Using a Mixed Methods Approach to Investigate University Student Success after Support Service Interaction: A Case Study and Analysis

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Abstract

This article discusses methods for assessing academic success after a student’s initial interaction with university support services. Student services are an important part of institutional support within Australian higher education and service efficacy and effectiveness assessments are likewise important for delivering optimal support. Methods of service assessment may vary in application but are likely to target academic performance, social wellbeing and/or mental health as potential success outcomes after service interaction. The author presents a mixed methodological approach as a novel way to counter potentially ineffective investigative techniques that can fall short of considering the broad contributions that a support service interaction can make to student success. The potential drawbacks of single-method approaches are considered, as are the obstacles to a mixed-methods design. The article draws on the work of previous mixed-method research to demonstrate the benefits of its application in examining support service influence on student success while paying particular attention to the work of Stone, Walton, Clark and Ligertwood (2016), whose methodology is unpacked and discussed in detail.

Keywords

University support services, mixed-methods, multilevel modelling.

Introduction

This article discusses the application of mixed methods in assessing the influence of student interaction with support services at UNSW Australia. Previous assessments of support service effectiveness are outlined to underpin the relevance of the proposed analytical method. A case study frames the context within which the approach has been trialled by the author, including ways in which the application succeeded, required adjustment, or failed. The article is structured to detail a particular method of the mixed-methods process, which is followed by a discussion surrounding how and why that particular method was engaged in Stone, Walton, Clark and Ligertwood (2016). The methods engaged by Stone et al. (2016) included a multilevel statistical analysis of a university database, the use of survey questionnaires, and in-depth interviewing.

Assessment of the effectiveness of support services

Millions of dollars are spent on intervention and support strategies in Australia (Devlin, Kift, Nelson, Smith and Mckay, 2012) and around the world (Robbins, Oh, Le and Button, 2009). “The problem facing Student Services units is the difficulty in finding empirical evidence of a demonstrable link between the services they provide for students and positive academic outcomes” (White, 2011, p.4). Robbins et al. (2009, p.1166) report that “despite the popularity of [higher education] interventions, our current knowledge about their effectiveness is very limited”. A common limitation of support service studies is “they do not assess whether developmental programs have a causal effect on student retention” (Lesik 2007, p.585), which often translates into a potential lack of effort on behalf of some institutions in monitoring their support structures (Shah and Nair, 2011).
There are some examples of investigative reports into support initiative efficacy, such as the overseas-based studies of Burk and Bender (2005), Penalber (2005), Scrivener et al. (2008), Robbins et al. (2009), Sefor, Mamun and Schirm (2009) and Bettinger and Baker (2013). Locally, Nelson, Clark, Stoddle and Creagh (2014) utilise and promote maturity models to assess institutional capabilities for student success, including support and interaction services. Devlin et al. (2012) used interview evidence to study the success of mentoring programs, sociability-enabling spaces and support networks for targeted students. Tones, Fraser, Elder and White (2009) explored the significance of support for mature-age students through similar qualitative approaches. McNaught and Beal (2012, p.200) sought to gain a better understanding of student needs and the efficacy of support services through a survey questionnaire design, concluding, “This survey did not capture demographic data specific to student backgrounds”, adding “the collation of data could be useful”.

Most studies into the effectiveness of student support services (such as those mentioned above) are largely qualitative in design, employing questionnaire and interview techniques to source data. Lesik (2007) expresses the opinion that similar studies are limited by a reliance on cross-sectional, retrospective designs despite the longitudinal nature of the research. In contrast, Lesik (2007) used a discrete-time survival analysis using logistic regression to map the impact of support program participation on academic performance and identify a positive quantitative relationship between student engagement with support programs and course retention. In another quantitative-focused study, Denny, Doyle, McMullin and O’Sullivan (2014) evaluated the success of a university access program for students from admission to exit by employing ordered probit models to correlate student success dependent on their involvement in an access program, while modelling the impact of varying levels of support (in terms of financial aid) over time. Denny et al. (2014, p.181) note that the majority of studies in this area focus on one support program and are almost exclusively North American in focus, “thus it is important to consider the likely effects of [support] programs in countries with different social and cultural contexts”. In an Australian study, Wimshurst and Allard (2008) used multiple linear regression analyses to examine course and student characteristics in relation to academic performance, finding that personal and institutional factors interacted to increase the risk of failure. Similarly, French, Muurlink and Wilson (2014) utilised multiple linear regression analyses in an Australian context to determine relationships between variables of degree preference, grade point average (GPA), course load and support service engagement (including number of consultations and number of workshops attended). Many of the statistical analyses reported in French et al. (2014, p.8) returned a non-significant result because of small sample sizes, which lead to the authors positing, “this study is effectively a pilot study for a larger analysis”.

