Transforming Access
and Student Outcomes
in Higher Education

Trial protocol
Institutional Data Use: University of East Anglia – Peer Assisted Learning (PAL)

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QA:
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VERSION	DATE	REASON FOR REVISION/NOTES
Any changes to the design to be agreed between the implementation partner(s) and the evaluators. Note any agreed changes in the table below.		
5	5/3/24	Formatting and typographical changes.
4	1/3/24	Instrument changed to Tariff Points as “Prior help seeking behaviour” is not available.
3	21/2/24	Fixed issue with incorrect number of covariates specified in the model equations. Faculty (4 levels) replaces course (380 levels) as a co-variate for parsimony.
2	13/2/24	Clarified that analysis includes modelling of mentee and mentors.
1.0 [*original*]	8/2/24	Original version post QA.
Pre-registration		This design has been pre-registered on the Open Science Framework.[1]

The QA rating system is based on the Evaluation Security tool presented in the TASO Monitoring and Evaluation Framework.[2]

[1] https://osf.io/b4xqa/
[2] https://taso.org.uk/evidence/evaluation/

QA	Comments	Rating (out of 5)
Design	This is a strong design and includes aspects of considering the selection process into the PAL programme with the use of an instrumental variable. I would have liked more details on the composition of the instrument (prior help seeking behaviour) and look forward to seeing the results. I would like a little more focus on the longitudinal aspects the data makes available. Could we identify think about the modelling in terms not just the process to being a mentee (with the IV) but the process to mentor (maybe with an IV of previous engagement as a mentee). There is a longitudinal aspect to the data which would produce 6 cohorts in which this transition could be exploited more.	5 Thinking about making use of the process to becoming a mentor could add to the model
Sample size	There is a sufficient sample size for the model proposed. I wonder if we could explore more the COVID impact and the link to the drop off of mentees and mentors in 2021/22, 2022/23. This may need thinking in case COVID or other factors have impacted the programme.	4 More thought about the impact of COVID? on the numbers joining as mentees or mentors
Outcome measure	I am happy with the outcome measures proposed and they fit the research questions.	5 Good selection of outcomes
Attrition	This is a one year programme and so attrition is likely to be limited, the team my wish to do some work with descriptive statistics to see if engagement with PAL decline over the first year. It is possible that one term is sufficient for an effect, and this could inform the next round of the programme	5 Attrition impact minimal and can be explored with descriptive statistics
Validity	This is a well designed study which is likely to produce results with high validity. I would like to encourage the team to explore more the longitudinal aspects of the data	5 Validity likely, more consideration of longitudinal aspects of the data recommended

Overall	**A well thought through design including consideration of the selection process on PAL. Could be improved with thought about the student journey through PAL making using of the longitudinal aspects of the data**	**5**

1. Summary

Background

This evaluation design has been developed as part of a project funded by TASO on the use of institutional data to generate causal (Type 3) evidence for interventions designed to increase equality of opportunity within the Higher Education (HE) sector. Four HE Providers (HEPs) are taking part in the project and a team from Staffordshire University are designing and carrying out the evaluation. Two types of evaluation for each HEP's intervention will be conducted: an impact evaluation and an implementation and process evaluation. This analysis protocol covers the impact evaluation of the Peer Assisted Learning (PAL) programme at the University of East Anglia (UEA).

Aims

PAL aims to ensure positive student outcomes of continuation and attainment by smoothing transition to university through personalised peer support. The aim of the evaluation is to determine the effect of PAL on student engagement, continuation, completion and attainment.

Intervention

PAL consists of regularly scheduled mentoring sessions throughout the academic year. Prior to the academic year, schools and courses decide whether their course will deliver one to one peer mentoring or group mentoring. Group mentoring is formalised through the timetable and one to one mentoring is typically scheduled every three weeks.

Design

This study will apply an ex-post quasi-experimental evaluation design to determine the relationship between PAL participation and the outcome measures of interest.

Outcome measures

There are three primary outcome measures for this study: course engagement, continuation to the next level of academic study and end of stage marks. In addition, there are two secondary outcome measures for this study: course completion and final degree award.

Analyses

We will apply a two-stage least squares or two-stage logistic regression (dependent on outcome variable tested) to test the effect of PAL on student engagement and outcomes.

