Reexamining Assumptions in Compartmental Models of Heterosexual HIV Transmission applied to Eswatini

Final PhD Defence

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Motivation

HIV Epidemic: Context

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Eswatini:

- Highest national HIV prevalence: 28%
- Recently achieved 95-95-95 treatment cascade

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Key Populations, e.g. Female Sex Workers:

- Disproportionate risk: acquisition + transmission
- Unique barriers to care

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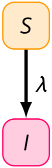

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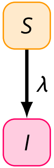

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- prior work: influences model outputs
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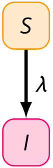

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Overall Research Question:

How do modelling assumptions influence outputs from HIV transmission models?

Overview

Chapter Research Questions: In compartmental models of HIV transmission …

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3. *How can we improve assumptions in **model design & parameterization**?*
4. *How can we improve assumptions in **incidence equations**?*

CHAPTER 2:

Scoping Review: Heterogeneity in Models

How might model assumptions influence prevention impacts of treatment?

Scoping Review: Missing Heterogeneity

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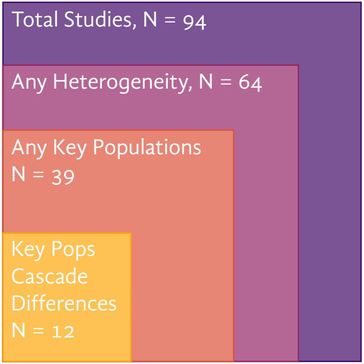

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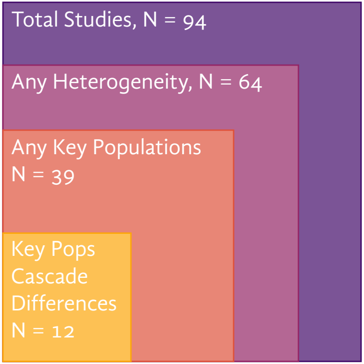

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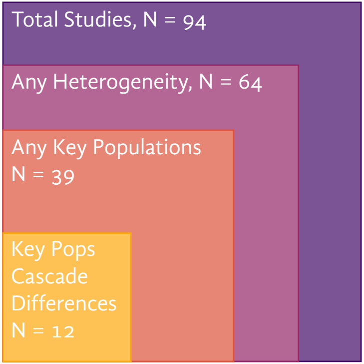

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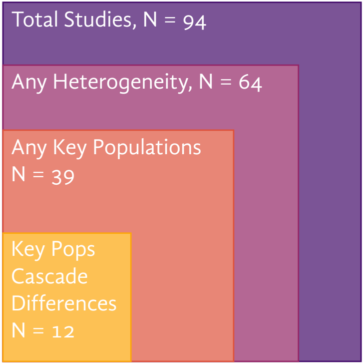

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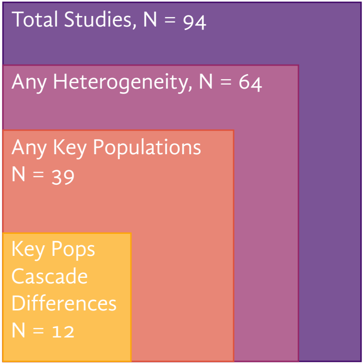

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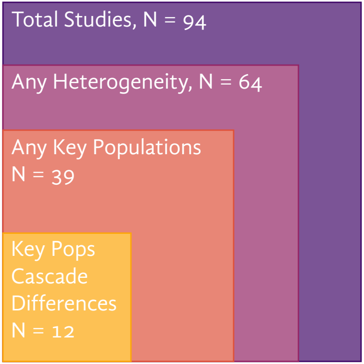

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- ↑ KP cascade prioritized
- ? ↓ KP cascade lagging

CHAPTER 5:
Intersecting Risk & Treatment Gaps

How might treatment coverage assumptions influence treatment impacts?

