletes in sports other than swimming.

7.4. Conclusion

In this thesis, I have demonstrated that mixed modelling can be used to develop objective solutions appropriate for monitoring and assessing the performance progression of swimmers. The solutions comprise evidence-based tools that allow coaches, scientists, administrators and national sporting organisations to assess progression of developing swimmers against elite benchmarks, predict their future performance, evaluate relationships between training and performance, and assess the performance effects of interventions. The objective data obtained through the application of these tools should provide useful information to guide the content and structure of future swim-specific models of long-term athlete development. Prospective studies extending the methods and findings presented in this thesis should improve our understanding of the multiple factors affecting career progression of swimmers.

REFERENCES

Allen, S. V., Vandenbogaerde, T. J., & Hopkins, W.G. (2014). Career performance trajectories of Olympic swimmers: Benchmarks for talent development. *European Journal of Sport Science, 14*(7), 643-651.

Amateur Swimming Association (2003). *The swimmer pathway: Long term athlete development.* Loughborough, UK: Amateur Swimming Association.

Anderson, A. (2014). Early identification of talent in cyclo-cross by estimating age-independent ability via probit regression. *International Journal of Performance Analysis in Sport, 14*(1), 153-161.

Australian Sports Commission. (2013). *Independent review of swimming.* Canberra, Australia: Australian Sports Commission.

Australian Swimming Inc. (1996, June 1996). Australian swimming multi-year age-group development model. Retrieved from
http://www.nwaswimaths.com/presentations/Development%20Model.pdf

Arellano, R. (2010). Interpreting and implementing the long-term athlete development model: English swimming coaches' views on the (swimming) LTAD in practice – A commentary. *International Journal of Sports Science and Coaching, 5*(3), 413-419.

Balyi, I. (1990). *Quadrennial and double quadrennial planning of athletic training.* Victoria, Canada: Canadian Coaches Association.

Balyi, I. (2010). *Specialization in sport, a tricky business.* Retrieved from
http://canadiansportforlife.ca/sites/default/files/resources/ C1%20Specialization.pdf

Barbosa, T. M., Costa, M. J., & Marinho, D. A. (2013). Proposal of a deterministic model to explain swimming performance. *International Journal of Swimming Kinetics, 2*(1), 1-54.

Barreiros, A., Côté, J., & Fonseca, A. M. (2014). From early to adult sport success: Analysing athletes' progression in national squads. *European Journal of Sport Science, 14*(S1), S178-182.

Bartlett, R. (2007). *Introduction to sports biomechanics: Analysing human movement patterns* (2nd ed.). Oxford, UK: Routledge.

Batterham, A. M., & Hopkins, W. G. (2006). Making meaningful inferences about magnitudes. *International Journal of Sports Physiology and Performance, 1*(1), 50-57.

Baxter-Jones, A. D. G., & Sherar, L. B. (2006). Growth and maturation. In N. Armstrong (Ed.), *Paediatric exercise physiology* (pp. 1-30). Edinburgh, UK: Elsevier Limited.

Berthelot, G., Hellard, P., Len, S., Tafflet, M., & Toussaint, J. F. (2010, 16-19 June 2010). *Technology & swimming: 3 steps beyond physiology.* Paper presented at the meeting of the XIth International Symposium on Biomechanics and Medicine in Swimming, Oslo, Norway.

Berthelot, G., Len, S., Hellard, P., Tafflet, M., Guillaume, M., Vollmer, J. C., ... Toussaint, J. F. (2012). Exponential growth combined with exponential decline explains lifetime performance evolution in individual and human species. *Age, 34*(4), 1001-1009.

Bouchard, C., Sarzynski, M. A., Rice, T. K., Kraus, W. E., Church, T. S., Sung, Y. J., ... Rankinen, T. (2011). Genomic predictors of the maximal O_2 uptake response to standardized exercise training programs. *Journal of Applied Physiology*, *110*(5), 1160-1170.

Brander, J. A., Egan, E. J., & Yeung, L. (2014). Estimating the effects of age on NHL player performance. *Journal of Quantitative Analysis in Sports*, *10*, 241-259.

Bullock, N., & Hopkins, W. G. (2009). Methods for tracking athletes' competitive performance in skeleton. *Journal of Sports Sciences, 27*(9), 937-940.

Cejka, N., Knechtle, B., Rüst, C. A., Rosemann, T., & Lepers, R. (2014). Performances and age of the fastest female and male 100-km ultra-marathoners worldwide from 1960 to 2012. *Journal of Strength and Conditioning Research*. doi: 10.1519/JSC.0000000000000370

Collins, S. (2008). New Zealand. In B. Houlihan & M. Green (Eds.), *Comparative elite sport development. Systems, structures and public policy* (pp. 218-241). Oxford, UK: Butterworth-Heinemann.

Costa, M. J., Marinho, D. A., Bragada, J. A., Silva, A. J., & Barbosa, T. M. (2011). Stability of elite freestyle performance from childhood to adulthood. *Journal of Sports Sciences, 29*(11), 1183-1189.

Costa, M. J., Marinho, D. A., Reis, V. M., Silva, A. J., Marques, M. C., Bragada, J. A., & Barbosa, T. M. (2010). Tracking the performance of world-ranked swimmers. *Journal of Sports Science and Medicine, 9*, 411-417.

Côté, J., Baker, J., & Abernethy, B. (2007). Practice and play in the development of sport expertise. In R. Eklund & G. Tenebaum (Eds.), *Handbook of sport psychology* (3rd ed.) (pp. 184-202). Hoboken, NJ: Wiley.

de Bosscher, V., Bingham, J., Shibli, S., van Bottenburg, M., & de Knop, P. (2008). *The global sporting arms race: An international comparative study on sports policy factors leading to international sporting success*. Oxford, UK: Meyer and Meyer Sport.

de Bosscher, V., de Knop, P., van Bottenburg, M., & Shibli, S. (2006). A conceptual framework for analysing sports policy factors leading to international sporting success. *European Sport Management Quarterly*, *6*(2), 185-215.

Edelmann-Nusser, J., Hohmann, A., & Henneberg, B. (2002). Modeling and prediction of competitive performance in swimming upon neural networks. *European Journal of Sport Science*, *2*(2), 1-10.

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, *100*, 363-406.

Fair, R. C. (2008). Estimated age effects in baseball. *Journal of Quantitative Analysis in Sports*, *4*(1). doi: 10.2202/1559-0410.1074

Figueiredo, P., Pendergast, D. R., Vilas-Boas, J. P., & Fernandes, R. J. (2013). Interplay of biomechanical, energetic, coordinative, and muscular factors in a 200 m front crawl swim. *BioMed Research International*, *2013*. http://dx.doi.org/10.1155/2013/897232

Fried, H.O., & Tauer, L. W. (2011). The impact of age on the ability to perform under pressure: Golfers on the PGA tour. *Journal of Productivity Analysis*, *35*(1), 75-84.

Gabbard, C. (2004). *Lifelong motor development*. San Francisco, CA: Benjamin Cummings.

Gaunt, T., & Maffulli, N. (2012). Soothing suffering swimmers: a systematic review of the epidemiology, diagnosis, treatment and rehabilitation of musculoskeletal injuries in competitive swimmers. *British Medical Bulletin*, *103*(1), 45-88.

Greyson, I., Kelly, S., Peyrebrune, M., & Furniss, B. (2010). Interpreting and implementing the long-term athlete development model: English swimming coaches' views on the (swimming) LTAD in practice – A commentary. *International Journal of Sports Science and Coaching*, *5*(3), 403-406.

Guillaume, M., Len, S., Tafflet, M., Quinquis, L., Montalvan, B., Schaal, K., ... Toussaint, J-F. (2011). Success and decline: Top 10 tennis players follow a biphasic course. *Medicine and Science in Sports and Exercise*, *43*(11), 2148-2154.

Gulbin, J., Weissensteiner, J., Oldenziel, K., & Gagné, F. (2013). Patterns of performance development in elite athletes. *European Journal of Sport Science*, *13*(6), 605-614.

Güllich, A., & Emrich, E. (2006). Evaluation of the support of young athletes in the elite sports system. *European Journal for Sport and Society, 3*(2), 85-108.

Güllich, A., & Emrich, E. (2012). Individualistic and collectivistic approach in athlete support programmes in the German high-performance sport system. *European Journal for Sport and Society*, *9*(4), 243-268.

Güllich, A., & Emrich, E. (2014). Considering long-term sustainability in the development of world class success. *European Journal of Sport Science*, *14*(sup1), S383-397.

Halson, S. L., & Jeukendrup, A. E. (2004). Does overtraining exist? *Sports Medicine*, *34*(14), 967-981.

Heazlewood, T. (2006). Prediction versus reality: The use of mathematical models to predict elite performance in swimming and athletics at the Olympic Games. *Journal of Sports Science and Medicine, 5*, 541-547.

Heazlewood, T., & Lackey, G. (1996, 30 September – 2 October, 1996). *The use of mathematical models to predict elite athletic performance at the Olympic Games.* Paper presented at the meeting of the Third Conference on Mathematics and Computers in Sport, Bond University, Queensland.

Helsen, W. F., Starkes, J. L., & Hodges, N. J. (1998). Team sports and the theory of deliberate practice. *Journal of Sport and Exercise Psychology*, *20*, 12-34.

Hewett, T. E., Myer, G. D., & Ford, K. R. (2002). The influence of growth and pubertal maturation on neuromuscular performance in high-risk female athletes. *Medicine and Science in Sports and Exercise*, *34*(5), Supplement abstract 1384.

Hodges, N. J., Kerr, T., Starkes, J. L., Weir, P. L., & Nananidou, A. (2004). Predicting performance times from deliberate practice hours for triathletes and swimmers: What, when, and where is practice important? *Journal of Experimental Psychology Applied*, *10*(4), 219-237.