2. Background

Table 1: Project Team

Organisation	Name	Role and responsibilities
TASO	Dr Rob Summers	Project/Contract Manager
TASO	Luke Arundel	Project Assistant
University of East Anglia	Prof Fabio Arico	HEP Project co-lead - Director of the Centre for Higher Education Research Practice Policy and Scholarship (CHERPPS)
University of East Anglia	Prof Helena Gillespie	HEP Project co-lead - Associate Pro Vice Chancellor for Student Inclusion
University of East Anglia	Michelle Hawthorne	HEP coordinator - Widening Access and Participation Evidence and Evaluation Manager
Staffordshire University	Sam Vizcaino-Vickers	Research Assistant
Staffordshire University	Dr Sally Andrews	Principal investigator - Pedagogic Projects Development Manager
Staffordshire University	Vanessa Dodd	Co-investigator - Head of Education Research and Evaluation

3. Aims

The aim of this evaluation is to determine the effectiveness of PAL at UEA in relation to student engagement and outcomes including continuation, completion and attainment. This evaluation is being undertaken to develop the evidence base related to the use of peer mentoring to support equality of opportunity in relation to academic engagement and student outcomes. This study has been funded by TASO as part of a larger project on institutional data use and evaluation in HE to enable the sector to better understand ‘what works.’

This study has seven research questions with relevant hypotheses listed below. The term PAL participation refers to both mentors and mentees.

RQ1: What is the effect of PAL participation on student engagement on their course in the first year of study relative to students who do not engage with PAL?

H_0: PAL participation has no relationship with course engagement in the first year of study.

H_1: Students who participate in PAL have significantly different levels of course engagement in comparison to those that did not take part in PAL.

RQ2: What is the effect of PAL on student continuation on their course at the end of the first year of study relative to students who do not engage with PAL?

H_0: PAL participation has no relationship with course continuation in the first year of study.

H_1: Students who participate in PAL participation have significantly different course continuation in the first year compared to those that did not take part in PAL.

RQ3: What is the effect of PAL participation on end of stage grades relative to those that do not engage with PAL?

H_0: PAL participation has no relationship with end of stage grades in the first year.

H_1: PAL participants have significantly different end of stage grades in the first year compared to those that did not take part in PAL.

RQ4: What is the effect of PAL on student completion of their course relative to those that do not engage with PAL?

H_0: PAL participation has no relationship with successful course completion.

H_1: Students who participate in PAL participation have significantly different course completion rates in comparison to those that did not take part in PAL.

RQ5: What is the effect of PAL on good degree awarding relative to those that do not engage with PAL?

H_0: PAL participation has a relationship with the final degree award.

H_1: Students who participate in PAL have significantly different good degree outcomes in comparison to those that did not take part in PAL.

RQ6: Does variation in PAL delivery mode have an impact on student outcomes?

H_0: There is no relationship between PAL delivery mode and student outcomes.

H_1: There are significant differences between PAL delivery mode and student outcomes.

RQ7: Do underrepresented students who participate in PAL have better outcomes than underrepresented students who did not participate in PAL?

H_0: There is no relationship between underrepresented students who participate in PAL and underrepresented students who do not participate in PAL and student outcomes.

H_1: Underrepresented students who participate in PAL have significantly different student outcomes than underrepresented students who do not participate in PAL.

4. Intervention

PAL is a yearlong peer mentoring programme for first year students designed to support transition into higher education. Second year students are trained as mentors and matched with first year students on their course. As part of mentoring sessions, mentors share subject-specific knowledge and knowledge about UEA more generally to help first years settle in throughout their first year.

Courses choose whether mentoring is delivered in a group or in one-to-one sessions to best fit their learner context. Once mentors and mentees are matched, one-to-one mentoring is scheduled every three weeks by the PAL link tutor. Group mentoring is timetabled as part of the curriculum at regular intervals from the beginning of each academic year.

5. Design

This evaluation study will apply an ex-post quasi-experimental design to determine the relationship of PAL participation on student outcomes. This study will use matched administrative data with localised PAL engagement data from the PAL team. PAL-engaged students will form a treatment group matched to a 'non-treatment' group using UEA Home undergraduate population data from 2016 to 2023.

