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The Students We Don't See: Characterising Student Experience in Australian Higher Education using Latent Class Analysis

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Abstract

Australian higher education equity policy has traditionally relied on demographic indicators to identify students at risk. While these classifications remain essential for addressing structural disadvantage, they may obscure variation in how students experience university. Using a person-centred Latent Class Analysis (LCA), this study examined multidimensional patterns of underlying student experience and their associations with intention to leave and academic performance. Drawing on nationally representative data from the Quality Indicators for Learning and Teaching (QILT) Student Experience Survey (SES) from 2019 to 2022 (approximately 230,000 domestic undergraduate students), five latent classes were identified, characterised by distinct configurations of belonging, engagement, institutional support, satisfaction, and external pressures. These classes were stable across survey years and formed a clear hierarchy of risk. Students in the "Disengaged" and "Engaged but under-supported" classes consistently showed the highest likelihood of considering leaving university or reporting a fail grade, whereas those in the "Happy overall" class demonstrated the lowest risk. Each equity group contained a heterogeneous mix of experience classes. Findings suggest that experience-based approaches can complement existing equity frameworks by enabling more nuanced identification of student vulnerability.

***Keywords**:* Latent class analysis; student experience; intersectionality; higher education equity; student retention; academic performance.

Introduction

Intersectionality, or how multiple social identities and forms of disadvantage intersect to shape individuals' experiences and outcomes rather than operating independently (Bowleg, 2012), is now recognised as a central concept in Australian higher education equity policy. This reflects the understanding that disadvantage is rarely experienced along a single dimension and that it is often compounding in nature (Tomaszewski et al., 2020). Within this policy landscape, Australian higher education equity reporting has traditionally focused on four primary groups: First Nations Australian (Aboriginal and Torres Strait Islander) students, students with disability, students from low socio-economic status (low SES) backgrounds, and students from regional and/or remote areas (Australian Centre for Student Equity and Success [ACSES], 2024). These classifications were developed primarily to guide the allocation of funding, establish accountability, and allow for structured reporting (Naylor et al., 2016).

As a result, the use of policy-defined equity categories in student-centred contexts relies on two practical assumptions. First, that individuals can be classified within discrete administrative categories. Second, that students within a given equity category face similar patterns of challenge and risk, which enables policy responses to be designed at the group level (Naylor et al., 2016). While these categories play an important role in monitoring access and participation, variation nevertheless exists within equity groups in terms of living circumstances, forms of disadvantage, and exposure to academic and social risk. In addition, overlapping identities and intersecting forms of disadvantage may shape student experiences in ways that are not fully captured by single-category classifications (Naylor et al., 2016; Tomaszewski et al., 2020).

Consequently, in recent years, researchers have begun exploring complementary analytical approaches that can account for within-group diversity and intersectional complexity (Naylor et al., 2016; Naylor & Mifsud, 2020; Tomaszewski et al., 2020). One such approach is Latent Class Analysis (LCA), a statistical method used to identify groups of students who share similar patterns of responses across multiple aspects of their university experience (Rosato & Baer, 2012). In this context, the term "latent" refers to underlying, unobserved patterns that are inferred from observed survey responses. This approach aligns with intersectionality and multidimensionality perspectives, which recognise that student experiences are shaped by overlapping and interacting factors rather than single characteristics.

This study applies LCA to examine patterns of self-reported student experience among domestic undergraduate students in Australian higher education between 2019 and 2022, identifying distinct experience-based classes and assessing their association with student risk. The analysis identifies five latent classes that are stable across survey years. These classes form a clear hierarchy of risk, with students in the *"Disengaged"* and *"Engaged but under-supported"* classes consistently showing the highest likelihood of considering leaving university or reporting a fail grade, and those in the *"Happy overall"* class the lowest.

Literature Review

Intersectionality and Student Experience

Intersectionality becomes particularly apparent when examined through the lens of student experience. Within the Australian higher education context, student experience data reveal how disadvantage is lived and enacted within the university environment (Naylor et al., 2016; Tomaszewski et al., 2020). Experiences of belonging, academic engagement, institutional support, financial and work pressures, and freedom of expression are not distributed uniformly within equity groups; rather, they vary considerably across individuals, even among students who share the same demographic classification (Naylor et al., 2016; Slominski et al., 2024).