Treatment as Prevention: Impact of Who is Left Behind

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Observed 95-95-95: base case *vs*…

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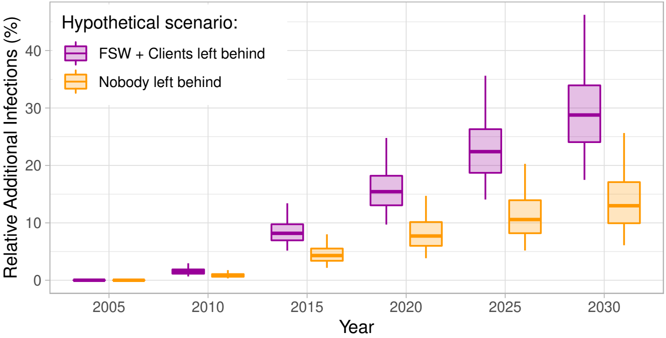

CHAPTER 3:
Model Design, Parameterization, & Calibration

How can we improve assumptions in model design & parameterization?

Model Design & Parameterization: Usual Assumptions

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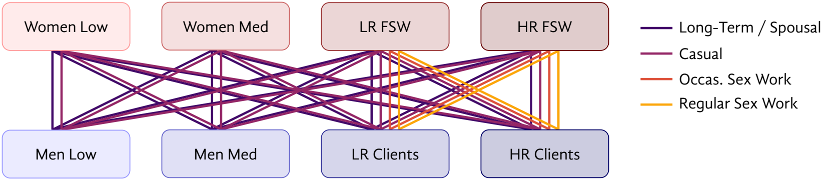
Model Design & Parameterization: Eswatini Model



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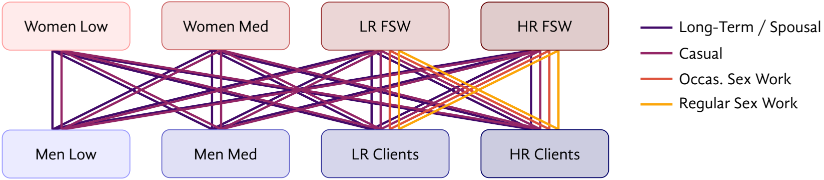

Eswatini data sources:

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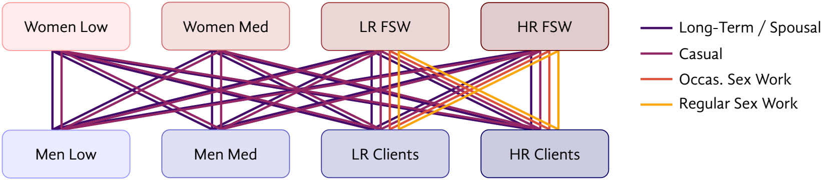

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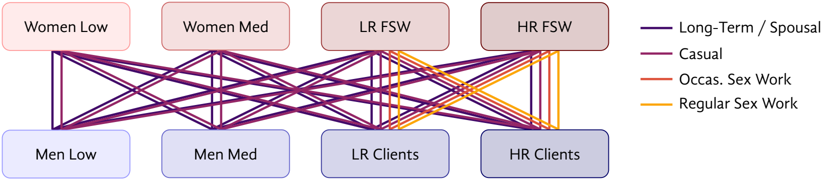

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CHAPTER 4:
Effective Partnerships Adjustment

How can we improve assumptions in incidence equations?

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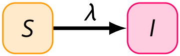

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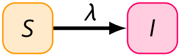

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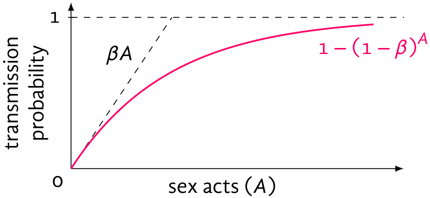

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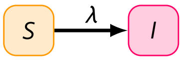

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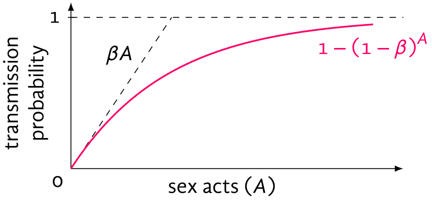

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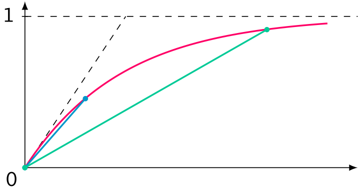

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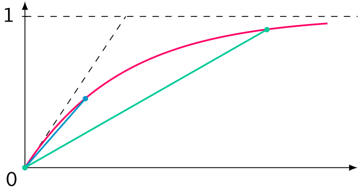