6. Outcome measures

We have identified three primary outcome measures and three secondary outcome measures (see Table 2) to test the hypotheses detailed in Section 2.

Primary outcome measures were identified due to their direct alignment with aims of PAL in relation to subject specific knowledge acquisition, course engagement and continuation to second year of study. Secondary outcome measures identified provide a fuller picture of long-term outcomes that may occur because of participation.

Table 2: Outcome measures

Outcome measure	Type	Level
Primary: Course engagement	Continuous	percent attendance to teaching sessions and advisor meetings scheduled
Primary: Continuation	Categorical	Continued, Withdrawn
Primary: Stage marks	Continuous	Numeric grade at the end of the first year of study
Secondary: Completion	Categorical	Completed, Withdrawn
Secondary: Degree award	Categorical	Good degree outcome, lower degree outcome

7. Sample selection

PAL is open to all first-year students on an opt-in basis. Mentor positions are open to all second-year students subject to an application, available spaces and completion of training.

The evaluation will use secondary data collected by UEA from students who are current students or graduates of UEA between 2016 – 2023.

Table 3 details both mentor and mentee participant count alongside nonparticipant count for each academic year included in the study.

Table 3: PAL participant and nonparticipant counts by academic year

Academic year	Mentee count	Mentor count	Nonparticipant	Total
2016-17	616	86	11,787	12,489
2017-18	546	87	11,173	11,806
2018-19	396	94	12,100	12,590
2019-20	283	112	13,184	13,579
2020-21	249	81	11,894	12,224
2021-22	60	52	7,604	7,716
2022-23	53	3	4,253	4,309
Total	**2203**	**515**	**71,995**	**74,713**

8. Identification strategy

We will not use methods to identify comparison groups (e.g. propensity score matching) because of the analytical strategy outlined in Section 11. If the assumptions for the analytical strategy are not met, we may consider the use of propensity score matching (PSM) or inverse probability of treatment weighting (IPTW) to test programme effects using observable characteristics outlined in Section 11.

9. Data collection

Data will be obtained from UEA's administrative records and local PAL monitoring data between 2016–23. No data will be collected by the researchers at any point.

10. Procedure

A high-level timeline of the project is presented in the table below.

Table 2: Project timeline

Timeline	Action
October 2023- January 2024	• Set up data sharing process and agreement • Conduct enhanced theory of change workshop • Achieve ethics approval • Complete draft enhanced theory of change • Complete Trial Protocol
February 2024 – March 2024	• Analyse data and deliver final report

11. Power calculations

As prior research has not established the common effect size of interventions like this, an assumption must be made for the predicted effect size. For this reason, we will conduct power calculations three times for small, medium, and large effect sizes. Within multiple linear regression analyses, small, medium, and large effects are considered to be f^2 = .02, .15 and .35 respectively.

The power analysis was calculated using G*Power 3.1, with the following parameters:

- Test family: "F tests"
- Statistical test: "Linear Multiple regression: Fixed model, R^2 increase"
- Type of power analysis: "A priori: Compute required sample size – given α, power and effect size"
- Effect size f^2 = .02, .15, & .35
- α err prob = 0.05
- Power (1 – β err prob) = 0.80

- Number of tested predictors = 3
- Total number of predictors = 19

Table 4: Power analysis results

Assumed f^2	Sample loss	Minimum sample size	Critical F	True Power
.02	0%	550	2.62	.80
	20%			.69
.15	0%	78	2.76	.80
	20%			.68
.35	0%	39	3.13	.81
	20%			.63

As the researchers have no control or influence over the total sample population, nor the allocation to the intervention or comparator groups, only the total required sample will be reported instead. The Critical F and Actual Power will also be reported. The table also gives values assuming a 20% loss to the minimal required sample, if the sample provided is less than the sample size desired by the evaluators for each given effect size due to missing data

12. Analytical strategy

12.1. Primary Outcome (Course Engagement)

The following model will be used to estimate the effects of the intervention on the course engagement, using the general linear model (multiple linear regression). The analysis will be conducted on an intention-to-treat basis, including all complete cases across both cohorts.

