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BMI Trajectories and the Influence of Missing Data

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Introduction

Estimates of BMI trajectories are important for understanding how BMI develops over time, and for use in cost-effectiveness analysis. However, missing BMI data is often stated as a limitation in longitudinal studies, with limited research into how missing data influences these trajectories. This study investigates the influences of missing data on estimated BMI trajectories and explores the effects this has on subsequent analysis.

Methods

Using data from the **English Longitudinal Study of Aging**, a **growth mixture model** (GMM) estimated distinct BMI trajectories in adults over 50 years. The GMM was adjusted using methods that assume data is **missing at random**: complete case analysis and multiple imputation, and assuming data is **missing not at random**: Diggle Kenward and Roy methods. Estimated trajectories are then used to predict the risk of developing type 2 diabetes (T2DM) using **discrete-time survival analysis**.

Results

Four distinct trajectories are identified: stable overweight, elevated BMI, increasing BMI, and decreasing BMI. However, the likelihoods of individuals following the different trajectories differs between the different methods (Fig1).

Figure 1: BMI trajectories estimated using standard GMM, multiple imputation, complete case, Diggle–Kenward selection model and Roy pattern mixture model (from left to right).

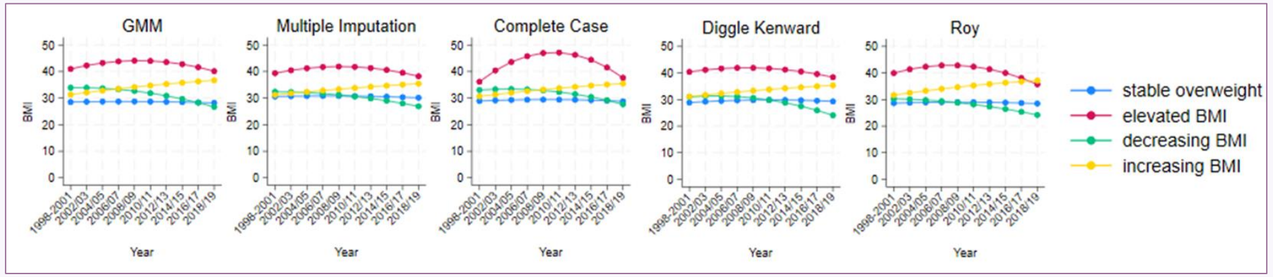

Table 1: Hazard Ratios and 95% Cis for T2DM by BMI trajectory and missing data method

Hazard Ratio (HR) for T2DM* (95% CI)	Elevated BMI HR~ (95% CI)	Decreasing BMI HR~ (95% CI)	Increasing BMI HR~ (95% CI)
Standard GMM	**9.091 (6.536, 12.5)**	**5.263 (3.300, 8.403)**	**2.03 (1.898, 3.846)**
Complete Case	**5.051 (2.242, 11.364)**	**2.890 (1.842, 4.525)**	1.116 (0.672, 1.852)
Multiple Imputation	**5.128 (3.861, 6.757)**	**2.392 (1.894, 3.030)**	**1.572 (1.261, 1.961)**
Diggle-Kenward	**5.985 (3.979, 7.991)**	**< 0.001 (< 0.001, 0.003)**	2.953 (< 0.001, 13.404)
Roy Pattern Mixture	**3.908 (3.002, 4.814)**	**0.401 (0.285, 0.516)**	**2.021 (1.647, 2.395)**

Significant values in bold. *Adjusted for age & sex; T2DM = type 2 diabetes, HR = Hazard Ratio.
~Compared to stable overweight.

The effect of BMI trajectory on T2DM is reduced after accounting for missing data. The different T2DM HRs, found across different missing data models, highlights their importance. Further research is needed to determine the preferred missing data methods for estimating BMI trajectories across different scenarios.

Conclusion

Missing data can significantly influence estimations of BMI trajectories. When BMI trajectories inform cost-effectiveness analysis or policymaking, missing data should be considered. More research is needed to examine the extent to which accounting for missing data might influence cost-effectiveness of interventions, e.g. weight management interventions.

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