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Predicting peer assisted study session attendance

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Abstract

Peer assisted study session attendance is associated with multiple indicators of student success. However, attendance levels are generally low. We applied an extended theory of planned behaviour model, incorporating student role identity, to the prediction of peer assisted study session attendance. Participants were 254 undergraduate students enrolled in 24 peer assisted study session supported units/modules. Attitudes, subjective norms, and perceived behavioural control each had a significant direct effect on attendance intentions, which had a significant direct effect on attendance. All three predictors also had significant indirect effects on attendance, mediated by intentions. After controlling for intentions, only perceived behavioural control had a significant direct effect on attendance. The model accounted for 61% and 42% of the variance in intentions and attendance respectively. Student role identity did not improve the predictive utility of the model. Theory of planned behaviour informed strategies for increasing peer assisted study session attendance are recommended.

Keywords: supplemental instruction; peer assisted study session; peer assisted learning; theory of planned behaviour; role identity; attendance

Peer assisted study sessions

Peer assisted study sessions (also referred to as peer assisted learning or supplemental instruction) is an academic support program in which weekly, voluntary peer-learning sessions, led by peer-facilitators, are deployed alongside challenging undergraduate units/modules, with the aim of increasing student comprehension, performance, and retention. The peer-facilitators are higher-year students with strong communication skills and a demonstrated record of success in the units they support (Arendale, 1994; Dawson et al., 2014). Their role is to guide learning, rather than reteach, and facilitate an environment where students can work with peers to consolidate knowledge, and develop problem solving and critical thinking skills (Jacobs et al., 2008). Peer assisted study sessions are not intended as a replacement for scheduled classes, and are most effective when used in conjunction with regular lecture and tutorial engagement (Kodabux and Hoolash, 2015). As attendance is voluntary and open to all students in supported units, peer assisted study sessions do not carry the 'remedial' stigma sometimes associated with other academic support programs (Arendale, 1994, 2001; Blanc et al., 1983).

The benefits of peer assisted study session attendance to students are well documented, and include improved grades and pass levels, as well as increased retention and graduation rates (Dawson et al., 2014). Despite these benefits, peer assisted study sessions, like many opt-in academic support programs (for example, Cornelius et al., 2016; Durkin and Main, 2002; Fox et al., 2010), attract relatively few regular attendees. For example, although a number of studies have reported in excess of 40% of eligible students attending at least one peer assisted study session in some units (for example, Arendale, 2001; Congos and Mack, 2005; Hensen and Shelley, 2003), fewer students attend at a level that could be considered 'regular'. To illustrate, Dancer et al. (2007) reported that 29% of 926 first-year econometrics students attended one or more peer assisted study sessions, but just 18%, 11% and 7% attended 4+, 7+ and 10+ sessions respectively. In larger studies conducted by Kochenour et al. (1997; N = 11,930) and Paloyo et al. (2016; N = 4,397), students attended an average of 1.26 (over a 10-week quarter; estimated based on data reported by Kochenour et al., 1997: 580) and 2.67 (over a 12-week semester) sessions respectively, with the majority of students in both studies opting never to attend.

Limited research has focused on why students elect not to attend peer assisted study sessions, despite their demonstrable benefits. McGee (2005) found motivational factors to be the best predictors of attendance, while Ginty and Harding (2014), Worthington et al. (1997), and Hodges (1997) all indicated that the non-attendees in their samples believed that peer assisted study sessions were unnecessary, or a waste of time. Hodges (1997; Hodges et al., 2001) attributed this belief, at least partially, to these students' unrealistic perceptions regarding their academic abilities. It has additionally been observed that some students simply do not enjoy working with peers (Blunt, 2008), while others find scheduling peer assisted study sessions around other commitments to be too difficult, or impossible (Ginty and Harding, 2014; Hodges, 1997; Worthington et al., 1997). While important, this research is fragmented and largely atheoretical.