Discussions of methodological approaches to assessing the effectiveness of support services

Tinto (2010, p.51) writes “we have not yet been able to develop a model of institutional action that would help institutions make progress in helping students continue and complete their degrees”. Gale and Parker (2014, p.734) remark that “future research [into the effectiveness of support services] needs to foreground students’ lived realities and to broaden its theoretical and empirical base”. “By looking at the impact of receiving different levels of treatment, this may help to illuminate whether these programs in conjunction with each other are effective” in helping students succeed (Lesik 2007, p.606). Naylor, Baik and James (2013, p.33) lament, “for many initiatives, there are too many variables to control in any rigorously methodological way, which makes establishing causal relationships between initiatives and effects extremely difficult”. Belot, Canton and Webbink (2007, p.274) write that quantitative data in the form of statistics do not provide information on changes in student performance admitting “we cannot
rule out the impact of other factors”. Wimhurst and Allard (2008, p.694) discuss the possibility that “some finer-grained qualitative study might identify other factors not adequately captured in a largely quantitative study”. What these authors highlight is that single-method approaches to investigating the influence of support services on students, either quantitative or qualitative, often fall short of elucidating the whole story. A combination of quantitative and qualitative methods to explore the relationship between student success and support service engagement may yield many of the desired outcomes proposed in the literature (such as Devlin et al., 2012; Naylor et al., 2013; Gale and Parker, 2014), and extend much of the existing knowledge (Denny et al., 2014; French et al., 2014), albeit in a localised context.

Mixed methods

Issues of causation have been cited in previous support service investigations as detrimental to research outcomes. For instance, Lesik (2007) states that a common limitation among service effectiveness studies is their failure to establish causal effects, and Naylor et al. (2013, p.33) add that the amount of variables involved “makes establishing causal relationships between initiatives and effects extremely difficult”. Conversely, Cohen, Manion and Morrison (2011, p.71) testify to the “power of mixed methodologies and mixed methods in investigating and establishing causation”. A mixed method design has been described as combining quantitative and qualitative methods to address a research question, as opposed to a multimethod design, which does not imply constraints on including at least one of each method paradigm (i.e. quantitative and qualitative) (Mark, 2015). Qualitative methods, in conjunction with quantitative methods, have been used to enlighten difficult subjects, add depth to statistical generalisations and sing the otherwise mute melodies of feelings, emotions, attitudes and beliefs (Plano-Clark, Huddleston-Casas, Churchill, O’Neil-Green and Garrett, 2008; Winchester and Rofe, 2010). Likewise a quantitative approach can complement qualitative methods. These combinations can provide, among other insights, both individual and group data related to a research topic, triangulation of analysis, or they may be used to cross-check results from different angles and help establish cause and effect (Winchester and Rofe, 2010).

Mixed method research can be performed in different ways. Ivankova, Creswell and Stick (2006) and Suldo et al. (2009) describe the implementation of a mixed methods sequential explanatory design, whereby a quantitative phase is followed by a qualitative phase. Ivankova et al. (2006, p.5) state that “the rationale for this approach is that the quantitative data and their subsequent analysis provide a general understanding of the research problem”, adding “the qualitative data and their analysis refine and explain those statistical results by exploring participants’ views in more depth”. This particular mixed-method approach could be summarised as constituting a sequential design with a multistage purposeful sampling scheme (as seen in Suldo et al., 2009).