Understanding student success therefore requires attention not only to who students are, but also to how they experience university life across multiple domains. Prior research has consistently identified the interdependent relationship between key dimensions of student experience, including belonging, engagement, institutional support, and overall satisfaction, and student retention and academic success (Gilmore et al., 2025; Kahu & Nelson, 2018; Naylor & Mifsud, 2020). A facet of this work focuses on how external pressures, such as financial strain and competing work commitments, further shape students' capacity to engage effectively with their studies and affect their perceived and actual wellbeing at university, particularly among equity cohorts (Bennett et al., 2023; Logan et al., 2016; Universities Australia, 2018).

This raises an important methodological question: how can intersectionality and multidimensionality be examined rigorously in large-scale survey research? One approach involves the detection of underlying latent structures that capture the multidimensional nature of student experience at the individual level (Bauer et al., 2021; Slominski et al., 2024; Stevens et al., 2023).

Traditionally, educational research has relied on variable-centred methods such as regression to estimate relationships between variables, typically by quantifying the independent effects of predictors on specific outcomes (Rosato & Baer, 2012). While powerful for hypothesis testing and prediction, these approaches are less suited to identifying naturally occurring subgroups characterised by complex, co-occurring patterns of experience. Controlling for a single social category can obscure diversity and oversimplify the structure of disadvantage, as student experiences are often shaped by intersecting identities (Bowleg, 2012; Stevens et al., 2023).

In response, researchers across psychology, social work, and public health have increasingly adopted person-centred approaches to better account for the intersectional and multidimensional nature of social experiences (Bauer et al., 2021;

Stevens et al., 2023). These approaches focus on patterns at the individual level, enabling the identification of subgroups characterised by distinct configurations of characteristics (Parviainen et al., 2020; Yang et al., 2023).

Latent Class Analysis

LCA is an unsupervised, person-centred approach that examines whether patterns of association among observed variables reflect an underlying latent structure (Rosato & Baer, 2012), assuming populations consist of underlying subgroups that differ from one another but are internally similar (Muthén & Muthén, 2000; Weller et al., 2020). In essence, LCA identifies latent subgroups based on shared response patterns across categorical indicators (Slominski et al., 2024).

In practical terms, LCA groups students based on similar patterns of survey responses, identifying subgroups who share common experiences across multiple domains. Rather than analysing individual variables separately, this approach captures how different aspects of student experience co-occur within individuals.

The key distinction between variable-centred and person-centred approaches lies in how the sample is characterised. Variable-centred methods describe relationships at the population level, whereas person-centred approaches identify subgroups defined by shared configurations of characteristics (Slominski et al., 2024; Weller et al., 2020). LCA has been widely applied across epidemiology, mental health, and education, including studies of discrimination, engagement, academic wellbeing, and diversity in higher education contexts (Byrd & Andrews, 2016; Korhonen et al., 2014; Lukkien et al., 2025; Yang et al., 2023).

In the context of Australian higher education, this approach offers a novel means to identify distinct experience-based classes within national survey data and to examine how these multidimensional patterns relate to key outcomes such as intention to leave and academic performance.

Research Questions

In using LCA to explore defined student groups in the Quality Indicators for Learning and Teaching (QILT) Student Experience Survey (SES) response set, this study addresses the following research questions:

Q1: What latent experience classes can be identified among Australian university students in the SES, based on patterns of engagement, belonging, and perceived support?
Q2: How do these latent experience classes intersect with traditional equity group classifications?
Q3: Are certain latent experience classes associated with elevated risk of disengagement or consideration of leaving university?