Hohmann, A., & Seidel, I. (2010). Talent prognosis in young swimmers. In P-J. Kjendlie, R. K. Stallman & J. Cabri (Eds.), *Proceedings of the XIth international symposium for biomechanics and medicine in swimming* (pp. 262-264). Oslo, Norway: Norwegian School of Sport Science.

Hollings, S. C., Hopkins, W. G., & Hume P. A. (2014). Age at peak performance of successful track & field athletes. *International Journal of Sports Science and Coaching*, *9*(4), 651-662.

Hollings, S., & Hume, P. (2010). Is success at the IAAF World Junior Athletics Championships a prerequisite for success at World Senior Championships or Olympic Games? *New Studies in Athletics*, *25*(2), 65-77.

Holt, N. L. (2010). Interpreting and implementing the long-term athlete development model: English swimming coaches' views on the (swimming) LTAD in practice – A commentary. *International Journal of Sports Science and Coaching*, *5*(3), 421-424.

Hopkins, W. G. (2000). Measures of reliability in sports medicine and science. *Sports Medicine*, *30*(1), 1-15.

Hopkins, W. G. (2003, May 2003). *Analysis of repeated measures*. Paper presented at the meeting of the Annual meeting of the American College of Sport Medicine, San Francisco, USA.

Hopkins, W. G. (2006a). A spreadsheet for combining outcomes from several subject groups. *Sportscience*, *10*, 50-53.

Hopkins, W. G. (2006b). Estimating sample size for magnitude-based inferences. *Sportscience*, *10*, 63-70.

Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, *41*(1), 3-12.

Houlihan, B., & Green, M. (2008). *Comparative elite sport development. Systems, structures and public policy.* Oxford, UK: Butterworth-Heinemann.

HPSNZ. (2012). *Strategic plan 2013-2020*. Auckland, New Zealand: High Performance Sport New Zealand.

Hunter, S. K., Stevens, A. A., Magennis, K., Skelton, K. W., & Fauth, M. (2011). Is there a sex difference in the age of elite marathon runners? *Medicine and Science in Sports and Exercise*, *43*(4), 656-664.

Issurin, V., Kaufman, L., Lustig, G., & Tenenbaum, G. (2008). Factors affecting peak performance in the swimming competition of the Athens Olympic Games. *Journal of Sports Medicine and Physical Fitness*, *48*(1), 1-8.

Johnson, M. B., Tenenbaum, G., & Edmonds, W. A. (2006). Adaptation to physically and emotionally demanding conditions: The role of deliberate practice. *High Ability Studies*, *17*(1), 117-136.

Kendall, B., & Eston, R. (2002). Exercise-induced muscle damage and the potential protective role of estrogen. *Sports Medicine*, *32*(2), 103-23.

Knechtle, B., Rüst, C. A., Rosemann, T., & Lepers, R. (2012). Age-related changes in 100-km ultra-marathon running performance. *Age*, *34*(4), 1033-1045.

Kovalchik, S. A. (2014). The older they rise the younger they fall: Age and performance trends in men's professional tennis from 1991 to 2012. *Journal of Quantitative Analysis in Sports*, *10*, 99-107.

Lackey, G., & Heazlewood, I. (1998, 9-12 July, 1998). *The use of mathematical models to predict elite swimming performance.* Paper presented at the meeting of the Fourth Conference on Mathematics and Computers in Sport, Bond University, Queensland.

Landsberger, H. A. (1958). *Hawthorne revisited.* Ithaca, NY: Cornell University.

Lang, M., & Light, R. (2010). Interpreting and implementing the long-term athlete development model: English swimming coaches' views on the (swimming) LTAD in practice. *International Journal of Sports Science and Coaching*, *5*(3), 389-402.

Lätt, E., Jürimäe, J., Haljaste, K., Cicchella, A., Purge, P., & Jürimäe, T. (2009a). Longitudinal development of physical and performance parameters during biological maturation of young female swimmers. *Collegium Antropologicum*, *33*, 117-122.

Lätt, E., Jürimäe, J., Haljaste, K., Cicchella, A., Purge, P., & Jürimäe, T. (2009b). Longitudinal development of physical and performance parameters during biological maturation of young male swimmers. *Perceptual and Motor Skills*, *108*, 297-307.

Law, M. P., Cöté, J., & Ericsson, K. A. (2008). Characteristics of expert development in rhythmic gymnastics: A retrospective study. *International Journal of Sport and Exercise Psychology*, *5*(1), 82-103.

Lees, A. (2002). Technique analysis in sports: a critical review. *Journal of Sports Sciences*, *20*, 813-828.

Lepers, R., Sultana, F., Bernard, T., Hausswirth, C., & Brisswalter, J. (2010). Age-related changes in triathlon performances. *International Journal of Sports Medicine*, *31*(4), 251-256.

Maglischo, E. W. (2003). *Swimming fastest.* Champaign (IL): Human Kinetics.

Malcata, R. M., Hopkins W. G., & Richardson, S. (2012). Modelling the progression of competitive performance of an academy's soccer teams. *Journal of Sports Science and Medicine*, *11*(3), 533-536.

Malcata, R. M., Hopkins, W. G., & Pearson, S. N. (2014). Tracking performance of successful triathletes. *Medicine and Science in Sports and Exercise*, *46*(6), 1227-1234.

Malina, R. M. (1994). Physical growth and biological maturation of young athletes. In J. O. Holloszy (Ed.), *Exercise and Sport Sciences Review* (Vol. 22, pp. 389-433). Baltimore, MD: Williams & Wilkins.

Maszczyk, A., Roczniok, R., Waśkiewicz, Z., Czuba, M., Mikolajec, K., Zając, A., & Stanula, A. (2012). Application of regression and neural models to predict competitive swimming performance. *Perceptual and Motor Skills*, *114*(2), 610-626.

Mikulic, P. (2011). Maturation to elite status: A six-year physiological case study of a world champion rowing crew. *European Journal of Applied Physiology, 111*(9), 2363-2368.

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Annals of Internal Medicine*, *151*(4), 264-269.

Morais, G. E., Garrido, N. D., Marques, M. C., Silva, A. J., Marinho, D. A., & Barbosa, T. M. (2013). The influence of anthropometric, kinematic and energetic variables and gender on swimming performance in youth athletes. *Journal of Human Kinetics*, *39*, 203-211.

Morgan, W. P., Brown, D. R., Raglin, J. S., O'Connor, P. J., & Ellickson, K. A. (1987). Psychological monitoring of overtraining and staleness. *British Journal of Sports Medicine*, *21*(3), 107-114.

O'Connor, L. M., & Vozenilek, J. A. (2011). Is it the athlete or the equipment? An analysis of the top swim performances from 1990 to 2010. *Journal of Strength and Conditioning Research*, *25*(12), 3239-3241.

Oldenziel, K., & Gagne, F. (2004). Factors affecting the rate of athlete development from novice to senior elite: How applicable is the 10-year rule. In K. Vasilis, K. Spiros & M. Hioannis (Eds.), *Pre-Olympic congress: Sports science through the ages. Challenges in the new millennium* (pp. 235-236). Thessaloniki, Greece: Aristotle University of Thessaloniki.

Pike, J., Hopkins, W. G., & Nottle, C. (2010, 16-19 June 2010). *Overall trends and individual trajectories of swimming performances in a decade of New Zealand national championships.* Paper presented at the meeting of the XIth International Symposium on Biomechanics and Medicine in Swimming, Oslo, Norway.

Pyne, D., Trewin, C., & Hopkins, W. (2004). Progression and variability of competitive performance of Olympic swimmers. *Journal of Sports Sciences, 22*(7), 613-620.

Rebecca Adlington announces retirement from swimming. (2013, February 5). *The Daily Telegraph.* Retrieved from http://www.telegraph.co.uk/sport/olympics/swimming/9849313/Rebecca-Adlington-announces-retirement-from-swimming.html

Régnier, G., Salmela, J., & Russell, S. J. (1993). Talent detection and development in sport. In R. N. Singer, M. Murphy & L. K. Tennant (Eds.), *Handbook on research on sport psychology* (pp. 290-313). New York, NY: Macmillan.

Rushall, B. S. (2011a). Commentary on the long term athlete development model for British Swimming and the misinformation it propagates. *Swimming Science Bulletin, 38.* Retrieved from http://coachsci.sdsu.edu/swimming/bullets/table.htm

Rushall, B. S. (2011b). *Swimming pedagogy and a curriculum for stroke development* (2nd ed.). Spring Valley, CA: Sports Science Associates [Electronic book].

Rushall, B. S. (2013). Fatigue in swimming: The good, the bad, and the ugly. *Swimming Science Bulletin*, *46a.* Retrieved from http://coachsci.sdsu.edu/swim/bullets/46aFATIGUE.pdf.

Rushall, B. S., & Pyke, F. S. (1991). *Training for sports and fitness.* Melbourne, Australia: Macmillan of Australia.

Rüst, C. A., Knechtle, B., Knechtle, P., Rosemann, T., & Lepers, R. (2012a). Age of peak performance in elite male and female Ironman triathletes competing in Ironman Switzerland, a qualifier for the Ironman world championship, Ironman Hawaii, from 1995 to 2011. *Open Access Journal of Sports Medicine*, *2012*(3), 175-182.

Rüst, C. A., Knechtle, B., Rosemann, T., & Lepers, R. (2012b). Sex difference in race performance and age of peak performance in the Ironman triathlon world championship from 1983 to 2012. *Extreme Physiology and Medicine*, *1*(15). doi: 10.1186/2046-7648-1-15

Rüst, C. A., Knechtle, B., Rosemann, T., & Lepers, R. (2013). Analysis of performance and age of the fastest 100-mile ultra-marathoners worldwide. *Clinics*, *68*(5), 605-611.