$$y_i = \beta_0 + \sum_{k=1}^{K=17} \beta_k x_i x_{ki} + \epsilon$$

where,

- y_i is the continuous outcome variable (Course Engagement)

- β_0 is the intercept term in the linear regression equation
- $\sum_{k=1}^{K=17}$ is the number of predictors. Specifically, K is the upper limit of summation and in this case it is 17 and k is the index variable, starting at 1.
- x_i is a vector of control covariates (Faculty, Qualification type, Programme mode, Commuter Status, IMD, Gender, Age, Ethnicity, Disability, Care leaver, Bursary, Fee Status, Role in PAL).
- x_{ki} is the corresponding predictors / covariates (Continuation, Stage Marks, Completion, Degree award)
- β_k are the corresponding coefficients for each predictor variable x_{ki}
- ϵ is a vector of residuals

12.2. Primary Outcome (Continuation)

The following model will be used to estimate the effects of the intervention on the primary outcome, using a general linear model called logistic regression. Analysis will be conducted on an intention-to-treat basis, including all complete cases across both cohorts.

$$log\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \sum_{k=1}^{K=17} \beta_k x_i x_{ki}$$

where,

- $log\left(\frac{\theta_i}{1-\theta_i}\right)$ is the logit function, or in other words, the natural logarithm of the odds ratio.
- θ_i is the probability of the outcome variable occurring (e.g. the probability of the binary outcome variable being 1) (Continuation).
- $1-\theta_i$ is the probability of the outcome variable (Continuation) not occurring
- β_0 is the intercept term in the linear regression equation
- $\sum_{k=1}^{K=17}$ is the number of predictors. Specifically, K is the upper limit of the summation and in this case it is 17 and k is the index variable, starting at 1.
- x_i is a vector of control covariates (Faculty, Qualification type, Programme mode, Commuter Status, IMD, Gender, Age, Ethnicity, Disability, Care leaver, Bursary, Fee Status, Role in PAL)
- x_{ki} is the corresponding predictors / covariates (Course engagement, Stage Marks, Completion, Degree award**)**
- β_k are the corresponding coefficients

12.3. Primary Outcome (Stage Marks)

The following model will be used to estimate the effects of the intervention on stage marks, using a general linear model called a multiple linear regression. Analysis will be conducted on an intention-to-treat basis, including all complete cases across both cohorts.

$$y_i = \beta_0 + \sum_{k=1}^{K=17} \beta_k x_i x_{ki} + \epsilon$$

where,

- y_i is the continuous outcome variable (Stage Marks)
- β_0 is the intercept term in the linear regression equation
- $\sum_{k=1}^{K=17}$ is the number of predictors. Specifically, K is the upper limit of the summation and in this case it is 17 and k is the index variable, starting at 1.
- x_i is a vector of control covariates (Faculty Qualification type, Programme mode, Commuter Status, IMD, Gender, Age, Ethnicity, Disability, Care leaver, Bursary, Fee Status, Role in PAL)
- x_{ki} is the corresponding predictors / covariates (Course engagement, Continuation, Completion, Degree Award)
- β_k are the corresponding coefficients for each predictor variable x_{ki}
- ϵ is a vector of residuals

12.4. Secondary Outcome (Completion)

The following model will be used to estimate the effects of the intervention on the primary outcome, using a generalised linear model called logistic regression. Analysis will be conducted on an intention-to-treat basis, including all complete cases across both cohorts.

$$log\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \sum_{k=1}^{K=17} \beta_k x_i x_{ki}$$

- $log\left(\frac{\theta_i}{1-\theta_i}\right)$ is the logit function, or in other words, the natural logarithm of the odds ratio.
- θ_i is the probability of the outcome variable occurring (e.g. the probability of the binary outcome variable being 1) (Completion).
- $1 - \theta_i$ is the probability of the outcome variable (Completion) not occurring

- β_0 is the intercept term in the linear regression equation
- $\sum_{k=1}^{K=17}$ is the number of predictors. Specifically, K is the upper limit of the summation and in this case it is 17 and k is the index variable, starting at 1.
- x_i is a vector of control covariates (Faculty, Qualification type, Programme mode, Commuter Status, IMD, Gender, Age, Ethnicity, Disability, Care leaver, Bursary, Fee Status, Role in PAL)
- x_{ki} is the corresponding predictors / covariates (Course engagement, Continuation, Stage Marks, Degree Award)
- β_k are the corresponding coefficients for each predictor variable x_{ki}