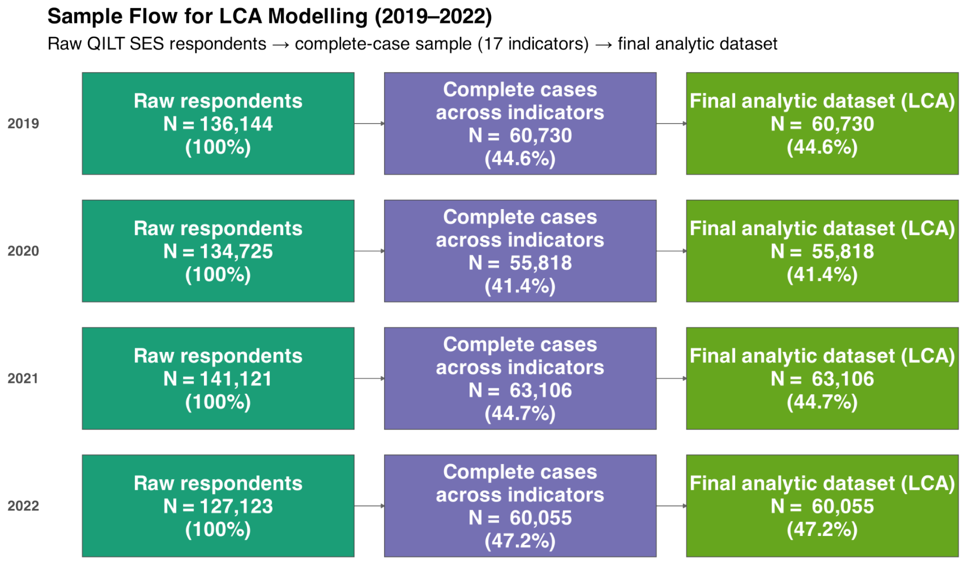
Methods

Data Source and Sample

The study utilised data from the Australian QILT SES, a nationally administered survey of higher education students, collected between 2019 and 2022 (Quality Indicators for Learning and Teaching, 2019, 2020, 2021, 2022). The QILT SES captures students' engagement, learning environment, and overall experience. Across these years, the raw dataset comprised 539,113 domestic undergraduate survey respondents. Following indicator recoding and restriction to complete cases on the experience measures required for LCA, the final analytic sample included 239,709 students. This reduction reflects item-level non-response across multiple experience indicators rather than exclusion based on demographic or equity characteristics. Complete-case analysis was adopted to preserve the integrity of students' reported experiences, given the subjective nature of QILT SES items. Sample flow of LCA applied in this study is provided in Figure 1.

Figure 1

Sample Flow for LCA Modelling 2019–2022



Measures

1. Experience Indicators

The LCA was conducted using a set of QILT SES categorical items capturing key dimensions of student experience. These included measures of belonging, engagement, perceived institutional support, and aspects of the learning and teaching environment. Indicators were selected to reflect students' lived experience of university rather than demographic or administrative characteristics. All indicators were treated as categorical variables for model estimation (Table 1).

Table 1

SES Indicators Used in Latent Class Analysis, Response Scales, and Coding Decisions

SES Indicator	Response Scale
INTEROUT: Interactions with peers outside study	4-point frequency scale (1 = Never, 4 = Very often)
INTERDIF: Interacted with different students	4-point frequency scale (1 = Never, 4 = Very often)
OPPLOC: Opportunities to interact with local students	5-point Likert (1 = Not at all, 5 = Very much)
TCHHELP: Teaching staff helpful and approachable	5-point Likert (1 = Not at all, 5 = Very much)
TCHACTIV: Teaching staff stimulate engagement or interest	5-point Likert (1 = Not at all, 5 = Very much)
QOTSAT: Satisfied with quality of teaching	Binary (0 = Not satisfied, 1 = Satisfied)
RESRSAT: Satisfied with learning resources	Binary (0 = Not satisfied, 1 = Satisfied)
SUPPSAT: Satisfied with student support overall	Binary (0 = Not satisfied, 1 = Satisfied)
OFFSUP: Offered relevant institutional support	5-point Likert (1 = Not at all, 5 = Very much)
DEVELSAT: Skills development and learning outcomes	Binary (0 = Not satisfied, 1 = Satisfied)
FOEXSAT: Freedom of expression and absence of discrimination	Binary (0 = Not satisfied, 1 = Satisfied)
ASTDLIV: Living arrangements negatively affect study	5-point Likert (1 = Not at all, 5 = Very much)
ASTDFIN: Financial circumstances negatively affect study	5-point Likert (1 = Not at all, 5 = Very much)
ASTDWOR: Paid work negatively affects study	5-point Likert (1 = Not at all, 5 = Very much)
DISCUSS: Participation in online or face-to-face learning discussions	4-point frequency scale (1 = Never, 4 = Very often)
WRKOTHER: Worked with other students on learning tasks	4-point frequency scale (1 = Never, 4 = Very often)