Salthouse, T. A. (2012). Consequences of age-related cognitive declines. *Annual Review of Psychology*, *63*, 201-226.

Savage, B., & Pyne, D. B. (2013). Physiological protocols for the assessment of athletes in specific sports: Swimmers. In R. K. Tanner & C. J Gore (Eds.), *Physiological tests for elite athletes* (2nd ed.) (pp. 435-448). Champaign, IL: Human Kinetics.

Schmitt, D. P., Realo, A., Voracek, M., & Allik, J. (2008). Why can't a man be more like a woman? Sex differences in Big Five personality traits across 55 cultures. *Journal of Personality and Social Psychology*, *94*(1), 168-182.

Schulz, R., & Curnow, C. (1988). Peak performance and age among superathletes: Track & field, swimming, baseball, tennis, and golf. *Journal of Gerontology*, *43*(5), 113-120.

Schulz, R., Musa, D., Staszewski, J., & Siegle, R. S. (1994). The relationship between age and major league baseball performance: Implications for development. *Psychology and Aging*, *9*(2), 274-286.

Schumacher, Y. O., Mroz, R., Mueller, P., Schmid, A., & Ruecker, G. (2006). Success in elite cycling: A prospective and retrospective analysis of race results. *Journal of Sports Sciences*, *24*(11), 1149-1156.

Shoak, M. A., Knechtle, B., Knechtle, P., Rüst, C. A., Rosemann, T., & Lepers, R. (2013). Participation and performance trends in ultracycling. *Open Access Journal of Sports Medicine*, *2013*(4), 41-51.

Silva, A. J., Costa, A. M., Oliveira, P. M., Reis, V. M., Saavedra, J., Perl, J., … Marinho, D.A. (2007). The use of neural network technology to model swimming performance. *Journal of Sports Science and Medicine*, *6*, 117-125.

Simonton, D. K. (1988). Age and outstanding achievement: What do we know after a century of research? *Psychological Bulletin*, *104*(2), 251-267.

Smith, T. B., & Hopkins, W. G. (2011). Variability and predictability of finals times of elite rowers. *Medicine and Science in Sports and Exercise, 43*(11), 2155-2160.

SNZ. (2012). *High Performance Strategy 2013 – 2020*. Auckland, New Zealand: Swimming New Zealand.

Sokolovas, G. (2006a, January 2006). When will you peak? *Swimming World Magazine*, *47*, 37-38.

Sokolovas, G. (2006b) Analysis of USA swimming's all-time top 100 times. In J. P. Vilas-Boas, F. Alves & A Marques (Eds.), *Biomechanics and medicine in swimming X* (pp. 315-317). Porto, Portugal: University of Porto.

Stanula, A., Maszczyk, A., Roczniok, R., Pietraszewski, P., Ostrowski, A., Zajac, A., & Strzata, M. (2012). The development and prediction of athletic performance in freestyle swimming. *Journal of Human Kinetics*, *32*, 97-107.

Stewart, A. M., & Hopkins, W. G. (2000a). Seasonal training and performance of competitive swimmers. *Journal of Sports Sciences*, *18*(11), 873-884.

Stewart, A. M., & Hopkins, W. G. (2000b). Consistency of swimming performance within and between competitions. *Medicine and Science in Sports and Exercise*, *32*(5), 997-1001.

Storm, R., & Nielsen, K. (2010). In a peak fitness condition? The Danish elite sports model in an international perspective: managerial efficiency and best practice in achieving international

sporting success. *International Journal of Sports Management and Marketing*, *7*(1/2), 104-118.

Sweetenham, B. (2001). Maximising a swimmer's talent development. In D. Hannula & N Thornton (Eds.), *The swim coaching bible* (pp. 71-95). Champaign, IL: Human Kinetics.

Tilinger, P., Kovář, K., & Hlavatá, P. (2005). A study on the dynamic progress of performances of prominent world-class athletes in selected track-and-field events. *Kinesiology*, *37*(1), 92-98.

Tiruneh, G. (2010). Age and winning professional golf tournaments. *Journal of Quantitative Analysis in Sports*, *6*. doi: 10.2202/1559-0410.1209

Treffene, B. (2010). Interpreting and implementing the long-term athlete development model: English swimming coaches' views on the (swimming) LTAD in practice – A commentary. *International Journal of Sports Science and Coaching*, *5*(3), 407-412.

Tucker, R., & Collins, M. (2013). What makes champions? A review of the relative contribution of genes and training to sporting success. *British Journal of Sports Medicine*, *46*(8), 555-561.

UK Sport. (2006). *Sports policy factors leading to international sporting success. An international comparative study*. London, UK: UK Sport.

Vaeyens, R., Güllich, A., Warr, C. R., & Philippaerts, R. (2009). Talent identification and promotion programmes of Olympic athletes. *Journal of Sports Sciences*, *27*, 1367-1380.

Vaeyens, R., Lenoir, M., Williams, A. M., & Philippearts, R. M. (2008). Talent identification and development programmes in sport: Current models and future directions. *Sports Medicine. 38*(9), 703-714.

Vandenbogaerde, T. J., & Hopkins, W. G. (2010). Monitoring acute effects on athletic performance with mixed linear modeling. *Medicine and Science in Sports and Exercise, 42*(7), 1339-1344.

Vandenbogaerde, T. J., Hopkins, W. G., & Pyne, D. B. (2012). A competition-based design to assess performance of a squad of elite athletes. *Medicine and Science in Sports and Exercise*, *44*(12), 2423-2427.

Vorontsov, A. R. (2005). *Periodisation of multi-year training (MYT/LTAD) of young swimmers* [PowerPoint slides]. Retrieved from
http://images.one.co.il/images/egood/swim/doc/Periodisation%20of%20%20MYT.ppt

Wolfrum, M., Knechtle, B., Rüst, C. A., Rosemann, T., & Lepers, R. (2013). Sex-related differences and age of peak performance in breaststroke versus freestyle swimming. *BMC Sports Science, Medicine and Rehabilitation*, *5*(29). doi: 10.1186/2052-1847-5-29

Zaryski, C., & Smith, D. J. (2005). Training principles and issues for ultra-endurance athletes. *Current Sports Medicine Reports*, *4*(3), 165-170.

APPENDIX A: SAS LINEAR MODELS

Examples of the SAS coding using to specify the mixed linear models for each of the original-research studies. I have also included a small sample of the dataset and variables used by each model.

Chapter 3- Mixed model for individual Olympic trajectories

Twelve observations for one swimmer in one event from the dataset datlog:

```
Obs Sex  Stroke      Distance Athlete              Age0     Age0sq Olympics01 Y2009 Y2010 SwimTime

  1 Male Backstroke     100   Arnamnart, Daniel   -6.38630 40.7848     0       0     0    6:53.36
  2 Male Backstroke     100   Arnamnart, Daniel   -5.42541 29.4351     0       0     0    6:46.63
  3 Male Backstroke     100   Arnamnart, Daniel   -4.42192 19.5534     0       0     0    6:43.99
  4 Male Backstroke     100   Arnamnart, Daniel   -2.78082  7.7330     0       0     0    6:42.12
  5 Male Backstroke     100   Arnamnart, Daniel   -2.67397  7.1501     0       0     0    6:40.72
  6 Male Backstroke     100   Arnamnart, Daniel   -1.43088  2.0474     0       0     0    6:40.62
  7 Male Backstroke     100   Arnamnart, Daniel    0.13699  0.0188     0       1     0    6:40.26
  8 Male Backstroke     100   Arnamnart, Daniel    0.73699  0.5431     0       0     1    6:39.95
  9 Male Backstroke     100   Arnamnart, Daniel    2.23836  5.0102     0       0     0    6:40.44
 10 Male Backstroke     100   Arnamnart, Daniel    2.50355  6.2678     0       0     0    6:38.99
 11 Male Backstroke     100   Arnamnart, Daniel    3.61370 13.0588     0       0     0    6:39.42
 12 Male Backstroke     100   Arnamnart, Daniel    4.45753 19.8696     0       0     0    6:39.73
```

Coding for mixed model:

```
proc mixed data=datlog covtest cl alpha=0.1 maxfunc=1000 convg=1E-6;
class Athlete &AgeGroup;
model SwimTime=Olympics01 Y2009 Y2010 Age0 Age0sq/ddfm=sat outp=pred
alpha=0.1 alphap=0.1 s residual;
repeated/group=&AgeGroup;
random int Age0 Age0sq/subject=Athlete type=&type s;
random Y2009 Y2010/subject=Athlete type=vc s;
estimate "Olympics" Olympics01 1/cl alpha=0.1;
estimate "Y2009" Y2009 1/cl alpha=0.1;
estimate "Y2010" Y2010 1/cl alpha=0.1;
estimate "Age0" Age0 1/cl alpha=0.1;
estimate "Age0Sq" Age0Sq 1/cl alpha=0.1;
ods output estimates=est;
ods output classlevels=clev;
ods output solutionr=solr;
ods output solutionf=solf;
ods output covparms=cov;
by Sex Stroke Distance;
run;
```

Chapter 4- Mixed model for individual Australian trajectories

Four observations for one Australian swimmer in one event from the dataset datlog:

```
Obs    Sex     Stroke   Distance   Athlete                    Weight

2845   Male    Back       100      RAY BORNMAN                0.54165
2846   Male    Back       100      RAY BORNMAN                0.77379
2847   Male    Back       100      RAY BORNMAN                1.10541
2848   Male    Back       100      RAY BORNMAN                1.57916


 Obs    Age0      Age0sq    Olympics02    AUS01    Olympics01   Y2009    Y2010

2845   -5.15068   26.5296       0           1          0         0        0
2846   -4.15342   17.2509       0           1          0         0        0
2847   -3.15616    9.9614       0           1          0         0        0
2848   -2.82540    7.9829       0           1          0         0        0
```

