



# Evaluation using ACG markers

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- **Outcomes do not directly assess quality of performance.** They only permit an inference about the quality of the process
- The degree of confidence in that inference depends on the strength of the predetermined causal relationship between **process and outcome**.

## Data Needs

- Because the relationship between process and outcomes is a probability, it is necessary to collect an appropriately large number of cases before one can infer if care is better or worse or meets specified standards.

## Time Window

- Outcome measurement requires specification of the appropriate **time window** which is the time when outcome differences caused by degrees of quality in health care are most manifest.



# OUTCOMES FROM DIFFERENT PERSPECTIVES

- Clinical Perspective
- Patient Perspective
  - Subjective health status
  - Quality of life
  - Satisfaction
- Societal Perspective
  - Utilization
  - Cost
- **Measures:** Structure – Process – Outcome  
(*Donabedian, A, 1988*)



- Outcome indicators of quality are more comprehensible to patients and the public than indicators of the process of technical care.
- However, they can cause misunderstanding by the public if the problem of multiple causation is not understood.

## Other Considerations

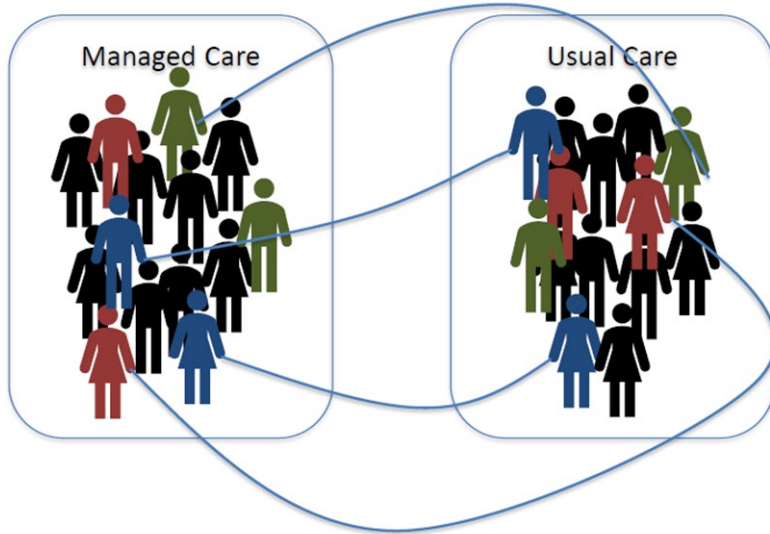
- Availability
- Completeness
- Accuracy
- Susceptibility to manipulation
- Information about delayed outcomes



- Want to know the participants' outcome with and without treatment
- Participants differ from non-participants
- Objective: find a large group of individuals who match the participants in all relevant pre-treatment characteristics
- Therefore difference (if well selected) can be attributed to the program
- With multiple characteristics to control for, suggested use of propensity score – e.g. Probability of participation in the program given the pretreatment characteristics



## PROPENSITY SCORE MATCHING (PSM)



- Score each patient, data prior to enrolment
- Managed Care to Usual Care matching (“counterfactual”)
- Nearest Score
- Can be paired or multiple e.g. 1-3, 1-4
- Follow-up and measure outcomes e.g. 6mth, 12mth, 24mth
- Compare results



- Establish measures and data collection from the outset, not retrospectively
- Decide on randomised study, or casemix adjust population cohorts
- Is there an obvious comparison population (Intervention v Control)
- Matched pairs create a population similar to those in managed care (“Intervention group”)
- Creation of a risk score or probability, assigned pre-enrolment



- Consider the time frame (time window), is it absolute (same months), or did individuals/groups join at different times
- Follow up measurement at specific time periods
- Lost to study – how do you measure/adjust when individuals leave the study or intervention
- Compare outcome measures of different groups
- Create strata of sub-groups to better understand impact e.g. PNGs