Theory of planned behaviour

The theory of planned behaviour proposes that behaviour is best predicted by intentions, which – in turn - are best predicted by a combination of attitudes ("a favourable or unfavourable evaluation or appraisal of the behaviour in question"), subjective norms ("perceived social pressure to perform or not perform the behaviour"), and perceived behavioural control ("perception of the ease or difficulty of performing the behaviour"; Ajzen, 1991: 183-188). Unlike attitudes and subjective norms, which only exert their effects on behaviour indirectly (via intentions), the effects of perceived behavioural control are proposed to be both direct and indirect. The theory of planned behaviour has been successfully used to predict voluntary engagement in a wide range of behaviours, in contexts ranging from health psychology (McEachan et al., 2011) to human-computer interaction (Allen et al., 2010). The theory's use as a model of student study related behaviour is less common, although it has been used to predict cheating (Beck and Ajzen, 1991), student research misconduct (Rajah-Kanagasabai and Roberts, 2015), the use of lecture podcasts (Moss et al., 2010), self-reported studying intensity (Sideridis et al., 1998), and class attendance (Ajzen and Madden, 1986).

Consistent with the theory, Ajzen and Madden (1986) found that attitudes, subjective norms, and perceived behavioural control each had a direct effect on college students' intentions to regularly attend classes. Collectively, these three predictors accounted for a significant 46% of the variance in intentions which, in combination with perceived behavioural control, accounted for a significant 14% of the variance in actual class attendance. However, there was no direct link between perceived behavioural control and attendance. Ajzen and Madden (1986) attributed this unexpected finding to volitional control issues. Specifically, they argued most students will encounter few control problems when trying to attend classes, and that perceived behavioural control is only expected to have a direct impact on behaviour in circumstances where volitional control is limited. Peer assisted study sessions give rise to such circumstances, as they are typically not scheduled until the start of semester (after students have organised other commitments), and are prone to being re-scheduled as facilitators attempt to find times which can accommodate the largest number of interested students. Indeed, research suggests that some students who would like to attend cannot, due primarily to scheduling conflicts (Gattis, 2002; Ginty and Harding, 2014; Hodges, 1997). These factors suggest that peer assisted study session attendance may be under less volitional control than attendance at lectures and tutorials, and therefore perceived behavioural control should exert both a direct and indirect influence on this behaviour.

The theory of planned behaviour has also been applied to predicting peer assisted study session attendance. For example, White et al. (2008: 480) invited 77 psychology undergraduates to self-report their attitudes, subjective norms, perceived behavioural control, and intentions regarding attending "every peer assisted study session for 1st year statistics this semester". Three months later, they matched these self-reports with the students' attendance records. Findings indicated that attitudes and perceived behavioural control (though not subjective norms) accounted for a substantial proportion of the variance in intentions, with intentions accounting for a more modest proportion of the variance in attendance. Furthermore, when intentions were statistically controlled, none of the theory of planned behaviour predictors accounted for unique variance in attendance. However, White et al. (2008) did not provide any formal tests of the *indirect* effects of attitudes, subjective norms, and perceived behavioural on attendance. Consequently, it is not possible to determine whether or not their influence on this behaviour was mediated by intent.

Three years later, White et al. (2011) reported a similar study, conducted over two 6-week terms. In term 1, psychology students' (N = 79) attitudes and perceived behavioural control (but not subjective norms) accounted for a sizable proportion of variance in peer assisted study session attendance intentions. In turn, intentions (but not perceived behavioural control) predicted a smaller proportion of variance in actual attendance, measured over the following six weeks. At the start of term 2, a sub-set of the original sample (n = 46) re-completed the measures of attitudes, subjective norms, perceived behavioural control, and intentions, and provided consent for the researchers to access their term 2 attendance records. After statistically controlling term 1 intentions, term 2 attitudes were able to predict term 2 intentions, which were able to predict term 2 attendance. Predictably, term 2 attitudes, subjective norms, and perceived behavioural control were unable to account for any variance in term 2 attendance after term 2 intentions were statistically controlled. Like White et al. (2008), White et al. (2011) did not test any indirect effects, and provided only limited support for a theory of planned behaviour model of peer assisted study session attendance.