Coding for mixed model:

```
ods listing close;
proc mixed data=datlog covtest cl alpha=0.1 maxfunc=1000 convg=1E-6;
weight weight;
class Athlete &AgeGroup Olympics02 AUS01;
model SwimTime=Olympics02*AUS01 Olympics01 Y2009 Y2010 Age0
Age0sq/ddfm=sat outp=pred alpha=0.1 alphap=0.1 s residual;
repeated/group=&AgeGroup;
random int Age0 Age0sq/subject=Athlete type=&type s;
estimate "Olympic Effect" Olympics01 1 0/cl alpha=0.1;
estimate "AUS Effect" Olympics02*AUS01 1 0/cl alpha=0.1;
estimate "Y2009" Y2009 1/cl alpha=0.1;
estimate "Y2010" Y2010 1/cl alpha=0.1;
estimate "Age0" Age0 1/cl alpha=0.1;
estimate "Age0Sq" Age0Sq 1/cl alpha=0.1;
ods output estimates=est;
ods output classlevels=clev;
ods output solutionr=solr;
ods output solutionf=solf;
ods output covparms=cov;
by Sex Stroke Distance;
run;
```

Chapter 4- Mixed model for swim time and age regression

Thirteen observations for five swimmers in one event from the dataset ausfilterlog:

Obs	Sex	Stroke	Distance	Athlete
1	Female	Back	100	ABBEY HELLINGA
2	Female	Back	100	ABBEY SWEENEY
3	Female	Back	100	ABBY DERBYSHIRE
4	Female	Back	100	ABBY DERBYSHIRE
5	Female	Back	100	ABBY DERBYSHIRE
6	Female	Back	100	ACACIA WILDIN-SNEDDEN
7	Female	Back	100	ACACIA WILDIN-SNEDDEN
8	Female	Back	100	ACACIA WILDIN-SNEDDEN
9	Female	Back	100	ADELAIDE HART
10	Female	Back	100	ADELAIDE HART
11	Female	Back	100	ADELAIDE HART
12	Female	Back	100	ADELAIDE HART
13	Female	Back	100	ADELAIDE HART

Obs	Year	Time12	Percent Diff	Age0	Age0sq
1	2007	.	24.9574	-2.87397	8.2597
2	2008	.	26.3267	0.16162	0.0261
3	2007	.	33.7961	-4.19178	17.5710
4	2008	.	32.7707	-3.18906	10.1701
5	2009	.	30.2879	-2.19178	4.8039
6	2009	.	35.2468	-4.30411	18.5254
7	2010	.	26.7697	-3.30685	10.9353
8	2011	.	26.3608	-2.30959	5.3342
9	2008	6:54.95	18.8485	-2.75965	7.6156
10	2009	6:54.95	16.5637	-1.75068	3.0649
11	2010	6:54.95	7.7923	-0.08767	0.0077
12	2011	6:54.95	6.6397	0.26301	0.0692
13	2012	6:54.95	8.6954	1.17205	1.3737

Coding for mixed model:

```
Proc mixed data=ausfilterlog cl alpha=0.1;
Class Athlete;
```

```
Model Time12=PercentDiff Age0 Age0sq/ddfm=sat outp=pred alpha=0.1
alphap=0.1 s residual intercept;
Repeated;
ods output classlevels=clev;
ods output solutionf=solf;
by Sex Stroke Distance;
run;
```

Chapter 5- Mixed model for analysing career training and performance relationships

22 observations for two swimmers in one event from the dataset train2:

Obs	Sex	Stroke	Distance	UniqueID	Year
1	Female	Backstroke	50	ADSR160400	2007
2	Female	Backstroke	50	ADSR160400	2008
3	Female	Backstroke	50	ADSR160400	2008
4	Female	Backstroke	50	ADSR160400	2009
5	Female	Backstroke	50	ADSR160400	2009
6	Female	Backstroke	50	ADSR160400	2010
7	Female	Backstroke	50	ADSR160400	2010
8	Female	Backstroke	50	ADSR160400	2011
9	Female	Backstroke	50	ADSR160400	2011
10	Female	Backstroke	50	ADSR160400	2012
11	Female	Backstroke	50	ADSR160400	2012
12	Female	Backstroke	50	ADSR160400	2013
13	Female	Backstroke	50	ADSR160400	2013
14	Female	Backstroke	50	ALEK101000	2010
15	Female	Backstroke	50	ALEK101000	2011
16	Female	Backstroke	50	ALEK101000	2011
17	Female	Backstroke	50	ALEK101000	2012
18	Female	Backstroke	50	ALEK101000	2012
19	Female	Backstroke	50	ALEK101000	2013
20	Female	Backstroke	50	ALEK101000	2013
21	Female	Backstroke	50	ALEK101000	2014
22	Female	Backstroke	50	ALEK101000	2014

Obs	SwimTime	Age0	Age0sq	Age Group	Swim Rank	Total DPTert	Cumult Others Tert
1	6:42.34	-8.4	70.56	1	1	0	0
2	6:37.03	-8.2	67.24	1	2	0	0
3	6:32.51	-7.4	54.76	1	1	0	0
4	6:21.46	-6.8	46.24	1	2	0	0
5	6:20.29	-6.4	40.96	1	1	0	1
6	6:09.71	-6.3	39.69	1	2	0	1
7	6:08.06	-5.4	29.16	1	1	1	1
8	6:01.87	-4.7	22.09	1	2	2	1
9	6:00.88	-4.4	19.36	1	1	2	1
10	5:54.10	-4.2	17.64	1	2	2	1
11	5:53.11	-3.8	14.44	1	1	2	2
12	5:51.54	-3.2	10.24	1	2	2	2
13	5:50.56	-2.6	6.76	2	1	1	2
14	6:14.31	-5.9	34.81	1	1	0	0
15	6:02.14	-4.9	24.01	1	1	1	0
16	6:02.65	-4.9	24.01	1	2	1	0
17	5:54.30	-3.9	15.21	1	1	2	0
18	5:56.02	-3.9	15.21	1	2	2	0
19	5:46.95	-2.8	7.84	2	1	1	0
20	5:48.46	-2.8	7.84	2	2	1	0
21	5:45.25	-2.5	6.25	2	2	1	0
22	5:43.20	-2.4	5.76	2	1	1	0

Coding for mixed model:

```
proc mixed data=train2 covtest cl alpha=0.1 maxfunc=1000;
class UniqueID Year AgeGroup SwimRank TotalDPTert CumultOthersTert;
```

```
model SwimTime=Age0 Age0sq AgeGroup*SwimRank AgeGroup*TotalDPTert
AgeGroup*TotalDPTert*CumultOthersTert/ddfm=sat alpha=0.1 alphap=0.1 s
residual;
repeated/group=AgeGroup;
random int Age0 Age0sq/subject=UniqueID type=un s;
random year/subject=UniqueID;
lsmeans AgeGroup*TotalDPTert*CumultOthersTert/diff cl alpha=0.1;
ods output classlevels=clev;
ods output solutionr=solr;
ods output solutionf=solf;
ods output covparms=cov;
ods output lsmeans=lsm;
ods output diffs=lsmdiffs;
by Sex Distance Stroke;
run;
```

Chapter 6- Mixed model for assessing performance effect of centralisation and development of club trajectories

Observations for ten swimmers in one event and year from the dataset datlog:

```
 Obs   Sex       Event       Athlete                 SwimTime

 1606   F     100Freestyle   ALICE ULTEE              7:26.69
 1607   F     100Freestyle   ALISHA SARGENT           6:55.43
 1608   F     100Freestyle   ALISON FITCH             6:42.52
 1609   F     100Freestyle   ALLANNAH PEAT            7:16.07
 1610   F     100Freestyle   ALYSHA WILSON            7:43.50
 1611   F     100Freestyle   ALYSSA JONES             7:20.44
 1612   F     100Freestyle   ALYSSA WONG              7:47.97
 1613   F     100Freestyle   AMAKA GESSLER            7:12.59
 1614   F     100Freestyle   AMANDA BROWN             7:04.79
 1615   F     100Freestyle   AMANDA BUNCKENBURG       7:24.09
 1616   F     100Freestyle   AMANDA CRAIG             7:04.12

 Obs    Age16     Age16sq    Year   HPC01    Club

 1606   -5.53056  30.5871     -7      0      CRMOT
 1607   -1.22419   1.4986     -7      0      ASTED
 1608    6.51269  42.4151     -7      1      NSSAK
 1609   -4.18630  17.5251     -7      0      TEPBP
 1610   -6.71288  45.0627     -7      0      HAWTR
 1611   -2.71840   7.3897     -7      0      MANCO
 1612   -8.20000  67.2400     -7      0      WHLAK
 1613   -4.26849  18.2200     -7      0      NELNM
 1614   -2.79452   7.8093     -7      0      ASTED
 1615   -4.71233  22.2060     -7      0      PCAWN
 1616    1.11215   1.2369     -7      0      STRTR
```

Coding for mixed model:

```
proc hpmixed data=datlog;
class Athlete Event Club Year;
model SwimTime=Event Age16 Age16sq HPC01*Year/s;
random int Age16 Age16sq/subject=Athlete*Event type=un s cl alpha=0.1;
random int Year/subject=Club s cl alpha=0.1;
output out=SS.predictions pred=predicted resid=residual lcl=lower
ucl=upper/alpha=0.1;
estimate "Age16" Age16 1/cl alpha=0.1;
estimate "Age16Sq" Age16Sq 1/cl alpha=0.1;
Estimate "HPC in 2002" HPC01*Year 1/cl alpha=0.1;
Estimate "HPC in 2003" HPC01*Year 0 1/cl alpha=0.1;
Estimate "HPC in 2004" HPC01*Year 0 0 1/cl alpha=0.1;
Estimate "HPC in 2005" HPC01*Year 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2006" HPC01*Year 0 0 0 0 1/cl alpha=0.1;
```

```
Estimate "HPC in 2007" HPC01*Year 0 0 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2008" HPC01*Year 0 0 0 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2009" HPC01*Year 0 0 0 0 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2010" HPC01*Year 0 0 0 0 0 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2011" HPC01*Year 0 0 0 0 0 0 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2012" HPC01*Year 0 0 0 0 0 0 0 0 0 0 1/cl alpha=0.1;
Estimate "HPC in 2013" HPC01*Year 0 0 0 0 0 0 0 0 0 0 0 1/cl
alpha=0.1;
ods output estimates=ss.est;
ods output classlevels=ss.clev;
ods output solutionr=ss.solr;
ods output parameterestimates=ss.solf;
ods output covparms=ss.cov;
by Sex;
run;
```

Poster presented at the 17th meeting of the European Congress of Sport Science, Bruges, Belgium, in July 2012.