Note. Freedom of expression items were introduced in the Student Experience Survey from 2021 onwards and were therefore unavailable for earlier survey years. Responses were dichotomised: 5-point scales (4–5 = endorsed), 4-point scales (3–4 = endorsed); binary items unchanged.

2. Equity Variables

Equity status was defined using standard Australian higher education classifications, including First Nations status, disability, low SES, and regional or remote background (ACSES, 2024), and was not included in LCA class formation.

3. Outcomes

Two outcomes were used to characterise risk across latent classes: consideration of leaving university and academic performance, operationalised using QILT SES self-reported measures. These outcomes were selected as indicators of student risk and success, reflecting both academic performance and intentions related to retention, and were not included in LCA class formation.

4. Missing Data Handling

A complete-case approach was adopted for LCA indicators. Descriptive comparisons were performed to assess potential selection effects between included and excluded students.

Latent Class Analysis

LCA was used to identify unobserved subgroups of students characterised by similar patterns of experience across the selected indicators. Models with increasing numbers of classes were estimated. Model selection was based on multiple criteria, including statistical fit indices (Bayesian Information Criterion, Akaike Information Criterion), entropy, class size, and interpretability (Yang et al., 2023). The final model was selected based on overall model fit and conceptual coherence.

Class Assignment

In LCA, individuals are not deterministically assigned to groups. Instead, based on their response patterns across the observed indicators, each respondent is assigned probabilities representing their likelihood of belonging to each latent class (k) (Slominski et al., 2024). For descriptive and comparative analyses, respondents were assigned to their most likely class using modal class assignment.

Modelling Workflow

Analysis proceeded in five steps. First, latent classes were identified using LCA. Second, classes were characterised based on their response patterns. Third, their distribution across equity groups was examined. Fourth, differences in consideration of leaving and academic performance were compared across classes. Finally, experience-based classes were compared with traditional equity classifications to assess the added value of a person-centred approach. All analyses were conducted in R (version 4.4.2), using poLCA (version 1.6.0.1).

Results

Identification of Experience-based Classes

Five distinct latent experience classes emerged consistently across 2019–2022 (Table 2).