Finally, Goldstein et al. (2014) recently reported that the attitudes of 74 accounting students (which is considerably less than minimum sample sizes typically recommended for the structural equation modelling techniques they employed; Kline, 2011) toward peer assisted study session attendance at the start and end of semester significantly predicted attendance intentions, which significantly predicted actual attendance levels. Subjective norms at the end (but not the start) of semester also predicted intentions. However, Goldstein and colleagues' (2014) data were not consistent with any other aspects of the theory of planned behaviour, with perceived behavioural control neither directly nor indirectly predicting intentions or attendance.

Student role identity

Whilst White et al. (2008, 2011) and Goldstein et al. (2014) were able to account for a significant proportion of variance in both peer assisted study session attendance intentions and behaviour with the standard theory of planned behaviour predictors, much variance still remained unaccounted for.

Fortunately, the theory is flexible, and can accommodate additional, theoretically relevant variables to the extent that they enhance the predictive utility of the model (Azjen, 1991). One such variable is identity. For example, in a meta-analysis of 40 studies (N = 11,607) targeting a diverse range of behaviours, Rise et al. (2010) observed an average correlation of r = .47 between self identity and intentions, and reported that intentions largely mediated the relationship between self identity and behaviour.

Notably, White and colleagues (2008, 2011) included role identity as an additional predictor of peer assisted study session attendance in both of their studies. In the 2008 study, role identity (as a psychology student) accounted for an additional 9% of variance in intentions, beyond that already attributable to attitudes and perceived behavioural control. Role identity did not have a direct impact on actual attendance and, as noted previously, the possibility of an indirect effect was not explored by the researchers. However, the non-significant correlation between role identity and attendance suggests that an indirect effect was unlikely. When White et al. (2011) extended this work with the inclusion of both role identity (as a student in a statistics unit) and ingroup identification (as a university student) as predictors, they found that these variables accounted for significant incremental variance in attendance intentions, though not attendance behaviour. Again, indirect effects were not reported, although this time there were significant bivariate correlations (r = .38 and .37 for term 1 and term 2 respectively) between role identify and behaviour. Ingroup identification was not significantly correlated with behaviour in either term, although the non-trivial magnitude of the term 2 correlation (r = .28) suggests this may be a Type II error. In summary, these two studies suggest there is value in including aspects of identity in a theory of planned behaviour model of peer assisted study session attendance. However, further research with a larger sample size, accompanied by appropriate tests of both direct and indirect effects, is required to fully explore the identity-attendance association.

Closer examination of the measures used by White and colleagues (2008, 2011) indicates that their 'role identity' scale captures the importance of peer assisted study session attendance to student identity (for example, "to what extent do you think that attending every peer-assisted study session for 1st-year statistics this semester is a significant part of your role as a student enrolled in the Bachelor of Social Science, Psychology?"), rather than student role identity itself. As such, this measure arguably reflects attitudes towards peer assisted study sessions more than actual student identity. Some support for this assertion comes from the high correlations observed between this measure and attitudes (r = .65 in White et al., 2008; and r = .71 and .55 for term 1 and term 2 respectively in White et al., 2011). Furthermore, to measure ingroup identification, White et al. (2011) used the four-item ingroup ties subscale from Cameron's (2004) social identity scale. This is only one of the three subscales that comprise Cameron's measure, with the other two being centrality and ingroup affect. To fully examine the utility of student role identity as an addition to the theory of planned behaviour when predicting peer assisted study session attendance, research including all three subscales is required.

In the study described in this article, two related concerns were addressed. First, can the theory of planned behaviour be applied to the prediction of peer assisted study session attendance? A key focus here was building on White et al. (2008, 2011) and Goldstein et al. (2014), by using contemporary statistical methods (Hayes, 2013) with an appropriately sized sample to provide a complete test of a theory of planned behaviour model of peer assisted study sessions attendance. Second, do the three facets of social identity, as defined by Cameron (2004), add to the utility of this model? Specifically, it was hypothesised that (H1a) attitudes, (H1b) subjective norms, and (H1c) perceived behavioural control would each have a significant direct effect on intentions, which would have (H2) a significant direct effect on peer assisted study session attendance. Furthermore, it was hypothesised that (H3a) attitudes, (H3b) subjective norms, and (H3c) perceived behavioural control would each have a significant indirect effect on peer assisted study session attendance, mediated by intentions. Additionally, it was hypothesised that (H4) perceived behavioural control would have a significant direct effect on peer assisted study session attendance, after intentions were controlled. Finally, it was hypothesised that, after controlling attitudes, subjective norms, and perceived behavioural control, (H5a) centrality, (H5b) ingroup ties, and (H5c) ingroup affect would each have a significant direct effect on intentions, and (H6a-c) a significant indirect effect on peer assisted study session attendance, mediated by intentions.