HIGH PERFORMANCE
SPORT NEW ZEALAND

SPORTS PERFORMANCE RESEARCH INSTITUTE NZ

Career Performance Trajectories of Olympic Swimmers

Sian V Allen, Will G Hopkins, Tom J Vandenbogaerde

Auckland University of Technology, New Zealand

INTRODUCTION

* Assessing the progression of a swimmer's competitive performance against benchmarks is a key element of talent identification and development. Information about changes in performance of elite swimmers during their formative years is needed to construct these benchmarks.

* Here we present the effect of age on swimming performance and estimates of the progression required to attain peak performance at the elite level.

METHODS

* The subjects were the top 16 swimmers in all events at the 2008 Beijing Olympics. Their age at the Olympics was 21.5 ± 3.5 y and 23.9 ± 2.9 y for females and males respectively (mean ± SD).

* We searched the Web for annual best times of each swimmer from their earliest available competitive performance through to 2011 (4285 times in the 13 stroke and distance combinations for each sex, for 391 swimmers, over 9.8 ± 2.9 y).

* Times were log-transformed for analysis of changes in performance as percentages. We used a mixed linear model (Proc Mixed procedure) in the Statistical Analysis System (Version 9.2, SAS Institute, Cary, NC) that included:
  * an effect for better performance in Olympic years;
  * an effect for the use of new-generation swimsuits in 2009;
  * the effect of age on each swimmer's times modeled as individual quadratic trajectories.

RESULTS & DISCUSSION

* Effects for Olympic years and the swimsuit year (2009) accounted for additional performance enhancements in all events of 1.2 ± 0.3 % and 1.1 ± 0.5 % respectively (mean ± between-event SD). The Olympic year effect is likely due to better preparation and motivation for this pinnacle event, but swimsuits probably also contributed in 2008, as in 2009.

* A performance trajectory for one swimmer, and the mean performance trajectory for their event, both adjusted for these effects, are shown in Figure 1.
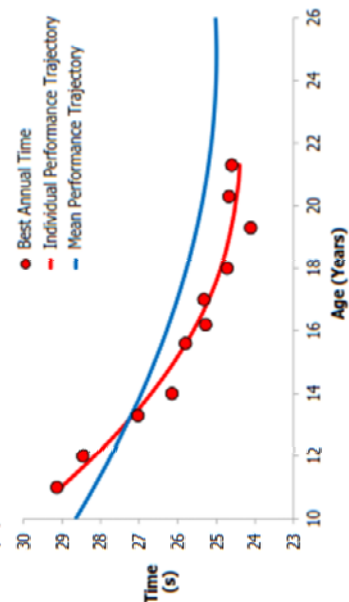
* The trajectories for females and males predicted peak performance occurring a year or two after the 2008 Olympics, at ages 23.2 ± 2.1 y and 24.7 ± 2.3 y respectively (mean ± SD).

* Peak performance occurred at later ages (by ~3 y) for the shorter distances. This difference may reflect different maturation of aerobic and anaerobic capacities and should be a consideration in event selection.

* Both sexes had similar progressions to peak performance: over ten years 11.6 ± 6.4 %, and over five years 3.0 ± 1.6 %.

Figure 1: Best annual times for a female 50-m freestyle swimmer, with her career performance trajectory and the mean performance trajectory for the top 16 swimmers in this event at the 2008 Olympics.

* Best Annual Time
- - Individual Performance Trajectory
— Mean Performance Trajectory

Time (s)

Age (Years)

CONCLUSIONS

★ Quadratic performance trajectories provided by mixed modeling are a potentially valuable benchmarking tool for talent identification.

★ Features of this approach:
  * adjustment for level of competition and other factors affecting performance;
  * estimation of age of peak performance;
  * estimation of progressions in performance in the years leading up to the peak.

Oral presentation given at the 11th International Symposium of Biomechanics and Medicine in Swimming, Canberra, Australia, in May 2014.

Background

Talent identification and development typically involves allocation of resources towards squads of swimmers selected on the basis of early performance.

Aim

To objectively evaluate the success of this approach...

...by retrospectively comparing the predictive accuracy of four diagnostic methods for early selection of Australia's 2012 Olympic qualifying swimmers.

Data

Official long-course performance times from all Australian swimmers (*n*=4413) in individual Olympic events at 101 regional, national and international age-group and open competitions between 2000 and 2012.

70 Australian swimmers faster than individual FINA 'A' Olympic qualifying times in 2012.

1.5% of our sample...

Analysis

Four methods retrospectively simulated early selection of swimmers for a "talent-development squad".

Analysis first performed with data up to 2007.
Analyses repeated for 2008, 2009, 2010 and 2011.

The analyses provided thresholds for squad selection in a given year that included 90% of the swimmers who eventually qualified for the Olympics.
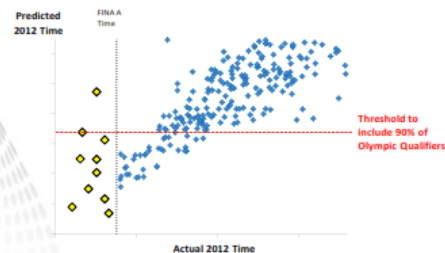
Methods

1. Best annual swim time as % of world record

Sex	Stroke	Distance	Swimmer	Year	Swim Time	% WR
Women	Fl50	100	LISBETH TRICKETT	2007	00:58.40	0.2%
Women	Fr	200	LASSELINA SCHITINAR	2007	02:06.29	0.4%
Women	Breast	100	LEISEL JONES	2007	01:06.71	1.3%
Women	IM	200	STEPHANIE RICE	2007	02:11.42	1.3%

2-4. Predicted swim times for 2012
- Linear regression of swim time and age
- Extrapolated quadratic career performance trajectory
- Neural network modelling of swim time and age

Methods

Predicted 2012 Time — FINA A Time

Threshold to include 90% of Olympic Qualifiers

Actual 2012 Time

Results

Proportions of the squad who were correctly identified qualifiers...

Method	2007	2008	2009	2010	2011
Swim Time %WR	9%	12%	22%	48%	54%
Swim Time Age Regression	11%	11%	32%	43%	66%
Quadratic Trajectories	12%	17%	22%	30%	38%
Neural Net	13%	12%	27%	47%	66%

Corresponding squad sizes...

	2007	2008	2009	2010	2011
Neural Net	475	498	226	129	92

Results

Neural net predictions with 90% of Olympic qualifiers...

	2007	2008	2009	2010	2011
Squad size	475	498	226	129	92

Actual Swimming Australia funded squads...

		2008	2009	2010	2011
Proportions of Olympic qualifiers selected		47%	57%	65%	78%
Squad size		91	90	69	67

Interpretation

- Consider variables other than age-related performance?

Adapted from Marinho et al. (2013)
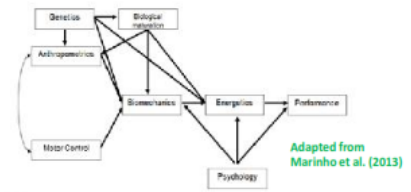
- Most effective resource allocation?
  - More medals?
  - Tiered support system?

Performance Trajectories Tool
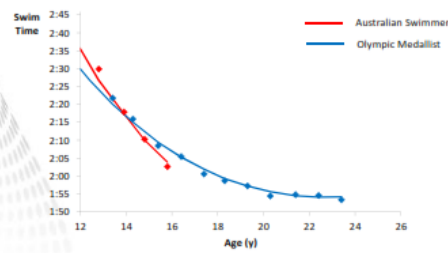
Mini-oral presentation given at the 19th European Congress of Sport Science, Amsterdam, The Netherlands, in July 2014. This presentation was awarded an ECSS Young Investigator Award (2nd place).

The performance effect of centralising a nation's elite swim programme

Allen, S.V.[1,2]; Hopkins, W.G.[2,3]; Vandenbogaerde, T.J.[2]

[1]Auckland University of Technology, NEW ZEALAND
[2]High Performance Sport New Zealand, NEW ZEALAND
[3]Victoria University, AUSTRALIA

Background:

Many national sporting organisations recruit talented athletes to well-resourced centralised training squads to improve their performance.

Purpose:

To develop a method to monitor performance progression of swimming squads, and to use this method to assess the progression of New Zealand's centralised elite swimming squad since its inception in 2002.

Contact: sian.allen@hpsnz.org.nz

Methods

Data: Best annual long-course competition times of all NZ swimmers between 2002 and 2013 (~281,000 times from ~8500 swimmers).