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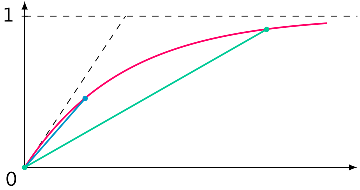

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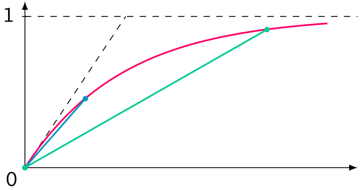

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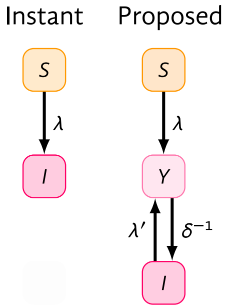

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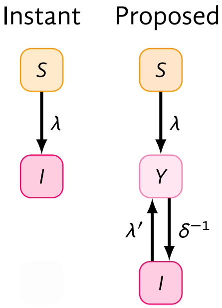

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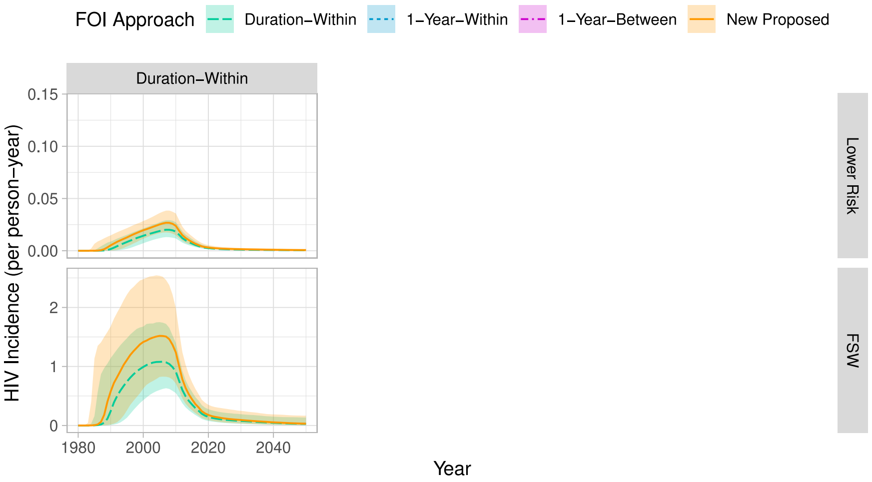

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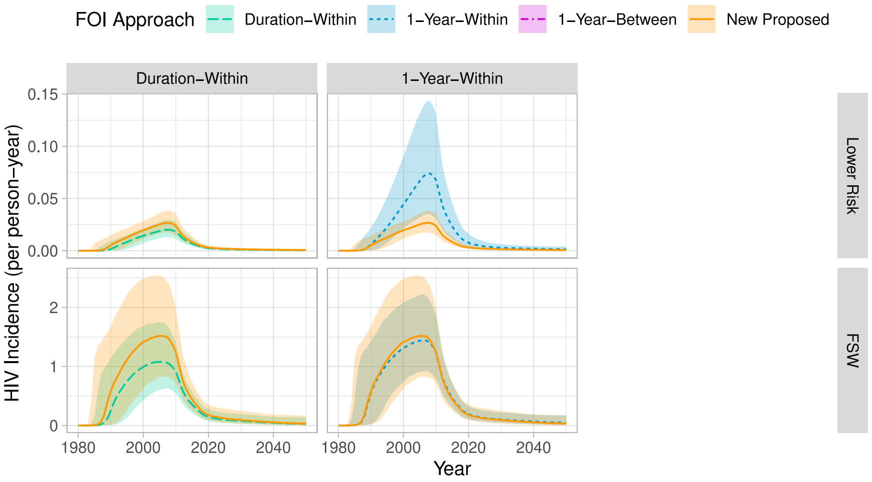