# Real-world application

Measuring the impact of a Diabetic MDT Service in Kent

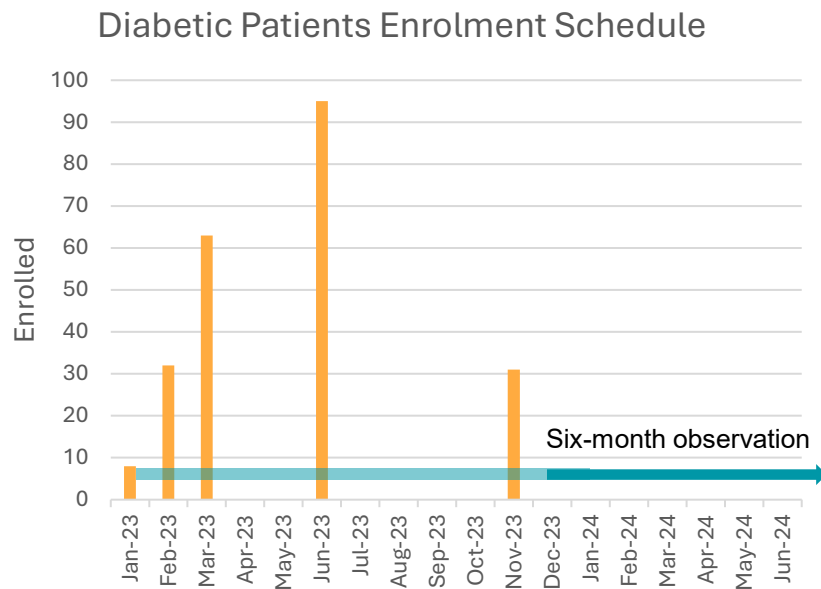
# Evaluating a Diabetic MDT service in Kent

## Kent and Medway ICB are an ACG user with Graphnet processing their whole population dataset

- **Situation:** Prevalence of diabetes is rising in East Kent. People with diabetes who live in areas of high deprivation are more likely to have multiple long-term conditions (MLTC) which contributes to health inequalities. NICE guidance recommends a collaborative approach to care that takes account of multimorbidity.
- **Kent's Approach:** Proactive identification of people with diabetes using ACG markers who are at risk of adverse health outcomes and provision of holistic joined up care to improve wellbeing, reduce unplanned hospital admissions, and ultimately reduce population health inequalities.
- **Enrolment:** Approximately 230 individuals received a different model of support. Using the ACG system, Johns Hopkins, Graphnet and Kent and Medway ICS collaborated in learning and implementing the techniques of causal modelling and conducted an illustrative evaluation of the service.

# Analytics Plan

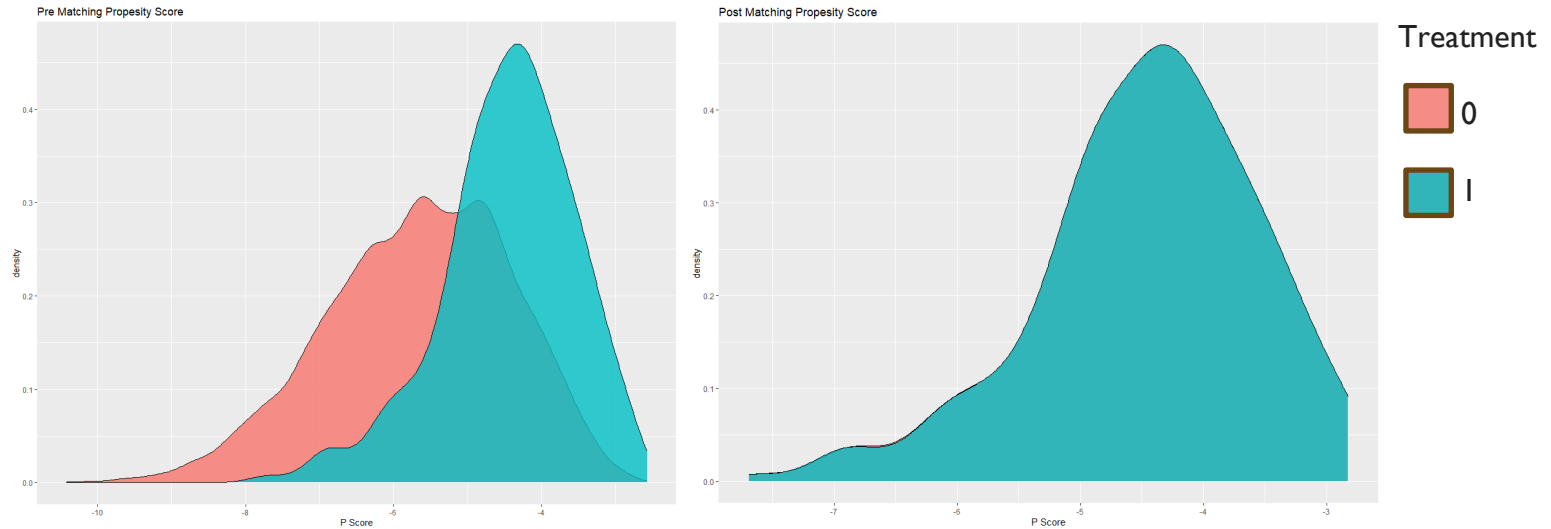
- We accessed monthly snapshots of the whole population of East Kent (700K+) that include their full set of ACG markers together with additional demographic and utilisation metrics
- Of these we isolated approximately 95K adults who have diabetes
- There were approximately 230 individuals who were identified as being enrolled into the diabetic MDT service who were enrolled at various stages (see right)
- In the observation period of 60 days post discharge from the service we will focus on ED visits as a proxy outcome metric
- Using propensity score matching we probabilistically matched members of our intervention group to reveal a control group for comparison