Model: Mixed linear model (Proc HpMixed) in SAS 9.4:
- Fixed effects: Event, Age, Year, Elite-squad Membership*Year
- Random effects: Swimmer, Age, Club, Club*Year

Outcomes:
- Mean estimates of the deviation of swimmers' performances from their individual performance trends after they joined the elite squad
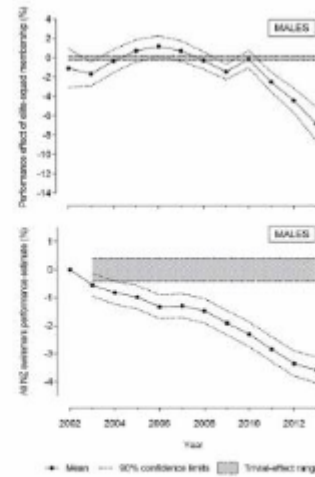- Estimates of mean annual performance for all NZ swimmers and for 175 NZ swim clubs

Results

Performance effect of centralisation:
- Mostly unclear and trivial to small before 2009
- Clear additional performance for both sexes from 2009-2013

Annual progression of NZ swimming:
- Gradual annual improvements
- Magnitude similar to world top-150 (~0.3% per year)

Results

Club performance trends:
- Effects of interventions can be evaluated for 175 NZ swim clubs

Conclusion

Our new method of quantifying deviations from individual trends in competition performance should be useful for coaches, scientists and administrators interested in evaluating performance-enhancement strategies introduced at national or club level in swimming and/or other similar sports.
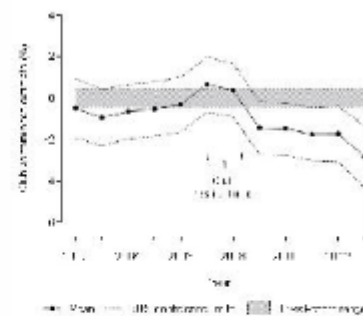
Mini-oral presentation of collaborative research given by lead author Pat Lipinska at the 19th meeting of the European Congress of Sport Science, in Bruges, Belgium, in July 2014.

Relationships between pacing parameters and performance of elite female 800-m freestyle swimmers

Pat Lipinska[1], Sian Allen[2,3], Will Hopkins[2,3,4]
[1]*Gdansk University of Physical Education and Sport, POLAND*
[2]*Auckland University of Technology, NEW ZEALAND*
[3]*High Performance Sport New Zealand, NEW ZEALAND*
[4]*Victoria University, AUSTRALIA*
Email: patlip@awf.gda.pl

Background
- Evidence for effects of changes in pacing profile on endurance performance is sparse.

Purpose
- To develop a method to characterize pacing.
- To relate changes in pacing and performance in 800-m freestyle swimmers.

Methods
- 192 best swims of 20 elite female 800-m freestyle swimmers in internationals between 2006 and 2012.
- Pacing for each swim was characterized with five parameters derived from a linear model.

- Example:
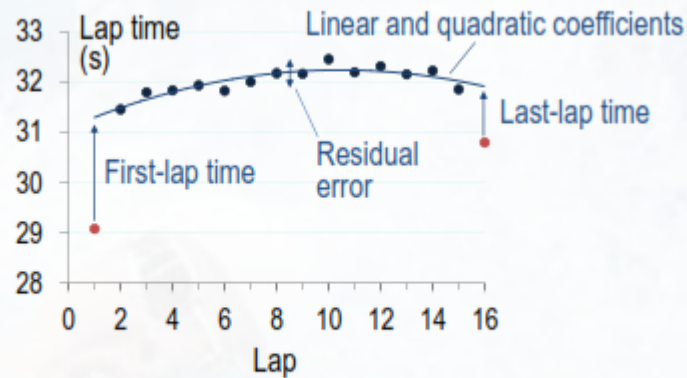
- Effect of within-swimmer changes in each parameter on changes in performance was then determined with a mixed linear model.

Results
- The linear and quadratic parameters and the residual error had likely trivial effects on final time (0.2%, 0.1%, 0.2% respectively).
  - At this elite level swimmers are close to their optimum profile.
- The last lap had a possibly trivial-small positive effect (0.3%).
  - The expected contribution of that lap to the overall time.
  - Due to changes in fatigue from race to race.
- The first lap had a possibly trivial-small *negative* effect (-0.3%).
  - The effect of a swimmer going out too fast sometimes?
  - Antagonism of changes in strength and endurance fitness?

Conclusion
- A five-parameter model is a useful approach to analysis of pacing.

Oral presentation of collaborative research given by lead author Pat Lipinska at the 5th World Congress of Performance Analysis in Sport, held in Opatija, Croatia, in September 2014.

Relationships between pacing parameters and performance of elite male 1500-m freestyle swimmers

Pat Lipinska[1], Sian Allen[2,3], Will Hopkins[3,4]
[1]Gdansk University of Physical Education and Sport, POLAND
[2]Auckland University of Technology, NEW ZEALAND
[3]High Performance Sport New Zealand, NEW ZEALAND
[4]Victoria University, AUSTRALIA
Email: patlip@awf.gda.pl

Background
- It is widely known that an athlete's pacing strategy can have a significant impact on performance (Tucker & Noakes, 2009, Thiel et all., 2012).
- By applying mathematical modelling to athletic performances, coaches and researchers have observed a variety of pacing strategies (Abbiss & Laursen, 2008).
- Knowledge pertaining to optimal pacing strategies during middle-distance to ultra-distance (Abbiss & Laursen, 2008) events is currently lacking. It concerns as well distance swimming.


Purpose
- To develop a method for characterizing and assessing effects of pacing in 1500-m freestyle swimming.
- To relate changes in pacing and performance in 1500-m freestyle swimmers.

Subjects
- 330 best swims of 24 elite male 1500-m freestyle swimmers in international and national events between 2000 and 2014,
- Swimrankings.net and other websites provided 50-m split and final race times over in 100 national and international competitions,
- Number of swims for each swimmer ranged from 6 to 30.
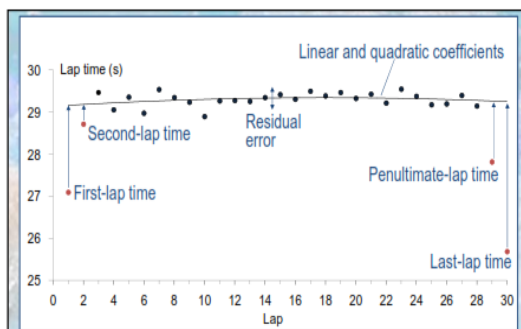
- Race time was then plotted against each parameter for each swimmer, a quadratic was fitted:
  - to help identify the value of the parameter associated with the swimmer's optimum performance
  - to determine the deviation of the swimmer's mean from his optimum

---

Example of ... parameter (First-lap ti...)
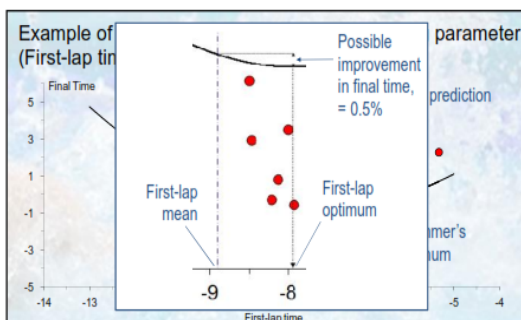
Results
- The average quadratic profile represented a practically linear reduction in pace of 1.0% between the first lap and the last lap.
- Times for the first, second, penultimate and last lap were shorter than the time predicted from each subject's quadratic profile by 7.9 ± 1.1, 0.8 ± 0.7, 1.7 ± 0.8 and 6.0 ± 1.7 respectively (%, mean ± SD),
- The residual error (%) was 0.7 ± 0.2.

Results

- The optimum value of each parameter gave a substantially faster swim than the average value for 1/3 to 1/2 of swimmers.
- These swimmers could make the following improvements on average in their final time:
  - 1.4% and 0.8% by changing the shape of the profile (linear and quadratic coefficients, respectively);
  - 0.7% and 0.9% by swimming *slower* in the first lap and second lap by 1.1% and 0.8%, respectively;
  - 0.5% and 0.7% by swimming faster in the penultimate lap and last lap by 0.3% and 0.9%, respectively;
  - 1.0% by reducing error from ±0.8% to ±0.6%.

Conclusion

- These effects indicate that some swimmers could make small to moderate improvements on average by changing their pacing.
- One surprising change was improvement by *slowing* the first and second lap.
  - Antagonism of changes in strength and endurance fitness?
  - An effect of „blowing up" by starting too fast?
- Improvements were also possible by speeding up the last two laps.
  - An effect of „gas in the tank".
- The two-step linear modeling method might be appropriate to assess pacing in other endurance sports with multiple laps.

Sample of the report provided to Swimming NZ and the HPSNZ board in October 2012 to review the performance of individuals within the New Zealand swim team at the London Olympics and assess the prospects for future progression of Olympic team members.

London Olympics 2012: NZ Swim Performance Report

Tom Vandenbogaerde, Sian Allen, Rita Malcata, Will Hopkins
High Performance Sport New Zealand, Auckland, New Zealand and Sport Performance Research Institute of New Zealand, AUT University, Auckland, New Zealand

We first present an analysis of the performance of New Zealand in Swimming, using a novel method developed by Will Hopkins, Rita Malcata and Tom Vandenbogaerde. In many sports such as Swimming, medal count at major competitions is the usual measure of country performance. This approach has several problems. First, a medal count does not reflect a country's talent base, because it excludes performances of athletes not winning medals. Secondly, the count is biased against countries with more talent when (as is usually the case) there is a cap on the number of entries from each country. Finally, medal counts are low and therefore inherently imprecise: in any one year they provide only an approximate assessment of performance. The novel method, which solves these problems combines world rankings of individual athletes into a country score by summing the inverse of the athletes' ranks. The resulting score is equivalent to the top-rank or gold-medal capability of the country. A paper on this method has been submitted for publication in Medicine and Science in Sports and Exercise. Please contact Rita or Tom for more info.