Table 2

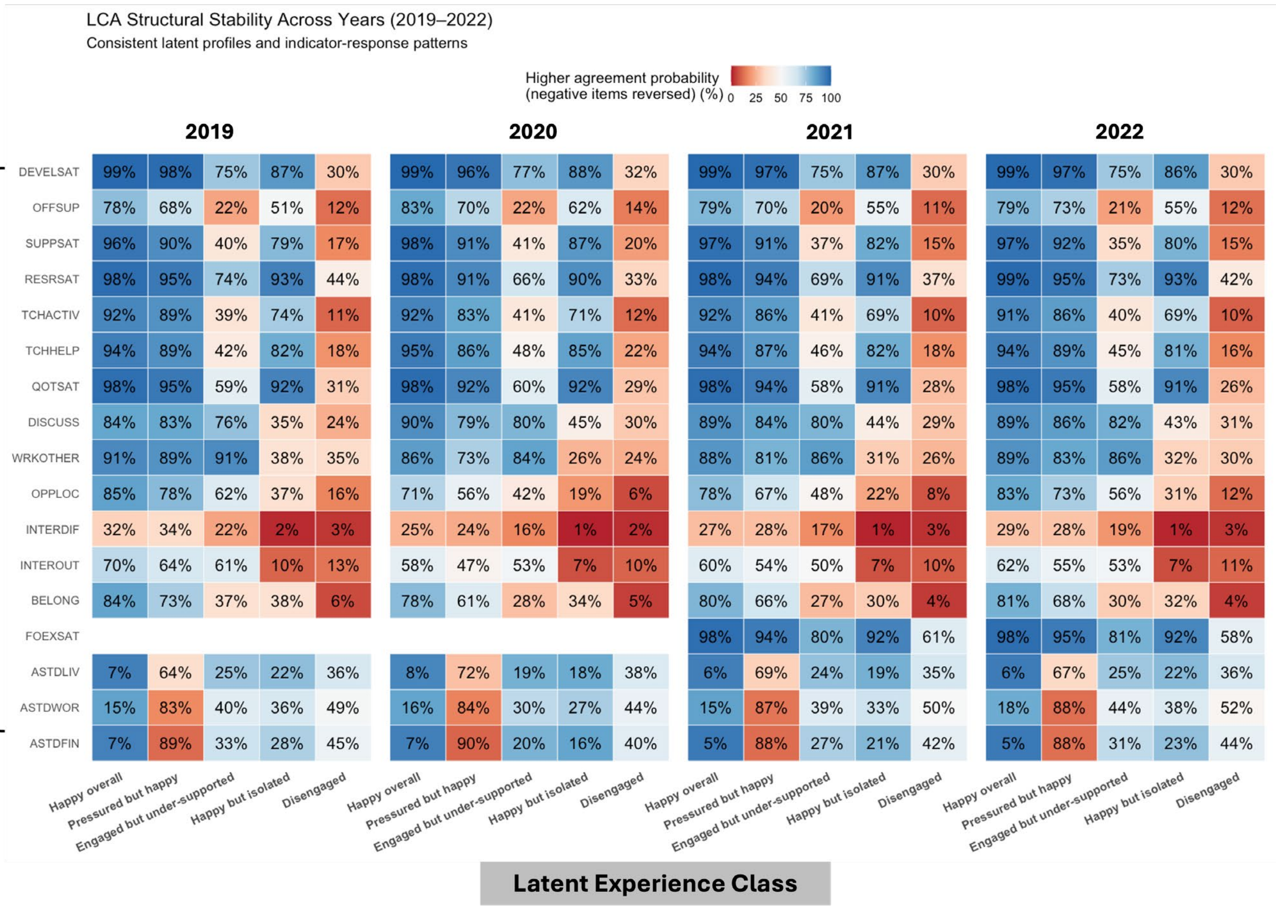
Summary of Latent Experience Classes

Class	Core pattern
Happy overall	High belonging, engagement, teaching quality; low external pressures
Pressured but happy	Positive institutional experiences; high work/financial/living pressures
Engaged but under-supported	High engagement and skills development; lower perceived support/resources
Happy but isolated	High teaching satisfaction; low social integration and belonging
Disengaged	Low endorsement across engagement, belonging, support, and satisfaction

Class structures were highly consistent across years, indicating stable patterns of student experience over time (Figure 2).

Figure 2

Latent Experience Classes by Year (2019–2022)