# Comparing apples and pears



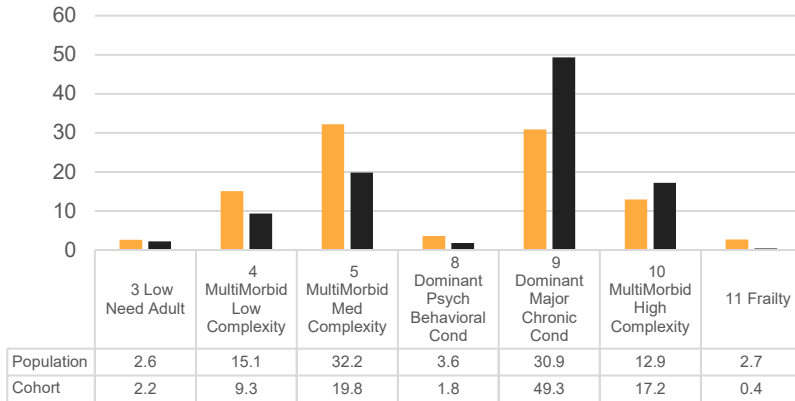
Examining distributions of **propensity** scores (see below) we can see how different our intervention group were compared to the total diabetic population. The score estimates the probability of receiving the treatment based on observed confounders. The graphic below shows how similar the two groups were after the matching process.



# Creating the right match

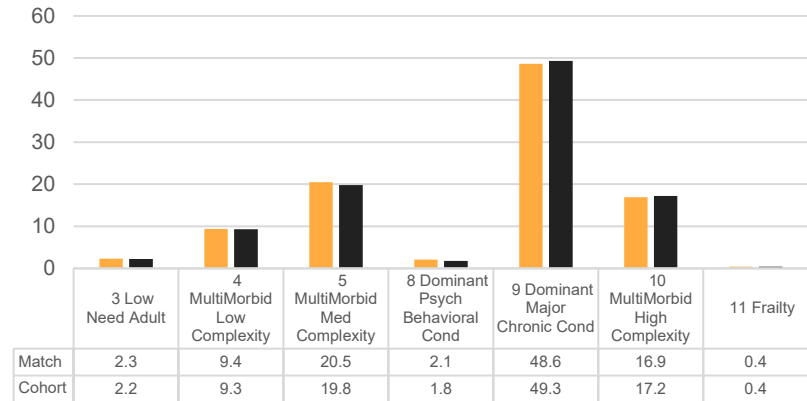
One such confounder that was balanced as part of the matching process was the Patient Need Group (PNG) that people were assigned to (see before/after below). The PNG is a representation of each person's total clinical position at a point in time and if left unadjusted we would be unfairly comparing outcomes between groups.