A demonstration of how a mixed-method design can inform the influence of support services on higher education student success is offered by Stone et al. (2016) (in this issue). Stone et al. (2016) utilise a sequential mixed design that includes a qualitative narrative analysis of interviewed participants following a quantitative account of student support evaluation and academic success. The latter incorporated an ethnographic study of a select university cohort identified from population data. The use of large datasets to analyse student engagement with university support services – such as drawing on an entire university cohort consisting of all current and past students – has yielded significant results in past research (for example Chowdry, Crawford, Dearden, Goodman and Vignoles, 2013, who use linked databases to examine determinants of higher education participation, and Edwards and McMillan, 2015,
who draw on information from a data collection of multiple institutions to explore predictors of student success). Moreover, small sample size has been referenced as an issue for a number of studies (for example Robbins et al., 2009; McNaught and Beal, 2012; Denny et al., 2014; French et al., 2014). Quantitative data analysis of a large student cohort in the context of service influence on student success must account for multiple factors (Rumberger, 1995; Gale and Parker, 2014). This can be partially achieved by using the statistical technique of multilevel modelling.

**Multilevel modelling**

A multilevel model (MLM) (also known as a hierarchical linear model) is a statistical analysis technique that is in many ways similar to a regression. However, a MLM can be employed when observations in a data sample are not independent – for example, a student within a faculty is more directly comparable to students in the same faculty as opposed to students in a different faculty. Regression models do not take this clustering of data into account. Studies that attempt to estimate effects of student- and faculty-level variables in a single model, either by including faculty-level variables in a student-level model or by incorporating aggregated values of student-level variables in a faculty-level model, can produce faulty results (Rumberger, 1995; Raudenbush and Bryk, 2002). Rumberger (1995, p.598) explains that the first technique produces aggregation bias, which underestimates the effects of variables estimated at the inappropriate level, and “the second technique fails to capture the effects of certain variables, such as socioeconomic status, that operate at both levels of analysis”. Bell, Ene, Smiley and Shonenerber (2013, p.1) report that “research has shown that ignoring a level of nesting in data can impact estimated variances and the available power to detect treatment or covariate effects. As a corollary, MLMs tend to be used most commonly in educational data modelling where data tend to be nested (correlated) within levels – such as a student within a tutorial class, within a program, within a faculty (Raudenbush and Bryk, 2002; Twisk, 2006; van de Vijver, van Hemert and Poortinga, 2008).

Previous research illustrates the use of MLMs in the context of exploring support and development program contributions to student success. Stewart (2008) used multilevel modelling to investigate the extent of school- and individual-level factors on academic performance, while Allen, Robbins, Casillas and Oh, (2008) engaged multilevel modelling to investigate the effects of academic performance and social connectedness on retention and attrition behaviour. For Pan, Guo, Alikonis and Bai (2008), multilevel modelling facilitated an examination into the effects of intervention programs on student grades and retention. Pan et al. (2008) detail a study similar to that performed by Stone et al. (2016). Pan et al. (2008) were able to assess the influence of support programs, which were specifically targeted at first-year student retention and grades, on academic performance outcomes, and show that the programs had been effective in their contribution to student success. Pan et al. (2008) performed two separate analyses in response to the dichotomous and continuous nature of the outcome variables in their study – i.e. retained versus not retained (dichotomous) and student grades (continuous). Stone et al. (2016) similarly applied different variations of multilevel modelling to data.

Research undertaken in contribution to Stone et al. (2016) is drawn on to highlight the potential benefits of multilevel modelling to relevant scholarship. A practical example from this study is likewise presented later on in discussion of qualitative contributions to mixed methodologies.
**Case study context: Multilevel modelling**

Multilevel modelling was identified as a viable alternative to ordinary least squares (OLS) models, such as regression, during enquiries into the most appropriate way to analyse individual student grades before and after an initial support service interaction. One of the assumptions of OLS models is that individual scores are independent of each other. However, this is not the case for a student’s scores before and after a service interaction, where scores are quite obviously related to each other – i.e. not independent – because they belong to a distinct individual. Analysing student grades before and after an interaction using OLS regression would require taking the average of scores before interaction and the average of scores after interaction for each student, which would result in the loss of much data. The use of a MLM allowed all student scores to be used and then nested within individual students. The same logic applies to students within a faculty, and student data nested within faculties were also considered in multilevel analyses.