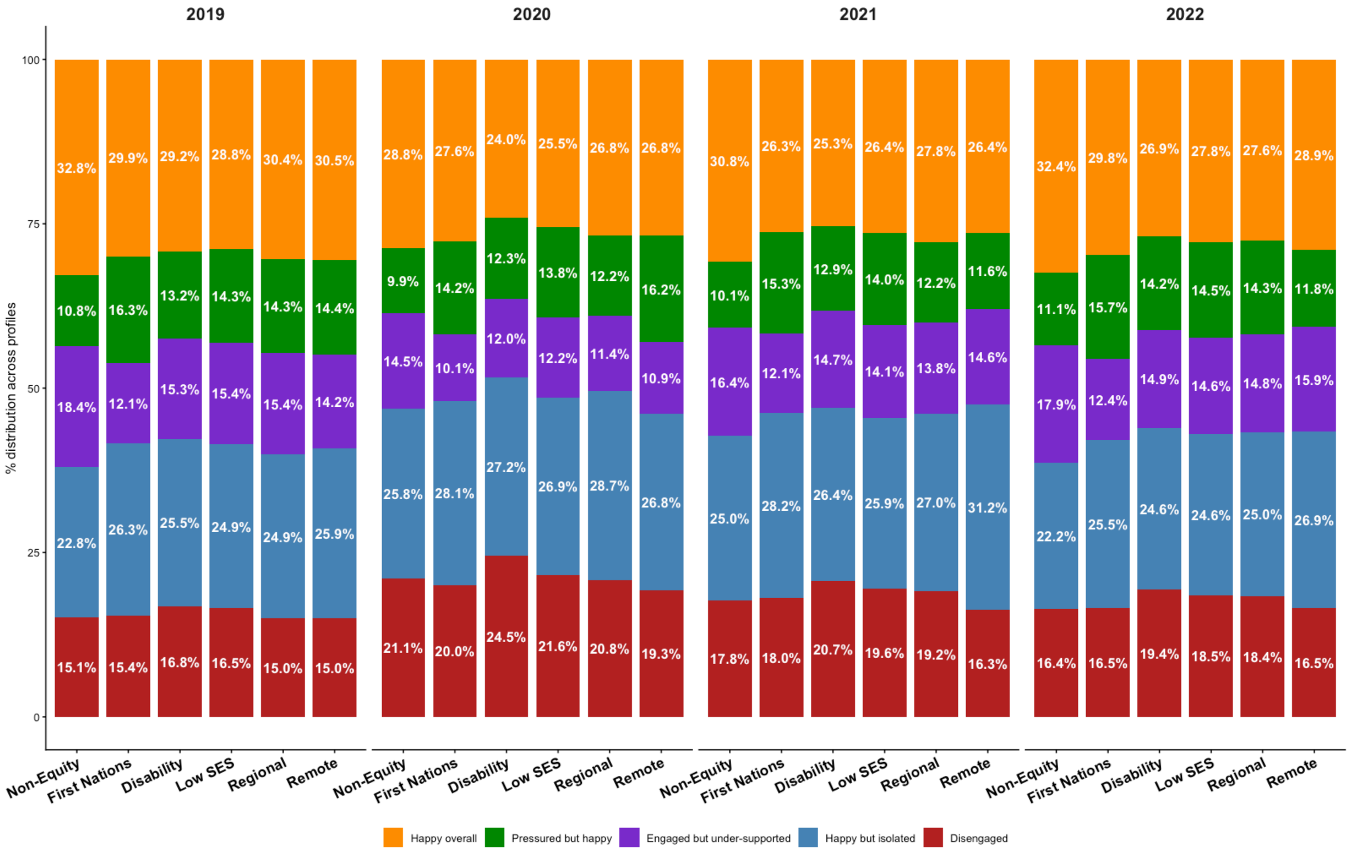


Distribution of Classes Across Equity Groups

Figure 3 presents the distribution of latent experience classes across policy-defined equity groups. All five classes were observed across every equity category, indicating substantial heterogeneity within administratively defined groups and demonstrating that no equity group was characterised by a single dominant class. Compared with non-equity students, equity groups showed higher representation in classes characterised by lower belonging or higher external pressures; however, sizeable proportions of equity students were also classified within more positive experience classes, including *"Happy overall"* and *"Pressured but happy"*. This pattern was evident across First Nations Australians, low SES, disability, and regional or remote groups and remained consistent across cohorts from 2019 to 2022. Collectively, these findings underscore the limitations of group-level equity classifications and highlight the value of experience-based classes uncovering patterns of student experience that standard measures frequently obscure.

Figure 3

The Distribution of Latent Profiles by Equity Group Across the Years (2019–2022)