Before Matching



■ Population ■ Cohort

After Matching

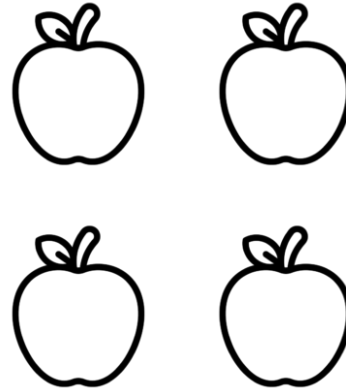


■ Match ■ Cohort

# Balancing between groups

This approach addresses confounding variables by creating a balanced comparison between treatment and control groups. Confounders are variables that influence both the treatment assignment and the outcome, potentially biasing the estimated treatment effect. Other confounders that were balanced in this analysis include:

- Age
- Sex
- Deprivation
- Patient Need Group (see previous slide)
- Date of enrolment (to adjust for seasonality)
- Active ingredients
- Risk strata (risk of hospitalisation)
- Major adjust diagnostic groups (ADGs)



# Comparing outcomes

**With our illustrative control group identified we can measure the difference in outcomes between our test and control groups.**

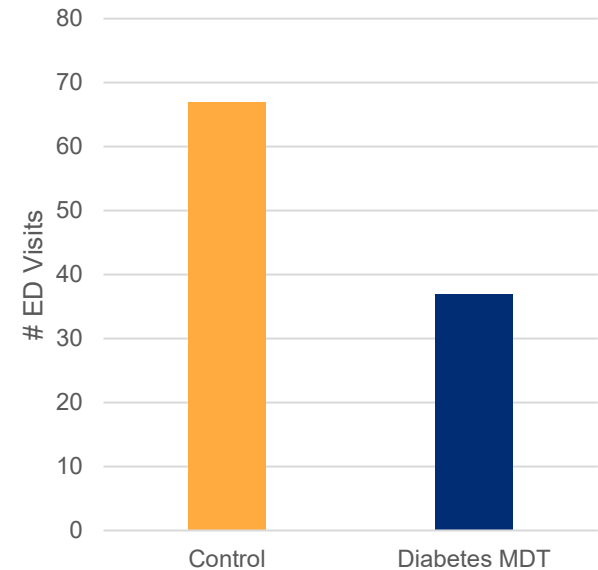
- Estimate | 0.13 less ED visits per member
- P Value 2.3% (significant to 2sd)

Intervention group	N	Mean ED Visits	Total ED Visits
No	227	0.295	67
Yes	227	0.163	37

This result is **very encouraging** as it is statistically significant and has yielded a positive result. This would suggest that the diabetic MDT service has been successful in the avoidance of ED visits.

We would recommend routine and rapid evaluations to ensure this is a consistent effect and also to examine sub-groups to determine if some people respond better than others.

First 60 days Post Intervention  
(N=227) | Total Ed Visits



# Building capacity & capability using ACG



## Benefits of Using the Johns Hopkins ACG System

Using ACG in this context provides a number of different benefits and demonstrates how versatile the system is.

### **1.Enhanced Analytical Precision with Pre-Built Markers:**

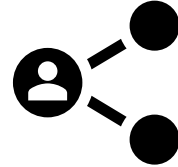
1. Proven Framework: The ACG system provides validated clinical markers that are widely recognized and trusted.
2. Accelerated Analysis: Eliminates the need to engineer new markers, saving time and reducing complexity in data preprocessing to support and drive rapid evaluation
3. Comprehensive Data Model: Delivers nuanced insights into patient health and resource utilization patterns.

### **2.Efficient Workflow Acceleration:**

1. Ready-to-Use Tools: Minimizes the burden of developing custom algorithms for population health management.
2. Rapid Implementation: Enables faster evaluation cycles, ensuring more timely decision-making.



# Knowledge Transfer



**Objective:** Collaborated with Graphnet and Kent to enhance their capability in applying propensity score matching using ACG markers for robust analytical insights.