We then show performance times of the New Zealand Olympic Team swimmers at the London Olympics and other major competitions 2010 through 2012. We've compared performance progression rates between trials and Olympics, personal best and Olympics, and heats vs semi-finals vs finals, for New Zealand, Great Britain, Australia, USA, China and Japan. We've also included comparisons in number and percentage of total number of performances in individual events that had improved between competitions and from heats to semi-finals and/or finals at the Olympics.

We then present performance trajectories of our London Olympic Team swimmers that qualified for an individual event, and trajectories of medal winners and of the top 16 in the respective event. These modelled trajectories include only best performances each year and do sometimes not reflect performance at the major competition. Nevertheless, we believe these trajectories are a useful tool to track performance progression. We also provide some statistics on the mean age of medalists, finalist and semi-finalists, and on times required to win medals, make finals and make semi-finals.

Finally, we report some general comments and observations, and we've included additional figures and tables in addenda.

## Men's 100 Backstroke, Gareth Kean:

Gareth Kean's performance progression in the 100-m backstroke has been much steeper compared to those of London Olympic medal winners. He is substantially younger compared to medal winners in both the 100-m and 200-m backstroke. His personal best time from the 2012 NZ trials would have ranked him 5th at the Olympics.

	Medalists	Finalists	Semi-Finalists	GK
Time Required for…	52.97	53.74	54.36	54.00
Mean Age (y) of…	25.4	26.0	24.7	20.8
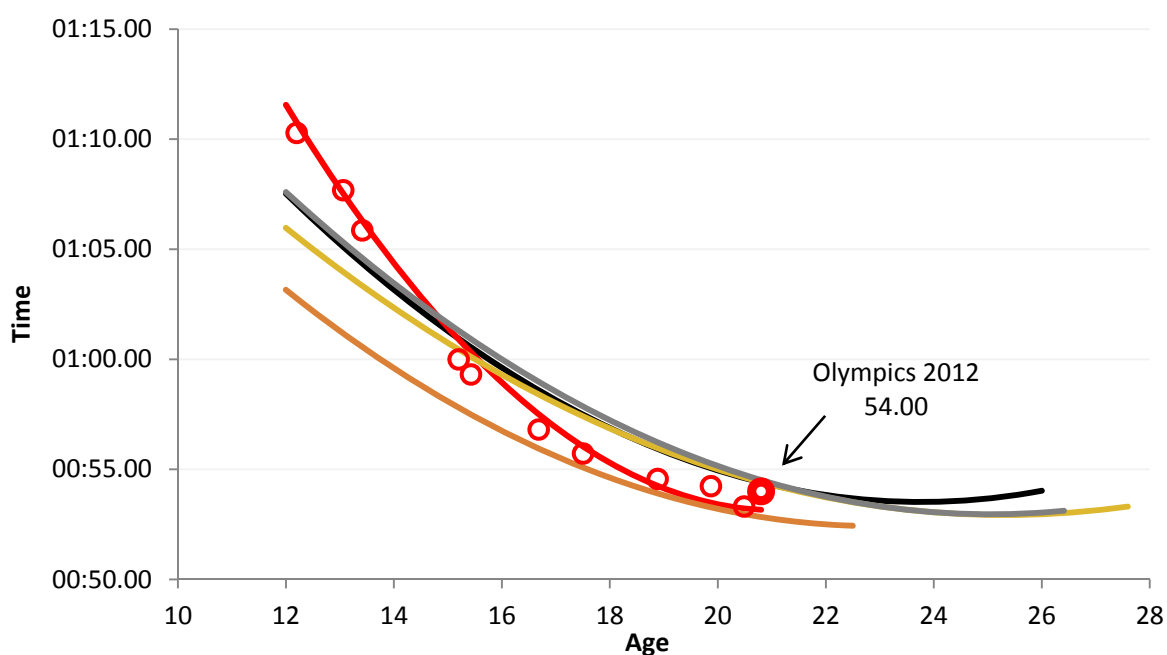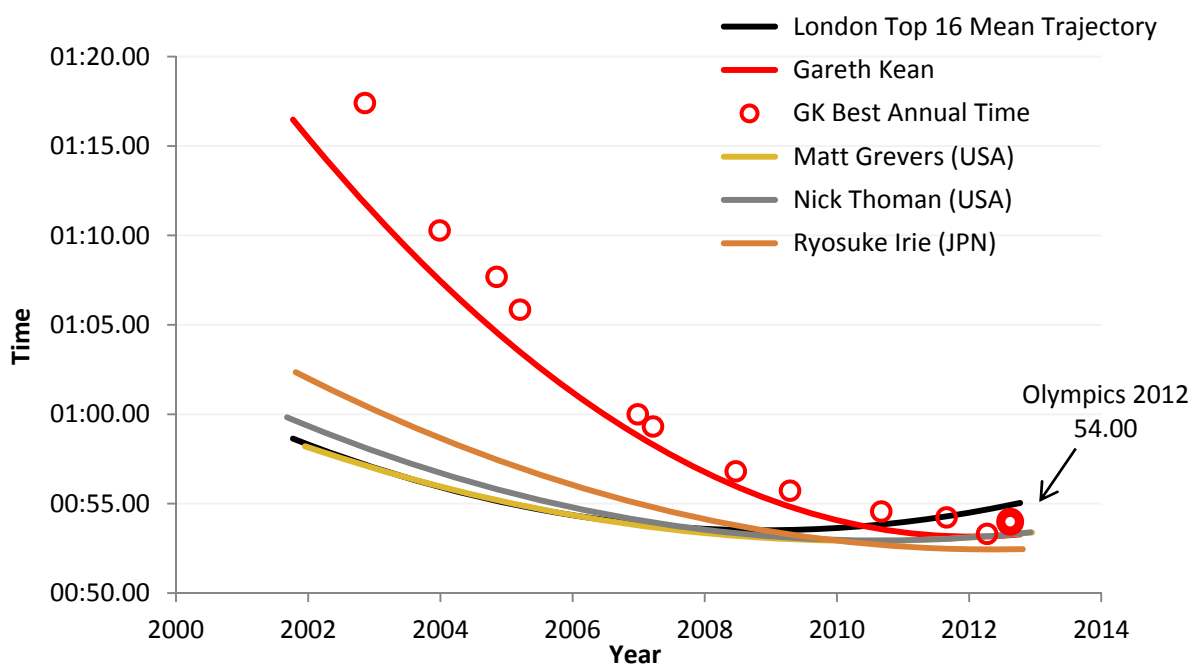
Men's 200 Backstroke, Gareth Kean:

	Medalists	Finalists	Semi-Finalists	GK
Time Required for…	1:53.94	1:57.33	1:58.22	2:00.54
Mean Age (y) of…	24.6	22.4	23.3	20.8
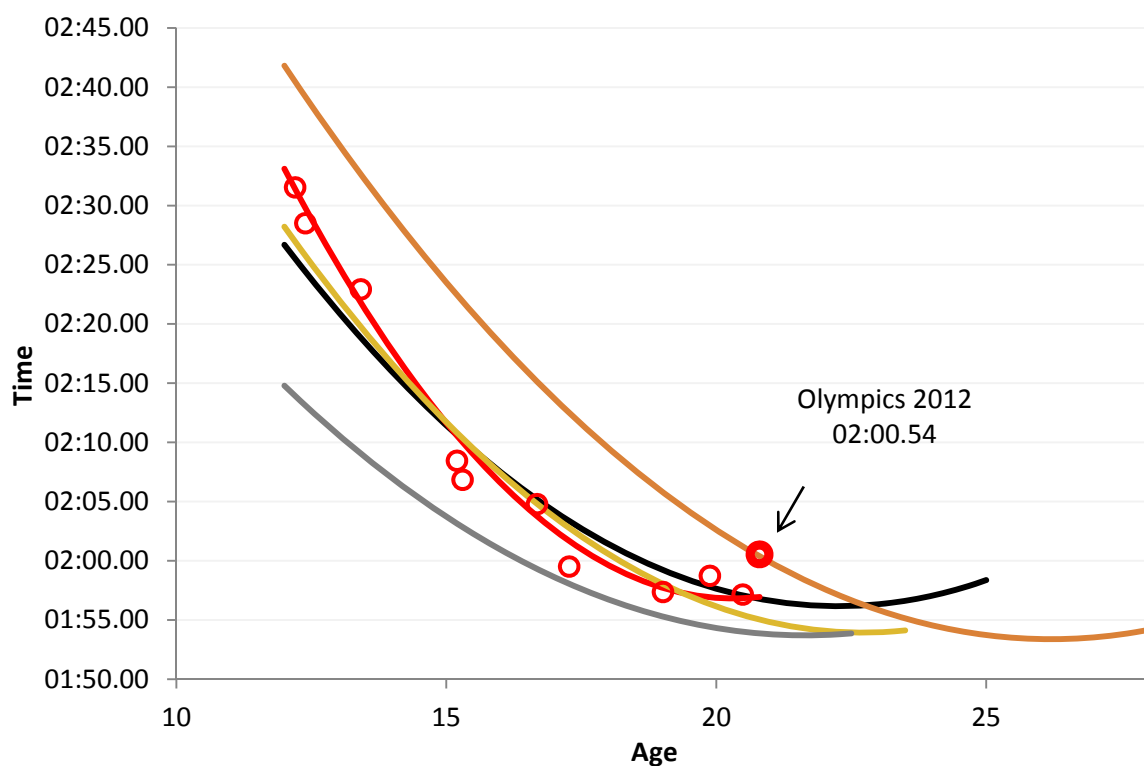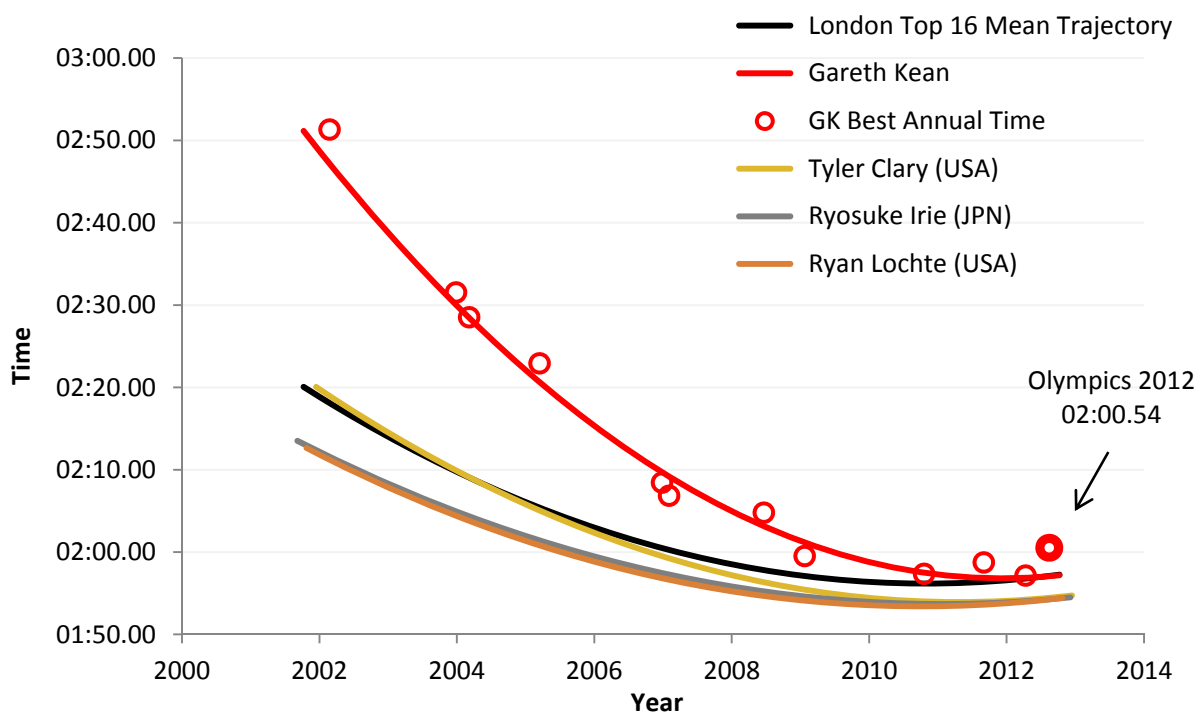
An Excel-based application designed to allow Swimming NZ to assess the performance progression of any individual swimmer against the performance progression benchmarks of Olympic top-16 swimmers from Beijing and London. An example is shown here for one New Zealand male swimmer.

MEN

Type Name	Joe Bloggs
Select Event	1500 Free
London Gold Time	14:31.02

Swimmer Age	Time	Performance Time Difference (%)
17.8	15:48.36	8.9
17.5	15:58.39	10.0
15.5	16:30.50	13.7
14	17:45.00	22.3

Instructions for Use:

Type the swimmers name in cell C4. Select their event in cell C5.
Enter each age and time for the swimmer in the cells highlighted pink.
The benchmarks on the graph are for a typical **middle-distance (200m)** swimmer.

For sprint events (50-100m) 1 year is subtracted from each age of your swimmer before plotting the points.
For distance events (400-1500m) 1 year is added to each age of your swimmer before plotting the points.
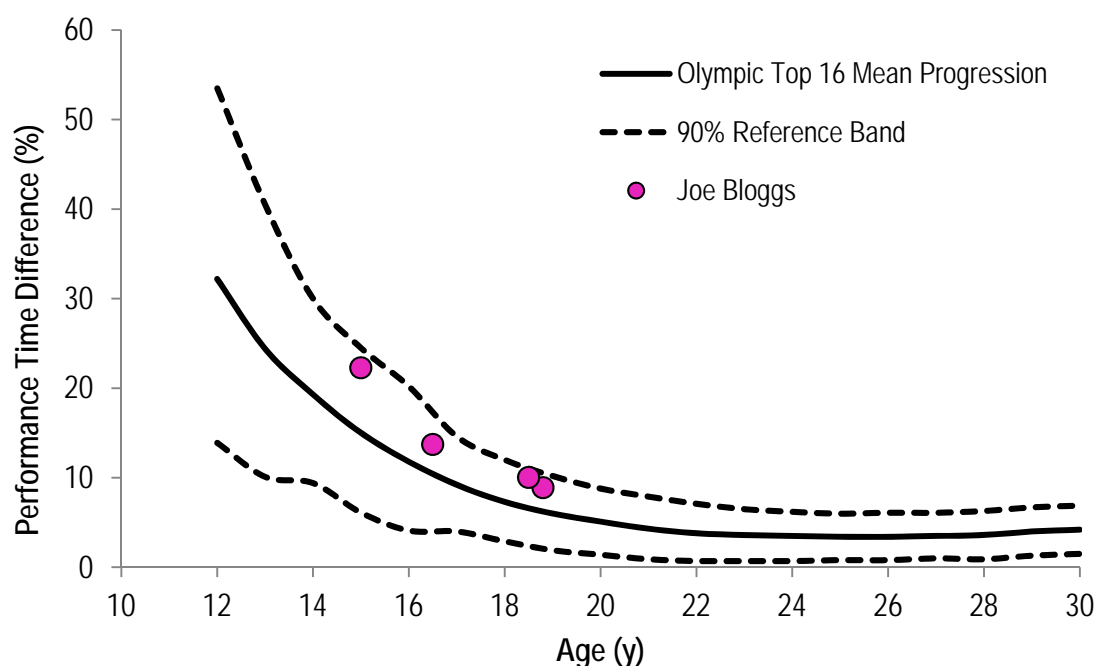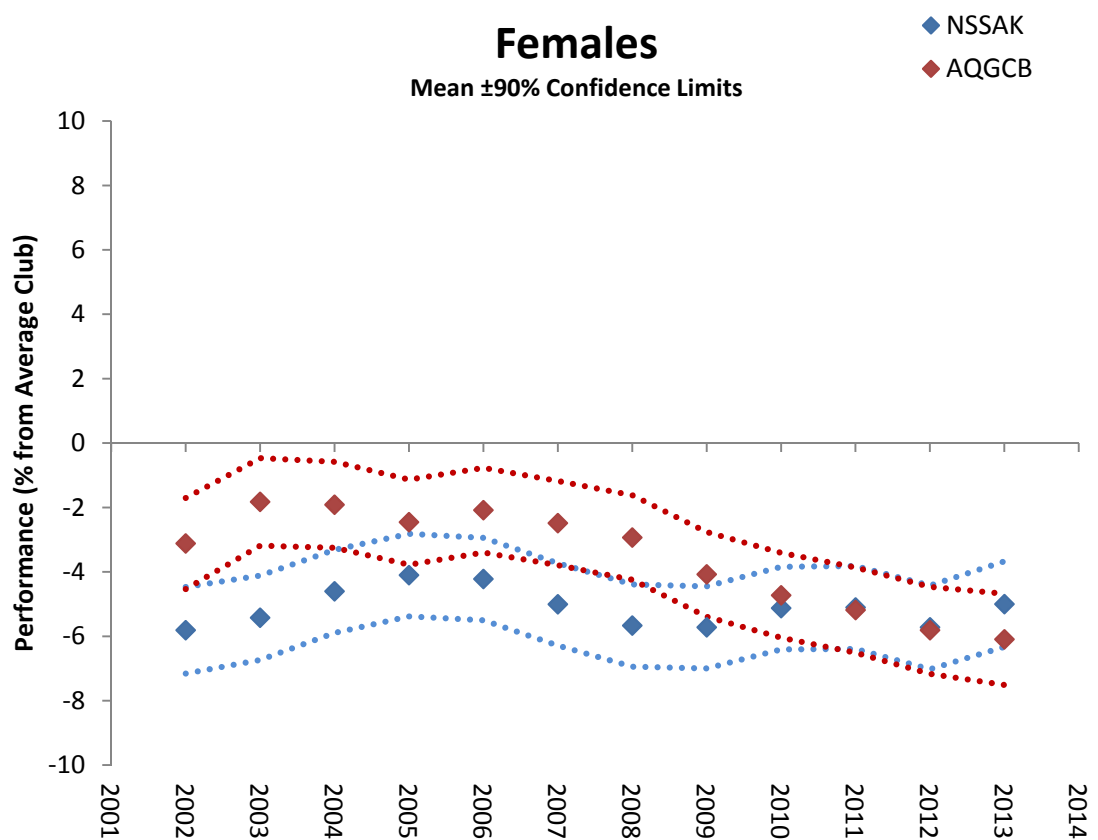
An Excel-based application designed to allow Swimming NZ to assess the performance progression of all New Zealand swimming clubs since 2002, and to compare progressions between clubs. An example is shown here for female swimmers for two top swimming clubs.

Select 1st Club   NSSAK

Select 2nd Club   AQGCB

Females
Mean ±90% Confidence Limits

◆ NSSAK
◆ AQGCB

Notes
Negative performance effect values mean better performance
Downward slope shows an improving club