Method

Context

The UniPASS program at Curtin University is accredited by the Australasian Centre for PASS, and closely adheres to the Centre's guidelines for best practice (Australasian Centre for PASS, 2010). Specifically, the program is managed by a trained and accredited supervisor, student driven, and regularly evaluated with reference to attendance data, student feedback, and grades. Evaluation reports are prepared annually, and disseminated to key stakeholders. The UniPASS peer-facilitators are current students, who have been trained, and are provided with ongoing professional development opportunities (including regular peer/supervisor observation and feedback). They are paid employees of the university. In UniPASS sessions, peer-facilitators avoid re-teaching or simply 'giving answers', and focus on the development of academic skills in addition to unit content. They are not involved in student assessment (for example, marking or awarding grades). Sessions have an ideal attendee to facilitator ratio of less than 20 to 1, although may exceed this during peak times (for example, during exam revision). UniPASS is advertised widely at the commencement and throughout each semester, and although attendance is encouraged, it is always strictly voluntary. The UniPASS program places significant emphasis on the instructional skills of facilitators, which differentiates UniPASS from many peer assisted study session programs elsewhere. For example, facilitators receive 27 hours initial training, focusing on developing the theory and practical skills needed for fostering collaborative peer learning. Such skills include Socratic questioning, redirecting questions, concept checking, managing group dynamics, giving instructions, minimising hierarchy, making appropriate referrals, and session planning.

In the second semester of 2015, when this study was conducted, there were 29 UniPASS supported units on the main University campus, and 39 peer-facilitators, collectively servicing a total population of 6,770 students. Around 21% of eligible students attended at least one UniPASS session, while just 8% attended five or more. On average, students attended 0.86 sessions *per supported unit* in which they were enrolled.

Research design

This study adopted a longitudinal, correlational design. The predictor and mediator variables were measured at the start of semester, and the criterion variable was measured approximately three months later.

Participants

A convenience sample of 254 (68 males, 185 females, and 1 unspecified, with a mean age of 23.7 years, SD = 7.56 years) undergraduate students from more than 50 degree programs enrolled in 24 UniPASS supported units during semester 2, 2015, participated in this research. The majority (n = 202) were recruited through advertising in UniPASS supported units, and were offered the opportunity to win a gift card in appreciation of their time. The remainder were recruited via a participant pool, and provided with course credit in exchange for their participation. These two groups of students did not differ in terms of gender distribution, χ^2 (2, N = 254) = 4.67, p = .10, ϕ = .13, or age, $t(248)$ = 0.91, p = .362, Hedges g = 0.14, and were thus combined for all subsequent analyses.

Just over half (52.40%) of the sample attended one or more UniPASS sessions during the semester, attending an average of 8.46 (SD = 5.85) sessions each. The mean attendance count for the full sample was 4.50 (SD = 6.00) sessions each. When attendance was weighted by the number of UniPASS supported units that participants were enrolled in (range = 1 to 4), the mean number of sessions attended *per unit* was 3.40 (SD = 4.30). This was significantly higher than that of the population from which they were sampled, $t(253)$ = 9.40, p < .001, d = .59.

Sensitivity power analysis with G*Power 3.1 (Faul et al., 2009) indicated that any coefficients with effects larger than f^2 = .02 in the models presented herein would be statistically significant at α = .05. Per Cohen's (1988) conventions, f^2 = .02 can be characterised as 'small'.

In conducting this study, we complied with the National Health and Medical Research Council's (2007) guidelines for the conduct of research involving human participants, and followed best-practice recommendations for the ethical use of online surveying in educational research (Roberts & Allen, 2015). Prior to recruitment, the study was reviewed and approved by the Human Research Ethics Committee at Curtin University.