12.5. Secondary Outcome (Degree Award)

The following model will be used to estimate the effects of the intervention on the primary outcome, using a generalised linear model called logistic regression. Analysis will be conducted on an intention-to-treat basis, including all complete cases across both cohorts.

$$log\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \sum_{k=1}^{K=17} \beta_k x_i x_{ki}$$

- $log\left(\frac{\theta_i}{1-\theta_i}\right)$ is the logit function, or in other words, the natural logarithm of the odds ratio.
- θ_i is the probability of the outcome variable occurring (e.g. the probability of the binary outcome variable being 1) (Degree award).
- $1-\theta_i$ is the probability of the outcome variable (Degree award) not occurring
- β_0 is the intercept term in the linear regression equation
- $\sum_{k=1}^{K=17}$ is the number of predictors. Specifically, K is the upper limit of the summation and in this case it is 17 and k is the index variable, starting at 1.
- x_i is a vector of control covariates (Faculty, Qualification type, Programme mode, Commuter Status, IMD, Gender, Age, Ethnicity, Disability, Care leaver, Bursary, Fee Status, Role in PAL)
- x_{ki} is the corresponding predictors / covariates (Course engagement, Continuation, Stage Marks, Completion)
- β_k are the corresponding coefficients for each predictor variable x_{ki}

12.6. Multiple Model Comparisons

This study includes a large number of statistical tests.

For all the following models, the model comparison procedure will use the deviance to explain how good the model-fit is, whilst using the maximum likelihood estimation parameters. It is denoted below:

$$Deviance = -2logL(\hat{\alpha}, \hat{\beta}|D)$$

Where,

- $Deviance$: This is the measure of the difference between the likelihood of the data under the fitted model and the likelihood under a saturated model. The saturated model is a model that perfectly fits the data, often containing as many parameters as there are data points.
- $logL(\hat{a}, \hat{\beta}|D)$ represents the log-likelihood of the data given by the estimated parameters $\hat{a}$ and $\hat{\beta}$. The likelihood function measures how well the model explains the data.
- D represents the observed data
- $-2 \times logL(\hat{a}, \hat{\beta}|D)$ the factor of -2 is used to make the deviance comparable to the chi-square distribution.

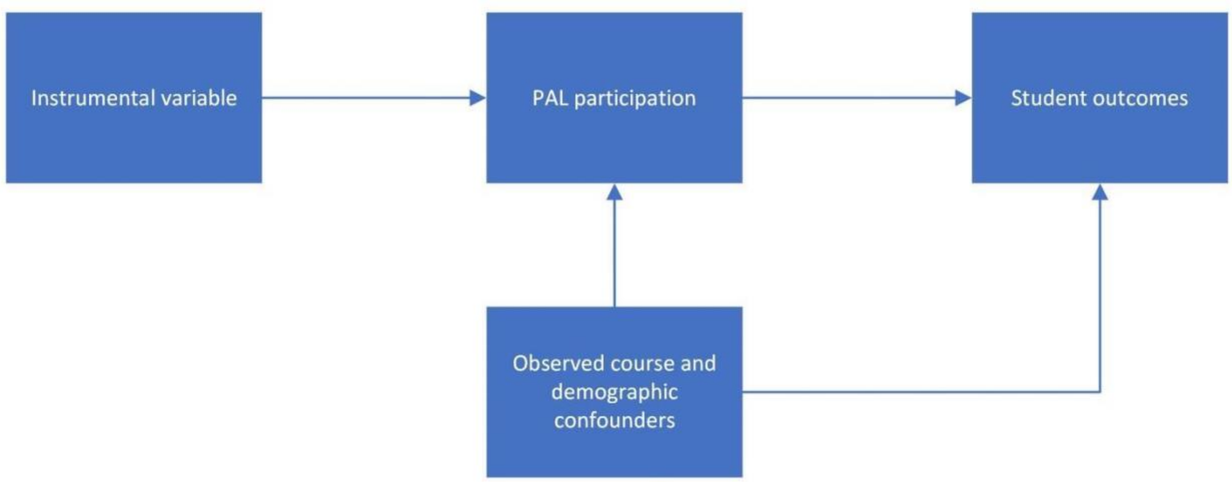

Figure 1: Two Stage Model of PAL and student outcomes.