McConney and Perry (2010) outline the widely recognised understanding that multilevel modelling is ideal for estimating unique associations of student- and faculty-level variables on student performance, while highlighting that:

“[A MLM] relies on often unspoken assumptions that relationships among variables under study are linear. The approach can thereby result in the unintended consequence that departures from linearity in relationships for particular subgroups of students within the dataset, which may become evident with a finer grained analysis, are masked.” (p.439).

Thus, the relationship between student success and support service interaction was approached by Stone et al. (2016) by drawing on database analysis in the form of multilevel modelling *in tandem with* the finer-grained methods of purposive questionnaire sampling and interview narrative analysis.¹

**Questionnaire**

A MLM permits many demographic, academic, social or personal variables to be accounted for in the statistical analysis of interaction versus success. Variables might include age, birth country, grades, faculty, socioeconomic status, or personality traits – depending on available data. However, models do not take into account the multitude of other influences that may impact a student over the course of their academic career, influences that cannot be observed objectively. A questionnaire can be used to provide more detailed insights into these influences and the agents – internal and external to the higher education institution – to which students look for support, how helpful they find these, and how these factors vary within and between groups. In relevant examples, Burk and Bender (2005) surveyed students to ascertain the perceived effectiveness of support services, Belot et al. (2007) drew from questionnaire data in their assessment of higher education scholastic performance following the reduction of support intervention, and Robins et al. (2009) performed a meta-analysis of survey results regarding service effectiveness in order to direct future support. Yet the research conducted for these studies is described by the authors as limited. Specifically, Burk and Bender (2005) mention their inability to generalise results outward from their (small) sample, Belot et al. (2007, p.274) identify the influence of “unobserved factors” on their results as well as the need for an

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¹Notwithstanding an account of how multilevel modelling can contribute to research, this article does not contain a detailed account of how to perform a MLM. Interested readers should refer to textbooks by Field (2012) or Tabachnick and Fidell (2013) for introductory explanations, and Bell et al. (2013) and Ene, Leighton, Blue and Bell (2015) for specific software instructions and background.
extended research scope, and Robbins et al. (2009, p.1178) state “our study did not take into account various institutional characteristics, system-level factors and other variables that might influence student academic performance”. These conclusions suggest that questionnaire data can benefit from additional information, qualitative or quantitative, procured through multi or mixed methodologies. In addition, Secor (2010) states that a questionnaire provides a good supplement for interview-based research – as was the case in Stone et al. (2016).

Case study context: questionnaire

Stone et al. (2016) used a purposive sampling technique to target students that had interacted with support initiatives. An email calling for participation was distributed to the mailing lists of support service providers, which was a practical way to maximise response rates from students who had interaction history.

Questionnaire data primarily consisted of Likert-scaled responses to questions of support service effectiveness/helpfulness with regard to their contribution to the student’s social, financial, emotional or academic wellbeing. Quantitative survey data can be used to complement or contest the outcomes of the other methods in a mixed method design. This may serve to refute conclusions of service effectiveness or at least inform discussion regarding seemingly non-compliant results.

Nearly 800 questionnaires were completed for the Stone et al. (2016) study. However, interaction frequencies for individual services, combined with the separation of students into classifying groups, were low. As a result, statistically significant results were often hard to come by. This reduced the potential for questionnaire results to corroborate other data, and hence the questionnaire data were omitted in the analysis of the Stone et al. (2016) study.

The questionnaire was nonetheless valuable as student interview participants were recruited from questionnaire respondents. Participants were offered an opportunity to self-recruit for a follow-up interview at the conclusion of the questionnaire.