## Key Activities:

### 1. Training and Demonstration:

1. Explained the methodology of propensity score matching with ACG markers.
2. Walked through the process of generating actionable results using real-world data.

### 2. Code Sharing and Application:

1. Provided access to the full codebase.
2. Discussed customization and scalability for their specific use cases.

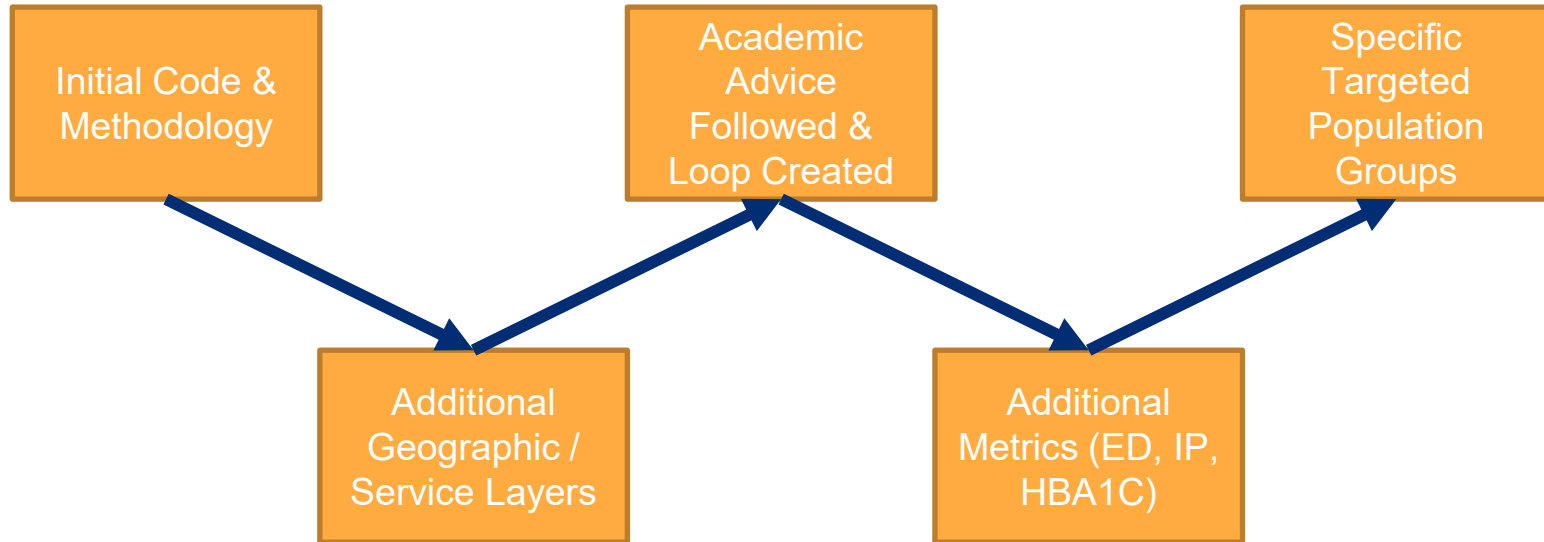
### 3. Pairwise Programming:

1. Worked collaboratively with their team in live coding sessions.
2. Addressed implementation challenges and explored best practices.

### Outcome:

- The customer gained hands-on experience and confidence to independently apply propensity score matching using ACG markers in their projects.
- Delivered a reusable codebase and ensured full understanding of its application.