Tables 5 and 6 outline the independent variables and covariates proposed as part of the analytical strategy outlined above.

Table 5: List of predictor variables

Variable name	Type	Levels

Role in PAL	Categorical	PAL participant, non participant
PAL attendance	Continuous	N sessions attended
PAL delivery	Categorical	Group, One-to-one
Instrumental variable	Continuous	UCAS entry tariff points

Table 6: List of covariates

Covariate name	Type	Levels
Academic year	Categorical	2016–17, 2017–18, 2018–19, 2019–20, 2020–21, 2021–22, 2022–23
Faculty	Categorical	4; Faculty of Medicine and Health Sciences, Faculty of Arts & Humanities, Faculty of Sciences, Faculty of Social Sciences
Qualification type	Categorical	2; A-Level, BTEC+ other
Programme mode	Categorical	2; Full-time, Part-time
Commuter status	Categorical	2; Commuter, Not Commuter
IMD	Categorical	5; Quintile 1, Quintile 2, Quintile 3, Quintile 4, Quintile 5
Gender	Categorical	4; Male, Female, Non-binary, Other
Age	Categorical	2; Young, Mature
Ethnicity	Categorical	4; Black/Black British, Asian/Asian British, Mixed Ethnicities, White/White British
Disability	Categorical	2; Disability declared, No disability declared
Care leaver	Categorical	2; Care leaver, Not care leaver
Bursary	Categorical	2; Bursary recipient/Not bursary recipient
Fee status	Categorical	2; Home/International

13. Ethical considerations

This project has received ethical approval from UEA's ethics committee. The following ethical considerations are key to the process:

Confidentiality and Privacy: We will safeguard the confidentiality and privacy of student data in line with GDPR (2016) regulation. In addition, the providers' privacy notice informs students that their administrative data may be used for research and evaluation purposes. We have implemented procedures to protect sensitive information and ensure that individual student identities are not disclosed without explicit consent. Data owners developed robust anonymisation protocols prior to disseminating data to evaluators. These protocols prevent the identification of individual participants when conducting analyses and reporting findings.

Data Security: Data owners and evaluators have implemented robust data security measures to protect student data from unauthorised access, disclosure, or loss. Data will be shared using secure servers, encrypted data files, and two factor authentication access controls to safeguard the integrity of the data.

Minimisation of Harm: We have taken steps to minimise any potential harm to students through the procedures outline above. This research will be undertaken using large scale secondary datasets which reduces the probability of identification. We will not report descriptive statistics on control or covariate data where counts are considered low (n<15) and will aggregate up where necessary. For example, it may be appropriate to report on ethnicity using the aggregate groupings Black, Asian, mixed ethnicities and white rather than disaggregating this data into more granular groupings.

14. Risks

The following risk register outlines the three main risks to the successful delivery of the project:

Part of evaluation	Risk	Mitigation strategy	Risk owner
Ethical approval	Failure to get ethical approval in time - Delay to UEA ethical approval would delay starting on data sharing and analysis	UEA to submit ethics early; UEA to collate data in anticipation of ethical approval	Fabio Arico; Michelle Hawthorne
Data curation	UEA does not agree to share required institutional data with independent evaluator - Limited access to some or all institutional data would impact the robustness of the evaluation	independent evaluator to lead data sharing agreement with UEA and TASO at the outset of the project Research protocols developed based on available data. Independent evaluator document if more relevant institutional data is available but not permitted. Independent evaluator will work flexibly with UEA to develop arrangements that work with UEA requirements	Fabio Arica; Helen Gillespie

		(e.g., temporary staff account for project members requiring data access negates the need for external data sharing)	
Data analysis	Institutional Data accuracy is limited – would impact on robustness of findings	Independent evaluator to maintain honest dialogue with UEA on data accuracy Recognising the messiness of real-world data, the independent evaluator will make an informed decision about how to balance depth of findings with robustness of data (using data cleaning and conversations to inform appropriacy)	Vanessa Dodd; Sally Andrews