Semi-structured in-depth interviewing

In-depth interviewing can be used to gain access to, and understanding of, activities and events that cannot be observed from a database or reported in a questionnaire. An interview is a “conversation that is directed more or less towards the researcher’s need for data” (Green and Thorogood, 2004, p.87). According to Minichiello, Aroni and Hays (2008, p.46), “Interviewing is the most commonly used form of qualitative research”. The purpose of the interview is to explore and understand actions within a specific setting (the influence of support initiatives on student success), to examine human and environmental relationships and unpack why people feel or act in the ways they do (McDowell, 2010). The narrative required for this amount of detail is beyond the scope of a questionnaire or a database. This is because written responses and longitudinal information are not the only determinants of the student’s ‘story’. An interview captures language and narrative to help paint a fuller picture of the discourse surrounding interaction and success.

Semi-structured or focused interviews employ an interview guide that is content focused and deals with issues and themes judged by the researcher to be relevant to the research question(s) (Minichiello et al., 2008; Dunn, 2010). The content of the semi-structured interview is focused on the issues central to the research themes while allowing for greater flexibility and discussion than a questionnaire. This reduces statistical comparability between interviews, “but provides
a more valid explanation of the informant’s perceptions and constructions of reality” (Minichiello et al., 2008, p.51). A benefit of the focused interview is that the data derived are more systematic and comprehensible than in an unstructured interview, while the tone remains fairly conversational and informal. Drawbacks can arise if the interviewee is not adequately ‘probed’ for information, or when the pre-determined topics outlined beforehand by the researcher prevent other important issues from being raised by the respondent (Minichiello et al., 2008). A researcher with good preparation can avert these issues with good interviewing skills and knowledge of the research topic (Dunn, 2010).

An interview is unlike a normal, organic conversation and assumptions ensue in the relationship between the researcher and the researched. The research interview is a one-way process where the interviewer receives, but does not give – doing so might bias the participant’s responses (Minichiello et al., 2008). Roberts (1981, p.30) explains that, “interviews are seen as having no personal meaning in terms of social interaction, so that their meaning tends to be confined to their statistical comparability with other interviews”. Regardless, spoken testimony in combination with quantitative observation can make known and operationalise otherwise unseen connections in the data. This was observed by Stone et al. (2016), as explained in the following section.

Case study context: Semi-structured in-depth interviewing

Stone et al. (2016) prepared a list of semi-structured interview questions to uncover student experiences with support services at UNSW. Students were also asked about ‘success’ – what this meant to them, what had influenced their success at UNSW and whether support service interaction had contributed. A sample of 20 or more interviews was identified as a sufficient size for attaining “saturation” (Guest, Bunce and Johnson, 2006, p.59). A total of 22 interviews were tape recorded and transcribed. A thematic analysis of the interview data was undertaken using the NVivo 10 software package. NVivo software does not replace the analytical thinking process of qualitative research, as it does not develop propositions from the data. However, it does facilitate the retrieval of unsystematised text material in a fast, flexible way, using structured nodes of topics, themes or categories (Minichiello et al., 2008). Creation of nodes in NVivo first requires the import of the transcribed text document into NVivo where it can then be accessed for coding. Nodes in NVivo are an indexing system created by the user by extracting snippets or chunks of text. These text chunks are coded as a specific theme or topic, and represented as a node. Nodes are organised into meaningful categories by the researcher that can be modified, extended or deleted as coding progresses.

Interview data collected by Stone et al. (2016) supported much of what was revealed by the multilevel modelling technique regarding support service contribution to students’ academic success. Moreover, interview data extended knowledge of how specific services support students and influence their success. The contribution of interview data to the mixed-method application of Stone et al. (2016) was most notable for support services that did not directly target academic performance, such as development and counselling programs and initiatives. Lived testimonies from student interviews unveiled how support services with a non-academic focus can contribute to (academic) success, which tended to implicate social inclusion, mental wellbeing or non-discontinuation/retention as success outcomes. In addition, interview data were drawn on to connect academic achievement to social and mental wellbeing by unpacking student narratives of university experiences, corroborating what has been expressed in the literature surrounding contributions to academic success (for example Payton et al., 2000; Zhao and Kuh, 2004; Kuh, Cruce, Shoup, Kinzie and Gonyea, 2008; Harper and Quaye 2014; Johnson, 2016).
Concluding remarks