# Analytics plan – Continual Development

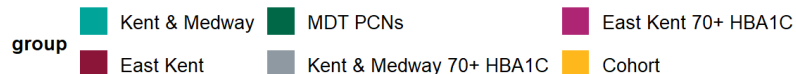
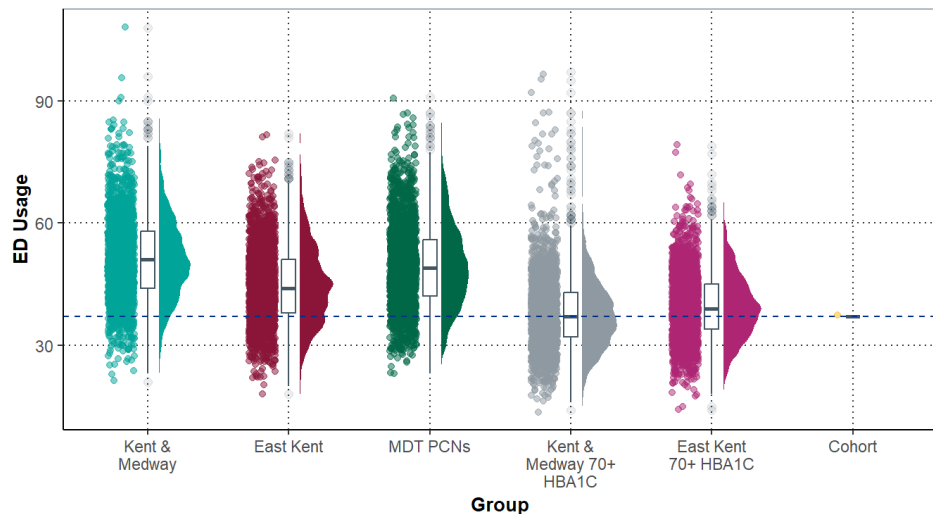


# Analytics plan – Continual Development

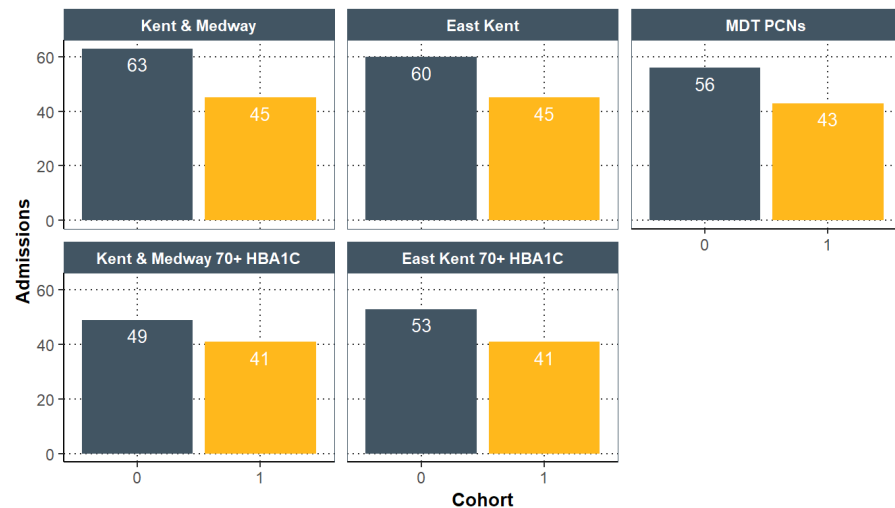
- **Phase 1** – 5 population groups investigated
- **Phase 2** – 2 specifically investigated and SMD balanced groups
  
- Started with a Kent & Medway wide focus
- Then a specific East Kent focus – where the evaluation took place
- Four PCNs where intervention was live
- 2 Groups specifically looking at historic AIC
- Controlling for AIC – right ranges and also the right PNGs
- Design optimisation – both population and in the running of the code for operational feedback
- May not have impacted on AIC – (Phase 2) is there a sub-group that seemed to respond well – i.e. PNG specific responses
- *Other programmes of work that need marking*
- Framework of evaluation together with the toolkit of ACG is helpful

# Analytics plan - findings

ED Usage for Matched Population vs Cohort: All Populations



Mean Admissions for Matched Population vs Cohort: All Populations



1 = Part of the Cohort, 0 = Part of the Comparison Population.

# Discussion

## Questions? Let's Discuss!

We've covered:

- Propensity score matching with ACG markers.
- Knowledge transfer process and outcomes.
- Practical application and hands-on collaboration.

## Your Turn:

- Any clarifications or deeper dives needed?
- How might this approach align with your own challenges?
- Feedback or thoughts on applying these techniques?

Let's keep the conversation going!