Measures
Measures of attitudes, subjective norms, perceived behavioural control, and intentions were adapted from Ajzen's online exemplar (https://people.umass.edu/aizen/pdf/tpb.questionnaire.pdf), by replacing the phrase "meetings of this class" with "UniPASS sessions". Participants responded to all items on 7-point semantic differential scales and, with the exception of intentions (two items), each measure was comprised of four items. Example items included, "for me to attend UniPASS sessions on a regular basis is extremely worthless/valuable" (attitudes), "most people who are important to me think that I should/should not attend UniPASS sessions on a regular basis" (subjective norms), "for me to attend UniPASS sessions on a regular basis is extremely difficult/easy" (perceived behavioural control), and "I definitely will/will not make an effort to attend UniPASS sessions on a regular basis this semester" (intentions). Cronbach's alpha for each measure can be found in Table 1 (along with alpha for each measure described below).

The three factor measure of social identity developed by Cameron (2004) was adapted to assess centrality (4 items), ingroup ties (4 items), and ingroup affect (4 items). In Cameron (2004), the items are presented in a generic form (for example, "In general, I'm glad to be a(n) *ingroup member*"), with the expectation that the phrase "ingroup member" be replaced with an appropriate group descriptor. In the current research, that descriptor was "student of my course". For example, "being a student of my course is an important part of my self image" (centrality), "I have a lot in common with other students in my course" (ingroup ties), and "generally I feel good about myself when I think about being a student of my course" (ingroup affect). Participants responded to each item on a 7-point scale ranging from "strongly disagree" to "strongly agree".

UniPASS session attendance data were recorded for each participating student for each supported unit in which they were enrolled in the second semester of 2015. As students in the sample had varying degrees of opportunity to engage with the UniPASS program, these raw attendance data were weighted by opportunity. However, it should be noted that the use of weighted versus unweighted attendance data had no substantive impact on any of the results that follow.

Procedure
Students were invited to participate in this study during the first four weeks of the second semester of 2015. Those interested were directed to an online questionnaire containing the measures described previously. On average, it took them 10 minutes to complete. At the end of the semester, UniPASS attendance data were collated, and merged with the self-report data.

Data preparation
After the two sources of data were merged, 38 cases were removed, as they were not enrolled in UniPASS supported units in semester 2, 2015. A further 8 cases were removed due to excessive (> 5%) missing data, leaving a final sample of $N = 254$. Remaining missing data (18 data points over 16 participants, with no more than two points missing on any given item) were not missing completely at random, as indicated by a statistically significant Little's test, $\chi^2(348) = 417.167$, $p = .006$. However, the volume of missing data was trivial relative to the size of the total data set (< 0.3%) and thus, following the reversal of 16 negatively worded items, missing data were replaced using expectation maximization. Subscale means were then computed, with higher scores (within a possible range of 1 to 7) reflecting stronger or more positive manifestations of the relevant characteristics.

Results

Means and standard deviations for each variable, as well as bivariate correlations between variables are presented in Table 1. As illustrated, all predictors were significantly correlated with both intentions and attendance.

[INSERT TABLE 1 ABOUT HERE]

To test the first four hypotheses, we used ordinary least squares path analysis, implemented via the PROCESS macro for SPSS (Hayes, 2013). As illustrated in Tables 2 and 3, attitudes, subjective norms, and perceived behavioural control all had significant direct effects on intentions, which had a significant direct effect on peer assisted study session attendance. Furthermore, all three predictors had significant indirect effects on attendance, mediated by intentions. Finally, after intentions were controlled, only perceived behavioural control had a significant direct effect on attendance. Therefore, hypotheses H1a to H4 were supported. As illustrated at the bottom of Table 2, we were able to account for a very large proportion of variance in both intentions (61%) and attendance (42%).