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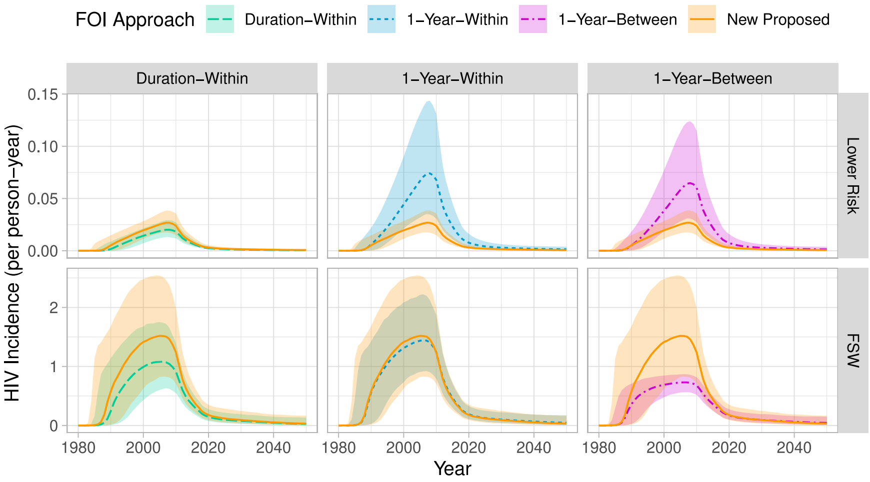

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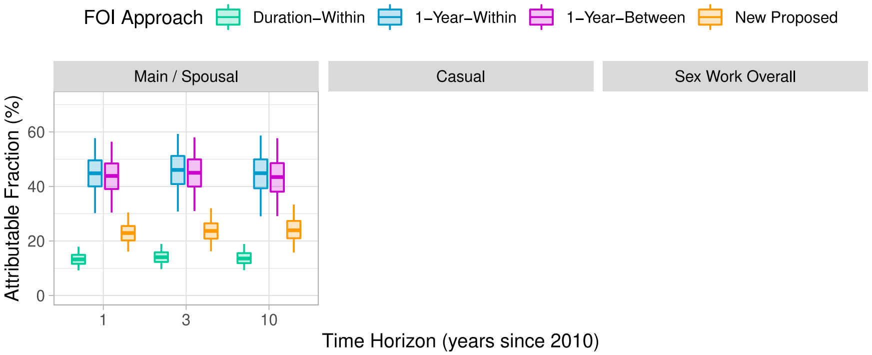

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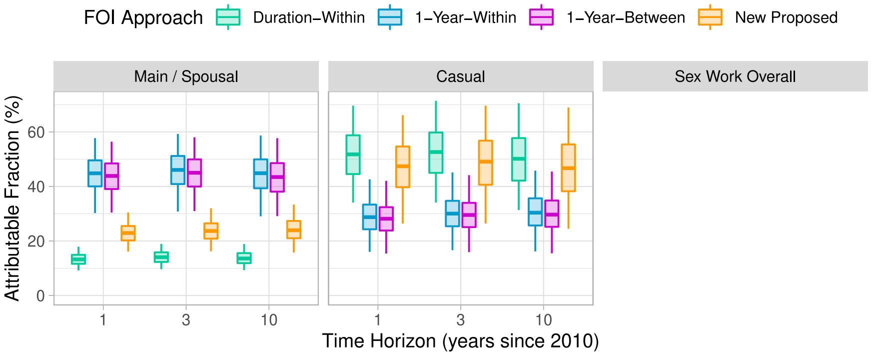

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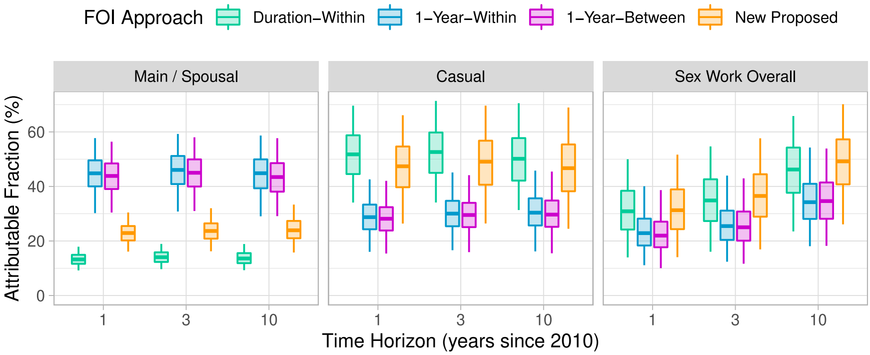

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→ **Thesis:** + methods to improve these assumptions

Thanks

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Laura Muzart
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NSERC CRSNG

Ontario

Digital Research Alliance of Canada

Ali, Friends & Family