Many previous support initiative studies have based their analyses on a single method approach. It was the intention of the author to present a more encompassing account of the subject matter. This was approached by offering an examination that incorporates often-overlooked or out-of-scope methods and analyses in collaboration with each other. For instance, multimethod investigations have been called for in the literature (Tinto, 2010; Naylor et al., 2013; Gale and Parker, 2014), and the multilevel modelling technique is an underused tool in educational data analyses in the support initiative context – despite advantages for its use in scholarship (as seen in Pan et al., 2008; Stewart, 2008; Goldstein, 2011), as well as recent calls for its use (Edwards and McMillan, 2015).

The mixed-methods approach used by Stone et al. (2016) has helped to expand understandings of support initiatives at a specific higher education institution, as well as explore service impact on student success. While insights were provided into how success was influenced by support initiatives it is understood that many of the forces and influences that act upon students are abstract, inconsistent in their occurrence and circumstantial. Notwithstanding the fruitful harvest of data that can result from engaging mixed methodologies, the author acknowledges that services may contribute to success in ways that have not been assessed or identified in this article (or that of Stone et al. 2016). However, this also serves to highlight the salience of using multiple methods to gather as much relevant data as possible to inform analyses. Moreover, there is a large array of methodologies that draw from multimethod, integrative or inter-trans and multi-disciplinary tenets, which may well contribute equally or more to education research than a mixed method approach.

The benefits of and need for employing mixed-method research of support services can be compounded by the lack of institutional incentive to self-assess student support structure efficacy (Shah and Nair, 2011). Difficulties can arise in mixed-method research from the requirement of time and resources needed for this type of approach, which, if considerable, could potentially restrict the data available to draw defensible conclusions from. This can be somewhat alleviated by techniques such as pooling previously collected data or ready-built databases, as well as a purposive sampling design to target specific groups. Though, while purposive sampling is often suited to certain studies it can possibly elide important data from excluded groups. In addition, qualitative research methods, and many quantitative methods, rely on assertions that have been interpreted from answers that may have been accidentally or intentionally falsified (Dumont, 2010). Some level of uncertainty must be considered when analysing self-reported data (Dumont, 2010).

Further to this point, reflexivity and the role of the interviewer and interviewee in research has scope for consideration in an interpretative analysis of support service influence. Interactions between people within the social arena are subject to rules concerning aspects such as power and authority, rapport and transference – a research interview is no different (Pile, 1991). For this reason, the neutral distanced relationship described by Roberts (1981) – where the researcher strives for objective observation outside the social realities being researched – may be optimal, but interaction and the consequent impact of embodied social characteristics of bias and prejudice nevertheless affect it. Language, bodies, clothes, gender, age, and so on, matter in the exchanges that take place in interviews (McDowell, 2010). From qualitative to interpretative research there is a shift from a distanced and abstract research position, towards an intersubjective relationship between the interviewer and the interviewed in which both attempt to create an understanding of what is taking place around them (Pile, 1991). Pile (1991,
p.460) argues that acknowledging positionality (and limitations) in research is tantamount to its performance, stating, “problematizing the research process must be an integral part of any [research] that wants to question its own power and enable the power of others”. An interpretative account of research discourse could add to a mixed-method design by deciphering the significance of the personal nature of the interaction and the consequent impact of embodied social characteristics that are central to the affects of language and analysis (Pile, 1991, 2010a; McDowell, 2010).

As this article has attested, mixed methods can provide an effective means of robust data collection. Multiple sources of data in multiple formats (i.e. quantitative and qualitative – and interpretative) are often needed to bolster research and inform sound policy and practice, especially in the higher education sector where student outcomes are influenced by numerous sources at varying levels. The benefits of mixed-method design have been highlighted in a number of contexts while pinpointing its contribution to a study on the impact of support service initiatives on student success. It is hoped that future research can draw on the experiences of Stone et al. (2016) to encompass the vast number of effects (and affects) that determine student success after support intervention.

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References


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