[INSERT TABLE 2 ABOUT HERE]

[INSERT TABLE 3 ABOUT HERE]

In Table 2, the unstandardised coefficients (*B*) represent the predicted change in the criterion variable (either intentions or attendance) associated with a one unit change in the relevant predictor, whilst holding all other variables in the model constant. For example, *B* = .43 for perceived behavioural control in the attendance model suggests that, after controlling all other predictors, a one point increase in perceived behavioural control (measured on a seven-point scale) predicts a .43 session increase in attendance. In other words, two students who differ by one point on perceived behavioural control, but have identical levels of subjective norms, attitudes, and intentions would be predicted to differ on attendance by just under half a session. Of these two students, the one with the greater perceived behavioural control would be predicted to have the higher attendance. Furthermore, the 95% confidence interval for this coefficient suggests that the 'true' impact of a one point increase in perceived behavioural control on attendance is likely to range between .11 and .74 sessions. With this in mind, Table 2 indicates that attitudes had the strongest direct effect on intentions, followed by perceived behavioural control, then subjective norms. Intentions had the strongest direct effect on attendance, followed by perceived behavioural control. Finally, the direct effects of subjective norms and attitudes on attendance did not differ reliably from zero.

The indirect effects reported in Table 3 estimate the degree to which two cases that differ by one unit on the relevant predictor, but are equivalent on all other predictors, differ on attendance as a result of the relevant predictor's influence on intentions which, in turn, influence attendance. For example, the indirect effect of perceived behavioural control on attendance is .54. This indicates that two students who differ by one point on perceived behavioural control, but have identical subjective norms and attitudes, are predicted to differ on attendance by .54 sessions as a result of the tendency for students with higher perceived behavioural control to express stronger attendance intentions, which translate into higher attendance behaviour. In other words, the influence of perceived behavioural control on attendance is mediated by intentions. As can be seen in Table 3, attitudes had the strongest indirect effect on attendance, followed by perceived behavioural control, and then subjective norms. This pattern of results is consistent with the theory of planned behaviour, which proposes that positive attitudes, perceived behavioural control, and subjective norms lead to strong behavioral intentions, and that strong behavioural intentions promote actual behaviour.

The remaining two hypotheses were also tested with ordinary least squares path analysis, implemented via PROCESS (Hayes, 2013). As illustrated in Tables 4 and 5, the addition of the three social identity factors did not improve the predictive utility of the basic theory of planned behaviour model. After controlling for attitudes, subjective norms, and perceived behavioural control, these additional variables were unable to predict intentions. Furthermore, their indirect effects on peer assisted study session attendance, mediated by intentions, were all non-significant. Therefore, no support was found for hypotheses 5 and 6.

[INSERT TABLE 4 ABOUT HERE]

[INSERT TABLE 5 ABOUT HERE]

Discussion and conclusions

Despite a large body of evidence indicating that peer assisted study session attendance is meaningfully associated with student success (Dawson et al., 2014), most students elect not to attend regularly (Dancer et al., 2007, 2015; Kochener et al., 1997; Paloyo et al., 2016). Understanding the factors predicting attendance is a necessary precursor to implementing evidence based strategies designed to increase such attendance, with the overall objective of conferring the benefits of peer assisted study sessions to largest possible number of students.

The first aim of this study was to examine the predictive utility of a theory of planned behaviour model of peer assisted study session attendance. Overall, we were able to account for 61% of the variance in attendance intentions and 42% of the variance in actual attendance using the standard theory of planned behaviour variables. Furthermore, the fit of the model was in accordance with the relationships posited by Ajzen (1991). Attitudes and subjective norms had indirect effects on attendance, via intentions, whilst the effects of perceived behavioural on attendance were both direct and indirect (via intentions). These findings build on earlier work (Goldstein et al., 2014; White et al., 2008, 2011), which only tested some theory of planned behaviour pathways, and increase the confidence we can have in applying the theory to peer assisted study session attendance behaviour.