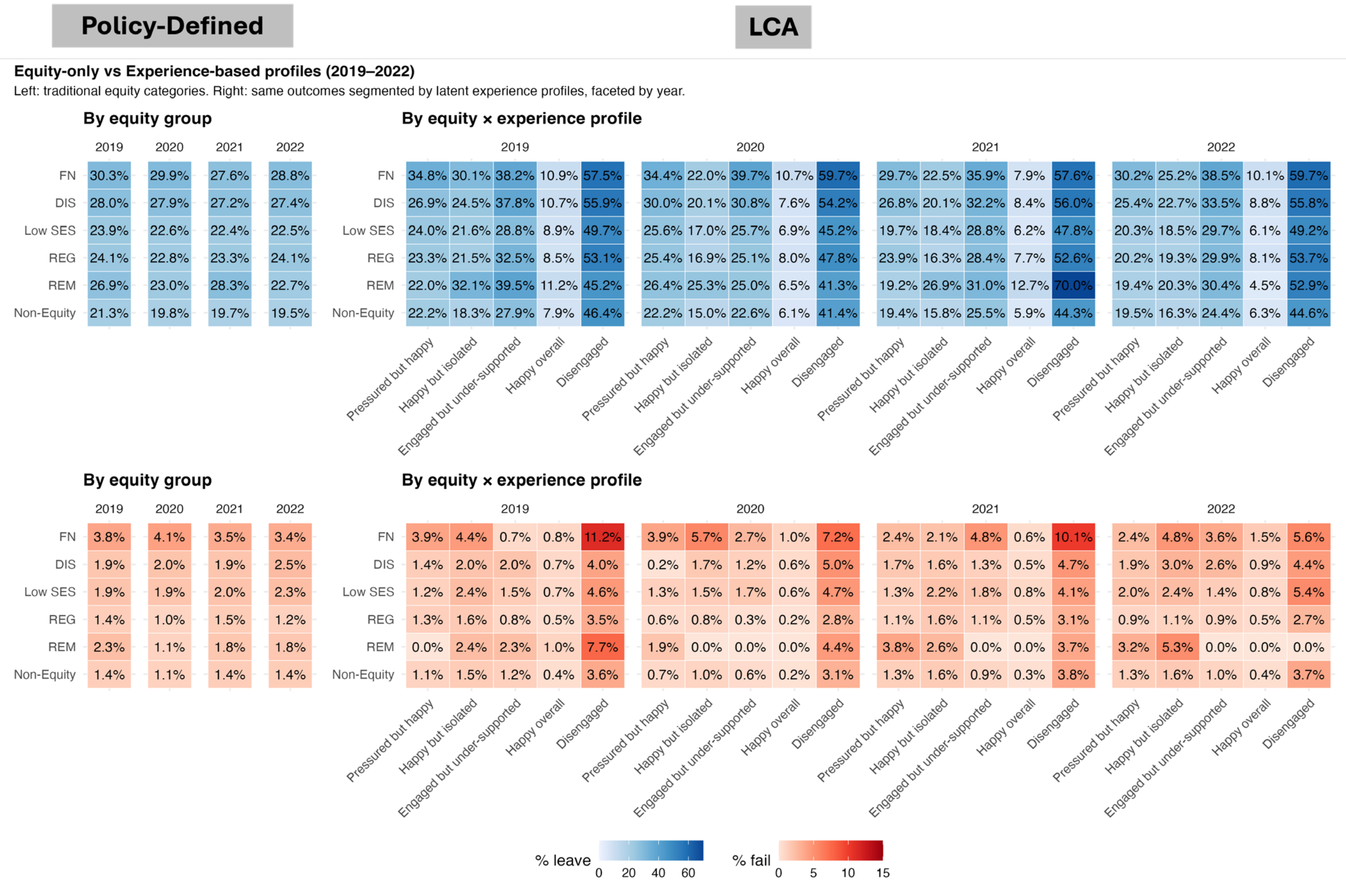


Experience Classes and Student Risk Indicators

Figure 4 compares risk outcomes — consideration of leaving university and academic performance (measured by failing subjects) — across both policy-defined equity groups and the latent experience classes. When viewed through the lens of equity categories alone, differences in risk appeared comparatively modest. In contrast, the experience-based classes revealed substantially greater differentiation across both outcomes, suggesting that demographic classifications alone mask meaningful variation in student risk.

Figure 4

Policy-defined Versus LCA Outcomes Across the Years (2019–2022)



Note. FN: First Nations Australians, DIS: Students with disability, Low SES: students from low socio-economic status (SES) background, REG: students from regional area, REM: students from remote area.