These findings suggest that interventions focused on increasing positive attitudes, subjective norms, and perceived behavioural control vis-à-vis peer assisted study session attendance should result in increased attendance intentions, followed by an increase in actual attendance behaviour. Such an intervention could take the form of an advertising campaign comprised of a series of short, targeted messages delivered to students via multiple media (for example, email, learning management system or student portal announcements, flyers, posters, and so on) across the duration of the semester. Each message could focus on a single theory of planned behaviour predictor or, alternatively, predictors could be combined. These messages should ideally be developed in consultation with students, to ensure that they capture issues most relevant to the cohort, and speak in an appropriate 'voice'. This could be achieved via focus groups and brainstorming sessions. Messages targeting attitudes should focus on the idea that peer assisted study session attendance is good, useful, pleasant, interesting, and so on. For example, they could make reference to research indicating that attendees consistently achieve higher grades than non-attendees, and that time spent engaged in active learning activities with colleagues is more productive than time spent reading alone. Messages targeting subjective norms should focus on the idea that attendance is a socially valued and normative behaviour. Testimonials from students describing the social benefits of attendance (for example, making friends or being part of a community) may prove particularly effective here. Finally, messages targeting perceived behavioural control could focus on reducing perceived barriers to attendance. For example, reminding students that time spent engaged in peer assisted study sessions reduces time needed for independent study, and that scheduling conflicts (for example, between paid employment and peer assisted study sessions) can often be resolved with proactive planning and negotiation. Similar interventions have been successful in other contexts (for example, Milton and Mullan, 2012).

The second aim of this study was to examine the incremental predictive utility of student role identity in an expanded theory of planned behaviour model of peer assisted study session attendance. Results indicated weak positive associations between each component of student role identity (centrality, ingroup ties, and ingroup affect) and both attendance intentions and behaviour. However, after controlling for attitudes, subjective norms, and perceived behavioural control, these role identity factors had neither direct nor indirect effects on intentions or behaviour. As such, they are of unlikely to have substantive value to educators seeking to develop theory of planned behaviour inspired interventions aimed at boosting peer assisted study session attendance levels.

Research applying the theory of planned behaviour to predicting peer assisted study session attendance (Goldstein et al., 2014; White et al., 2008, 2011) has relied on relatively small samples from within single academic disciplines. A key strength of this study was that a larger sample size, combined with modern analytic techniques, provided the statistical power required to examine both direct and indirect pathways in the theory of planned behaviour model. Further, the sample in this study comprised students from a wide range of disciplines enrolled in 24 different units. However, the use of an undergraduate convenience sample from a single Australian university remains a limitation, and future research using whole-of-population or random samples (both undergraduate and postgraduate) drawn from multiple higher education institutions is recommended. A further limitation of the current research is the poor reliability of the subjective norms measure. Subjective norms have historically been the weakest predictor in the theory of planned behaviour model, and this is at least partially attributable to weaknesses in measurement (Armitage and Conner, 2001; Manning, 2009). Further refinement of the subjective norms construct and its measurement is required.

In summary, peer assisted study session attendance is associated with multiple indicators of student success. Despite this, typical peer assisted study session programs attract relatively few regular attendees. The theory of planned behaviour has been used to successfully predict voluntary engagement in a wide range of behaviours. Research has suggested that the theory may provide a useful framework for understanding peer assisted study session attendance, but has also suffered from several methodological limitations. The study described herein addressed a number of these limitations, and offers substantial support for a theory of planned behaviour model of peer assisted study session attendance. However, the addition of student role identity to the model did not increase its explanatory power. Findings suggest that marketing activities focused on increasing students' positive attitudes, subjective norms, and perceived behavioural control vis-à-vis peer assisted study session attendance should result in increased attendance intentions, followed by an increase in actual attendance. However, research to establish the viability of these suggestions is required.

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Tables

Table 1

Intercorrelations, Reliability Coefficients, Means and Standard Deviations for all Measured Variables (N = 254)

	Pearson's *r*							*M*	*SD*
	2	3	4	5	6	7	8		
1 Weighted attendance	.63***	.45***	.32***	.44***	.14*	.13*	.16**	3.40	4.30
2 Intentions	.87[a]	.56***	.44***	.64***	.24***	.21**	.26***	4.84	1.91
3 Perceived behavioural control		.82[a]	.26***	.21**	.22***	.17**	.13*	4.77	1.60
4 Subjective norms			.52[a]	.45***	.10	.26***	.20**	4.40	1.03
5 Attitudes				.85[a]	.22***	.19**	.39***	5.54	1.15
6 Centrality					.61[a]	.29***	.27***	4.37	1.15
7 Ingroup ties						.84[a]	.34***	4.34	1.41
8 Ingroup affect							.83[a]	5.68	1.06

[a] Cronbach's alpha
* *p* < .05, two tailed. ** *p* < .01, two tailed. *** *p* < .001, two tailed.