Across all equity groups, students assigned to the "*Disengaged"* and "*Engaged but under-supported"* classes exhibited markedly higher levels of considering leaving university and failing subjects than students in more positive classes. These elevated risks were observed among both equity and non-equity students, suggesting that the vulnerabilities captured by the experience-based classes extend beyond what traditional equity markers are able to detect. Conversely, equity group students placed in positive classes such as "*Happy overall"* or "*Pressured but happy"* consistently exhibited lower risk levels than non-equity students in less favourable classes. These patterns highlight the value of experience-based classification in identifying heightened risk that may otherwise remain obscured within demographic groupings. To sum up, the findings show that the latent classes are stable across survey years and that the experience patterns they capture are strongly associated with key measures of student success. They further indicate that relying solely on policy-defined equity classifications can conceal meaningful heterogeneity in student experience, particularly in dimensions most closely linked to engagement, retention, and academic performance.

Discussion and Conclusion

This paper reports on the use of a person-centred approach — LCA — to identify five distinct latent classes of student experience spanning multiple dimensions. These classes — *"Pressured but happy"*, *"Happy but isolated"*, "*Engaged but under-supported"*, *"Happy overall"*, and *"Disengaged"* — represent empirically distinct patterns of how students experience university life.

The latent classes formed a clear and persistent hierarchy of risk. Students in the *"Disengaged"* and *"Engaged but under-supported"* classes consistently exhibited the highest likelihood of considering leaving university or reporting a fail grade, whereas those in the *"Happy overall"* class demonstrated the lowest risk. This ordering was not year- or cohort-specific; both the class structure and the associated risk gradient remained stable across survey years.

Beyond this risk hierarchy, the latent classes cut across traditional equity categories. This confirms the research and policy work around intersectionality that seeks to navigate the heterogeneous mix of equity students' lived experiences and offers a path to providing broader measures of such patterns rather than by equity demographic classification alone.

This accords with research on intersectionality, which highlights that disadvantage is rarely experienced along a single demographic axis but instead emerges through overlapping and multidimensional processes (Bowleg, 2012; Yang et al., 2023). While policy-defined equity categories remain essential for identifying structural disadvantage, the present results suggest that lived experience does not align neatly with those administrative classifications. This supports growing calls for more nuanced, person-centred approaches in social and educational research that move beyond additive models of risk (Goodwin et al., 2018; Naylor et al., 2016; Weller et al., 2020).

Limitations and Future Research

Several limitations should be acknowledged. The analysis relied on complete-case data across multiple subjective survey items, resulting in a reduction in sample size. However, this was consistent across years, and diagnostic checks suggested that equity students were not disproportionately excluded. The QILT SES is also cross-sectional, meaning that outcomes such as considering leaving reflect intent at the time of the survey rather than observed attrition. As the data reflect student experiences up to 2022, findings should be interpreted in light of potential changes in the higher education context in subsequent years. Future research using linked or longitudinal data would be valuable to examine whether these experience-based classes predict subsequent withdrawal or completion, and how they evolve over time.

Implications

By applying LCA within a national higher education dataset, this study extends intersectionality-informed approaches in the Australian equity context and demonstrates how empirically derived experience classes can reveal heterogeneity that variable-centred methods may overlook. Importantly, this does not challenge the relevance of existing equity frameworks; rather, it shows how person-centred analyses can complement policy-defined categories by illuminating how disadvantage is experienced within and across groups. Integrating experience-based insights alongside demographic classifications may therefore support more nuanced identification of student vulnerability.

These findings have important implications for practice. Experience-based profiling offers a complementary approach to traditional equity frameworks by enabling more targeted identification of students at risk. In particular, students in the *"Disengaged"* and *"Engaged but under-supported"* classes may benefit from interventions that strengthen belonging, engagement, and access to support services. Future research could examine how institutional strategies can be aligned with these experience-based profiles to improve student retention and academic success. Importantly, this would benefit from data integration between the SES and institutional datasets on student engagement and academic process. This would both motivate and inform new approaches that are complementary to existing mechanisms for identifying and addressing issues of student wellbeing, engagement, and outcomes.

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