Table 2

Unstandardised Model Coefficients (B) with Associated Standard Errors and 95% Confidence Intervals in the Basic Theory of Planned Behaviour Model

	Intentions				Attendance			
			95% CI				95% CI	
	B	*SE*	*LL*	*UL*	*B*	*SE*	*LL*	*UL*
Constant	-3.08***	.43	-3.93	-2.24	-6.20***	1.29	-8.75	-3.65
Perceived behavioural control	.51***	.05	.41	.61	.43**	.16	.11	.74
Subjective norms	.19*	.08	.03	.36	.11	.23	-.34	.57
Attitudes	.83***	.07	.69	.98	.34	.25	-.15	.83
Intentions					1.07***	.17	.73	1.42
	R^2 = .61 *F* (3, 250) = 130.49, *p* < .001				R^2 = .42 *F* (4, 249) = 45.36, *p* < .001			

Note. SE = Standard Error. CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.
* *p* < .05, two tailed. ** *p* < .01, two tailed. *** *p* < .001, two tailed.

Table 3

Indirect Effects of Perceived Behavioural Control, Subjective Norms and Attitudes on Peer Assisted Study Session Attendance, Mediated by Intentions, with Associated Bootstrap Standard Errors and Bias-Corrected Confidence Intervals

	Effect	*SE*	95% CI	
			LL	*UL*
Perceived behavioural control	.54*	.10	.38	.77
Subjective norms	.21*	.10	.03	.43
Attitudes	.90*	.15	.63	1.24

Note. *SE* = Standard Error. CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit. *SE*s and CIs based on 10,000 bootstrap samples.
* $p < .05$.

Table 4

Unstandardised Model Coefficients (B) with Associated Standard Errors and 95% Confidence Intervals in the Expanded Theory of Planned Behaviour Model

	Intentions				Attendance			
			95% CI				95% CI	
	B	*SE*	*LL*	*UL*	*B*	*SE*	*LL*	*UL*
Constant	-3.14***	0.53	-4.18	-2.10	-5.51***	1.56	-8.58	-2.44
Perceived behavioural control	0.50***	0.05	0.40	0.60	0.44**	0.16	0.12	0.77
Subjective norms	0.19*	0.09	0.02	0.36	0.12	0.24	-0.35	0.59
Attitudes	0.84***	0.08	0.68	0.99	0.39	0.26	-0.13	0.91
Centrality	0.05	0.07	-0.09	0.19	-0.11	0.20	-0.50	0.28
Ingroup ties	0.02	0.06	-0.10	0.13	-0.05	0.16	-0.37	0.28
Ingroup affect	-0.03	0.08	-0.20	0.13	-0.08	0.23	-0.52	0.37
Intentions					1.08***	0.18	0.73	1.42
	$R^2 = .61$				$R^2 = .42$			
	F (6, 247) = 64.77, $p < .001$				F (7, 246) = 25.80, $p < .001$			

Note. *SE* = Standard Error. CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit.
* $p < .05$, two tailed. ** $p < .01$, two tailed. *** $p < .001$, two tailed.

Table 5

Indirect Effects of Predictors in the Expanded Theory of Planned Behaviour Model, Mediated by Intentions, with Associated Bootstrap Standard Errors and Bias-Corrected Confidence Intervals

	Effect	*SE*	95% CI	
			LL	*UL*
Perceived behavioural control	.54*	.10	.37	.77
Subjective norms	.20*	.11	.02	.44
Attitudes	.90*	.17	.61	1.27
Centrality	.05	.09	-.09	.24
Ingroup ties	.02	.07	-.11	.15
Ingroup affect	-.04	.10	-.25	.16

Note. *SE* = Standard Error. CI = Confidence Interval, *LL* = Lower Limit, *UL* = Upper Limit. *SE*s and CIs based on 10,000 bootstrap samples.
* $p < .05$.